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Biometric Sample Quality and its Application to Multimodal Authentication Systems

–TESIS DOCTORAL–

Calidad de muestras biométricas y su aplicación en sistemas de autenticación multimodal

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Colophon

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The research described in this Thesis was carried out within the Biometric Recognition Group – ATVS at the Dept. of Ingeniería Audiovisual y Comunicaciones, Escuela Universitaria de Ingeniería Técnica de Telecomunicación, Universidad Politécnica de Madrid (in 2004); and at the Dept. of Ingeniería Informática, Escuela Politécnica Superior, Universidad Autónoma de Madrid (from 2004 to 2008). The project was partially funded by a PhD scholarship from Comunidad de Madrid and Fondo Social Europeo.

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Abstract[1]

This Thesis is focused on the quality assessment of biometric signals and its application to multimodal biometric systems. Since the establishment of biometrics as an specific research area in late 90s, the biometric community has focused its efforts in the development of accurate recognition algorithms and nowadays, biometric recognition is a mature technology that is used in many applications. However, we can notice recent studies that demonstrate how performance of biometric systems is heavily affected by the quality of biometric signals. Quality measurement has emerged in the biometric community as an important concern after the poor performance observed in biometric systems on certain pathological samples.

We first summarize the state-of-the-art in the biometric quality problem. We present the factors influencing biometric quality, which mainly have to do with four issues: the individual itself, the sensor used in the acquisition, the user-sensor interaction, and the system used for processing and recognition. After that, we give strategies to ensure the best possible quality of acquired biometric samples. Next, we present existing frameworks for evaluation of the performance of biometric quality measures. The relationship between human and automatic quality assessment, as well as the role of quality measures within biometric systems is then analyzed. Lastly, we summarize standardization efforts related to biometric quality and we point out further issues and challenges of the quality problem.

The experimental part of the Thesis starts with the study of quality in fingerprint images. We evaluate the impact of selected image quality measures in the performance of the two most used approaches for fingerprint recognition using a multi-session and a multi-sensor database. It is observed high correlation between the different quality measures in most cases, although some differences are found depending on the sensor. The behavior of the two matchers under varying image quality conditions has been also found to be different.

We then study the problem of quality assessment in *off-line* signature images. We present several measures aimed to predict the performance of off-line signature verification systems measuring factors like signature legibility, complexity, stability, duration, etc. We also present a new matcher based on local contour features, which is compared with two other approaches. Some remarkable findings of this chapter are that

[1]Se incluye un resumen extenso de la Tesis en español en el Capítulo 7.

better performance is obtained with legible signatures and skilled forgeries, or that performance is worsened with highly variable signatures.

Finally, we contribute with a quality-based multibiometric architecture that is generalizable to biometric systems working with multiple sources of information (different modalities, matchers, acquisition devices, etc.). In this approach, quality is used to switch between different system modules depending on the data source, and to consider only data of enough quality. We compare the proposed architecture with a set of simple fusion rules. It is demonstrated that the proposed system outperforms the rest when coping with signals originated from heterogeneous biometric sources, pointing out its effectiveness. An additional overall improvement of 25% is observed in the EER by incorporating a quality-based score rejection scheme, showing the benefits of incorporating quality information in biometric systems.

TO MY FAMILY AND LIGHT.

"I do not know what I may appear to the world, but to myself I seem to have been only like a boy playing on the sea-shore, and diverting myself in now and then finding a smoother pebble or a prettier shell than ordinary, whilst the great ocean of truth lay all undiscovered before me".

−Sir Isaac Newton.−

Physicist, mathematician, astronomer, natural philosopher, alchemist and theologian.

His PhilosophiæNaturalis Principia Mathematica, published in 1687, is said to be the greatest single work in the history of science, and is the basis for modern engineering.

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This Thesis summarizes the work I have carried out during my Ph.D. studies with the ATVS - Biometric Recognition Group since 2004. This research group was established in 1994 at the Dept. of Ingeniería Audiovisual y Comunicaciones (DIAC) of the Universidad Politécnica de Madrid (UPM) and since 2004, it is affiliated to the Dept. of Ingeniería Informática of the Universidad Autónoma de Madrid (UAM). The work presented in this Thesis has been conducted at both institutions. This Thesis has been mainly supported by a Ph.D. scholarship granted to the author by Comunidad de Madrid and Fondo Social Europeo, which covered the period between October 2004 and October 2008, and also by various Spanish and European projects referenced in the related publications.

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A las personas que me acompañan en el viaje de la vida y sin las cuales nada de esto tendría sentido, que no necesitan ser nombradas porque sabéis quiénes sois.

Fernando Alonso-Fernandez
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Chapter 1

Introduction

This PhD Thesis is focused on biometric sample quality assessment, and its application in multimodal biometric systems. In particular, this PhD Thesis explores the quality assessment problem in two traits: fingerprints and signature images. Contrarily to fingerprint images, where we can objectively define quality, in behavioral traits like signature it is not straightforward to define what quality is. We also explore the incorporation of quality information in multibiometric systems, showing the benefits of adapting the system to the quality of the sample at hand.

Every human being has experience in recognizing a familiar person based on his/her specific characteristics, like voice, face, gait, handwriting, signature and so on. Some people, more than others, have even the ability to recognize unknown persons, after having seen or heard them. Nowadays, due to the expansion of the networked society, there as increasing need for reliable personal identification by automatic means. Establishing the identity of individuals is recognized as fundamental not only in numerous governmental, legal or forensic operations, but also in a large number of civilian applications. This has resulted in the establishment of a new research and technology area known as biometric recognition, or simply *biometrics* (Jain *et al.*, 2006). The term "biometrics" refers to automatic recognition of an individual based on behavioral and/or anatomical characteristics (e.g., fingerprints, face, iris, voice, signature, etc.).

The difficulties associated with person identification and individualization were already highlighted by the pioneers of forensic sciences. Alphonse Bertillon developed in the eighteenth century an anthropometric identification approach, based on the measure of physical characteristics of a person (Bertillon, 1893). Automatic person authentication has been a subject of study for more than thirty five years (Atal, 1976; Kanade, 1973), although it has not been until the last decade when biometric research has been

established as an specific research area (Bolle *et al.*, 2004; Jain *et al.*, 1999, 2008; Li and Jain, 2004; Maltoni *et al.*, 2003; Nanavati *et al.*, 2002; Ratha and Bolle, 2004; Ross *et al.*, 2006; Wayman *et al.*, 2005; Zhang, 2002). In order to provide certain services, a variety of applications require reliable confirmation of a person's identity by recognizing an individual. The increasing interest of biometrics in the last years is also evidenced by efforts focused on the organization of specific conferences (AVBPA, 2005; BTAS, 2007; ICB, 2007; ICBA, 2004; SPIE-BTHI, 2008), several cooperative international projects (BioSec, 2004; BioSecure, 2004; COST-2101, 2006; COST-275, 2003), the standardization in the field of biometrics (BioAPI, 1998; CBEFF, 2001; INCITS M1, 2007; ISO/IEC JTC1 SC37, 2002) and the development of common benchmark tools and evaluation campaigns for biometric systems (BMEC, 2007; FpVTE, 2003; FRVT, 2006; FVC2006, 2006; ICE, 2006; Mansfield and Wayman, 2002; NIST SRE, 2006; SVC, 2004; Wayman *et al.*, 2005). There has been also in the last years an increasing institutional interest from government (DoD, 2007), industry (IBG, 2007), research bodies (NIST-ITL, 2007) and the establishment of international consortia dedicated specifically to biometric recognition (BC, 2005; EBF, 2003).

This introductory chapter presents the basics of biometric systems, including properties, common performance measures and the combination of multiple sources of biometric information into a *multibiometric* system. We also outline the topic of biometric quality assessment, from which the motivation of this Thesis is also derived. We finish the chapter by stating the Thesis, giving an outline of the Dissertation, and summarizing the research contributions originated from this work.

Although no special background is required for this chapter, the reader will benefit from introductory reading in biometrics as Jain *et al.* (2006, 2004b). A deeper reference is Jain *et al.* (2008).

1.1 Biometric systems

A biometric system essentially makes use of behavioral or anatomical characteristics to recognize individuals by means of pattern recognition techniques and statistical methods. Biometric systems are used nowadays in many government and civilian applications, offering greater convenience and several advantages over traditional security methods based on something that you *know* (normally a secret password or PIN, which can be shared, forgotten or copied) or something that you *have* (a physical object that is presented to receive access, such as keys, magnetic cards, identity documents, etc., which can be shared, stolen, copied or lost). Without sophisticated means, biometrics

are difficult to share, steal or forge and cannot be forgotten or lost. Therefore, this latter solution provides a higher security level in identity prove. In addition, the combination of possession and knowledge with biometrics makes the identity proof even more secure.

Such a system involves four aspects (Jain *et al.*, 2000): data acquisition and preprocessing, feature extraction, similarity computation and decision-making. The digital representation recorded in the system database, which describes the characteristics or features of a physical trait, is defined as a *template*. It is obtained by a feature extraction algorithm, and is generated through an *enrolment* or *training* process, which is depicted in Figure 1.1 (top). The recognition process can be performed in two modes by a biometric system (Jain *et al.*, 2008):

- **Identification**. In this mode, the correct identity of an unknown person is selected from the database of registered identities. It is called a "one to many" *matching* process, because the system is asked to complete a comparison between the persons biometrics and all the biometric templates stored in the database (Figure 1.1, middle). The system can take either the "best" match, or it can score the possible matches, and rank them in order of similarity. Two modes of identification are possible, positive and negative. The positive identification tends to determine if a given person is really in a specific database, whereas a negative identification determines if a given person is not in a "watchlist" database.

- **Verification**. This mode consists in verifying whether a person is who he or she claims to be. It is called a "one to one" matching process, as the system has to complete a comparison between the person's biometric and only one chosen template stored in the database (Figure 1.1, bottom). Such a method is applied when the goal is to secure and restrict specific accesses with obviously cooperative users.

This Thesis is focused on biometric *verification* (also called *authentication*). In this mode, the *clients* or *targets* are known to the system (through the *enrolment* process), whereas the *impostors* can potentially be the world population. The result of the comparison between the biometric sample X provided by the user and his/her claimed identity T is a similarity score s, which can be further normalized to s_n before comparing it to a *decision threshold*. If the score is higher than the decision threshold, then the claim is accepted, otherwise the claim is rejected.

Depending on the biometric trait used by the system, impostors may know information about the client that lowers verification performance when it is exploited (e.g.

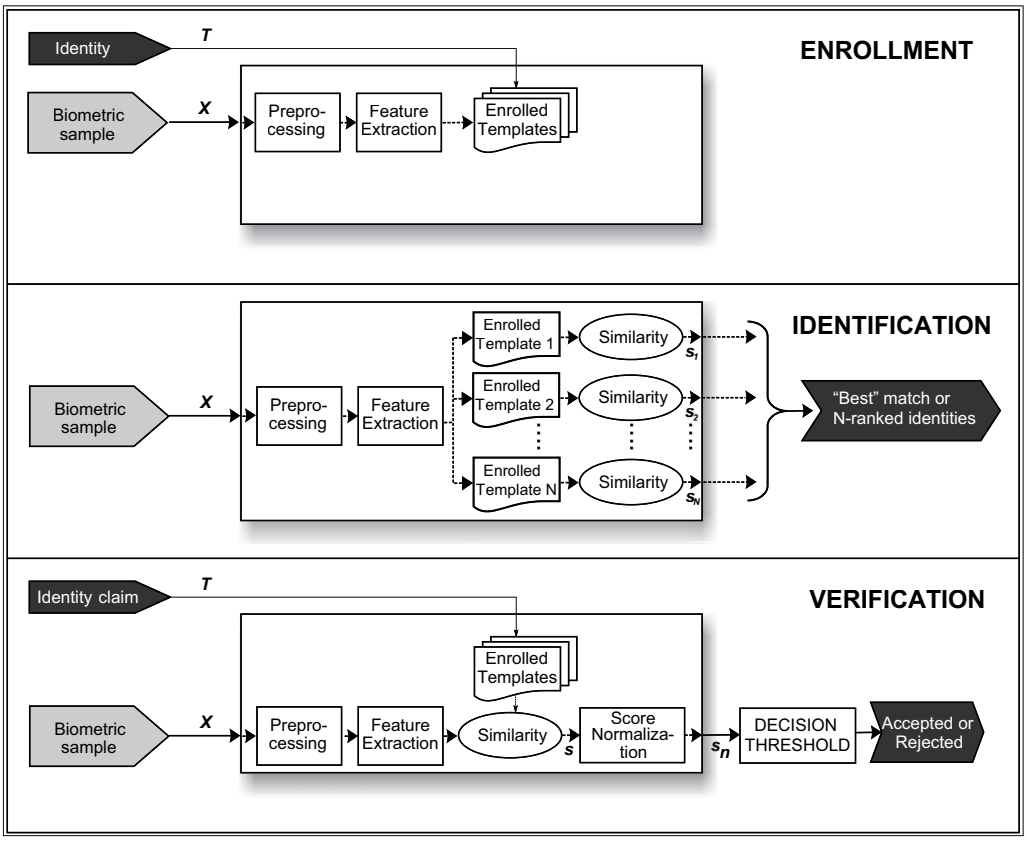


Figure 1.1: **System model of biometric authentication.**

signature shape in signature verification). As a result, two kinds of impostor are usually considered, namely: *i*) *casual impostors* (producing *random forgeries* in case of signature recognition), when no information about the target user is known, and *ii*) *real impostors* (producing *skilled forgeries* in the case of signature recognition), when some information regarding the biometric trait being forged is used.

Biometric traits can be classified into *anatomical* and *behavioral* traits (Jain *et al.*, 2006). Examples of anatomical traits are: iris, fingerprint, hand, retinal scan, DNA, etc. and examples of behavioral traits are: speech, signature, handwriting, etc. Anatomical characteristics can be measured on a part of the body at some point in time (passive), and are always *present*. On the other hand, behavioral characteristics are learned or acquired over time (active) and are produced with a special effort, requiring a "realization" (e.g. a signature realization or a voice utterance). Hence, they are dependent to some degree on the individual's state of mind. Because of that, anatomical traits show less time variability than behavioral traits. Voice biometric is viewed as a combination

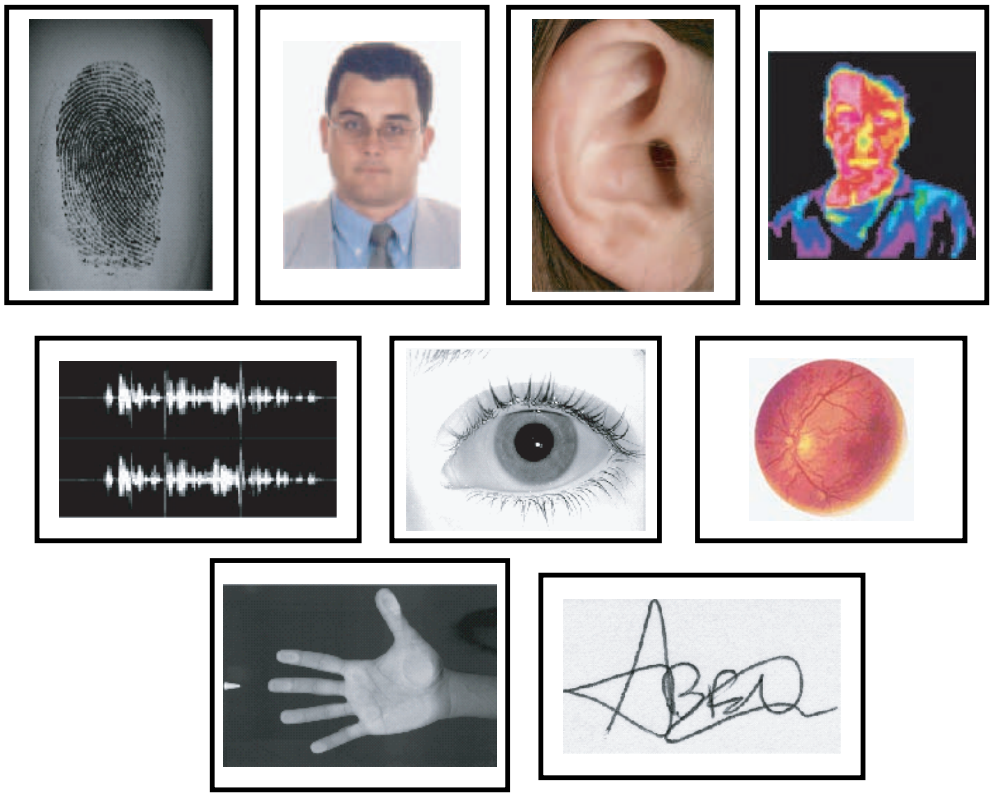


Figure 1.2: **Example of biometric traits.**

of anatomical and behavioral traits (Jain *et al.*, 2004b). Indeed, the voice depends on physical features such as vibrations of vocal cords and vocal tract shape, but also on behavioral features, such as the state of mind of the person who speaks.

Some of these traits have a long history and can be considered mature technologies. But contrary to the common belief, most of them, even the established traits like fingerprints (Maltoni *et al.*, 2003) are still challenging research topics. Examples of several biometric traits are given in Figure 1.2.

Ideally any human characteristic should satisfy the following properties to be used as a biometric identifier (Jain *et al.*, 2004b):

- **Robustness over time**: the characteristic should not change (*Permanence*).
- **Distinctiveness over the population**: a great variation of the characteristic should exist (*Uniqueness*).
- **Availability**: Ideally, the whole population should possess the characteristic (*Universality*).

- **Accessibility**: The characteristic should be easy to acquire (*Collectability*).

Besides these basic properties, some additional properties have to be considered in the context of a biometric system:

- **Performance**, which refers to all the factors that influence and affect the accuracy, efficiency, robustness, computational speed and resource requirements of a biometric system.
- **Acceptability**: The population should accept the fact that the characteristic is taken from them.
- **Circumvention**, which refers to the ability of a system to resist against potential threats and spoof attacks.
- **Exception handling**, which has to do with the ability to complete a manual matching process in the case of an impossibility of feature extraction and modality use for certain persons.
- **System cost**, which refers to all the costs of the system components, in adequate and normal use.

A practical biometric system should meet the specified recognition accuracy, speed, and resource requirements, be harmless to the users, be accepted by the intended population, and be sufficiently robust to various fraudulent methods and attacks to the system. Unfortunately, none single biometric satisfies all the above mentioned properties. While some biometrics have easy and friendly collectability (e.g. face or voice), their distinctiveness is low. Other biometrics with high distinctiveness are not easy to acquire (e.g. iris).

1.2 Multibiometric systems

In multibiometric systems, multiple sources of biometric information are combined with the purpose of overcoming some of the limitations shown by unibiometric systems (Ross *et al.*, 2006). Using a single trait for recognition is often affected by practical problems like:

1. Noise in sensed data due to imperfect or variable acquisition conditions, resulting in individuals being incorrectly rejected by the system.

2. Non-universality, due to individuals whose biometric data is not meaningful to the system, resulting in a Failure to Enroll (FTE) error and in the need of an exception procedure to handle with them.

3. Lack of distinctiveness of the biometric trait, due to an implicit upper bound in the recognition accuracy that a trait can provide.

4. Spoof attacks by means of imitation of behavioral traits (voice, signature, etc.) or synthetic reproductions of anatomical traits (e.g. fingerprint or iris), resulting in impostors being incorrectly accepted.

The use of multiple biometric indicators for identifying individuals has been shown to increase accuracy and population coverage, while decreasing vulnerability to spoofing. Multibiometric systems integrate the evidence presented by multiple sources. Two broad levels of fusion can be defined: fusion *before* matching and fusion *after* matching. Fusion before matching include fusion at the sensor and the feature level, while fusion after matching include fusion at the matching score, rank and decision levels. This classification is based on the fact that the amount of information available for fusion is enormously reduced once the matching is done. Integration at the matching score level is the most common approach in multibiometric systems due to the ease in accessing and processing the scores generated by different matchers (Fierrez-Aguilar, 2006; Ross *et al.*, 2006). In score-level fusion, the different scores are combined to generate a new matching score that is then used for recognition.

Fusion methods at the matching score level are broadly classified into three categories: density-based methods, transformation-based methods and classifier-based methods (Ross *et al.*, 2006). In *density-based fusion methods*, joint-density functions $p(\mathbf{s}|\omega_0)$ and $p(\mathbf{s}|\omega_1)$ of the genuine (ω_0) and impostor (ω_1) classes are estimated for a given score vector $\mathbf{s} = [s_1, s_2, \cdots, s_R]$, where R is the number of matchers. The Bayes decision rule is then applied (Duda *et al.*, 2004):

$$\begin{array}{c} \text{Assign} \quad \mathbf{s} \rightarrow \omega_i \quad \text{if} \\ \frac{p(\mathbf{s}|\omega_i)}{p(\mathbf{s}|\omega_j)} > \tau, i \neq j \quad \text{and} \quad i,j = \{0,1\} \end{array} \tag{1.1}$$

where $p(\mathbf{s}|\omega_i)/p(\mathbf{s}|\omega_j)$ is a *likelihood ratio* and $\tau = P(\omega_j)/P(\omega_i)$ is a pre-determined threshold that depends on the *a priori* probability of observing classes ω_j and ω_i[1].

[1]Bayes' rule as expressed here assumes that the cost of each type of misclassification error is the same for all possible classes (Duda *et al.*, 2004). Since this particularization has not been considered in this Thesis, we will not introduce misclassification costs for clarity.

Estimation of the density $p(\mathbf{s}|\omega_i)$ is done from a training set of matching score vectors using parametric or non-parametric techniques. Several approaches following this method have been proposed in the literature (Dass *et al.*, 2005; Kittler *et al.*, 1998; Ross *et al.*, 2006). In order to accurately estimate the density functions, a large number of training samples is usually needed, especially if the dimensionality of the vector $\mathbf{s}$ is large. In *transformation-based fusion methods*, matching scores are directly combined using simple fusion operators (such as the sum of scores, the maximum/minimum, etc.) (Kittler *et al.*, 1998). In this case, a normalization process is needed to transform the different matching scores into a common domain (Jain *et al.*, 2005). *Classifier-based fusion methods* use the matching scores from the multiple matchers as input to a trained pattern classifier (Duda *et al.*, 2004) in order to determine the class label (genuine or impostor), instead of giving an scalar value. In this case, the scores usually do not need to be transformed into a common domain prior to the classification, and a large number of training samples is also often needed to compute the parameters of the classifier. Several classifiers have been used in the biometric literature to combine scores from different matchers: hyper BF networks (Brunelli and Falavigna, 1995), k-Nearest Neighbors (Verlinde and Chollet, 1999), decision trees (Ben-Yacoub *et al.*, 1999; Ross and Jain, 2003; Verlinde and Chollet, 1999), linear logistic regression (Verlinde and Chollet, 1999), k-means and fuzzy clustering (Chatzis *et al.*, 1999), Support Vector Machines (SVM) (Ben-Yacoub *et al.*, 1999; Fierrez-Aguilar *et al.*, 2005a,e; Garcia-Romero *et al.*, 2003), multilayer perceptrons (Ben-Yacoub *et al.*, 1999), Fisher discriminants (Ben-Yacoub *et al.*, 1999; Wang *et al.*, 2003), Bayesian classifiers (Ben-Yacoub *et al.*, 1999; Bigun *et al.*, 1997) and neural networks (Wang *et al.*, 2003).

1.3 Quality information in biometric systems

Quality assessment algorithms have been developed mainly for fingerprint images (Alonso-Fernandez *et al.*, 2007c) and recently, for iris (Chen *et al.*, 2006a; Kalka *et al.*, 2005), voice, (Garcia-Romero *et al.*, 2006; Richiardi and Drygajlo, 2008; Richiardi *et al.*, 2007), face (Kryszczuk and Drygajlo, 2007) and signature signals (Alonso-Fernandez *et al.*, 2007a; Muller and Henniger, 2007). In many of these works, it is demonstrated that the performance of a biometric system is heavily affected by the quality of biometric signals. Biometric quality assessment is an active field of research in recent years (BQW, 2007; Grother and Tabassi, 2007) and even the best verification systems worldwide struggle in the presence of noisy images, as demonstrated in the series of International Fingerprint Verification Competitions, FVC (Cappelli *et al.*, 2006b). The series of FVC competi-

tions have been organized biannually since 2000 by the Biometrics Systems Laboratory of Bologna University, the Pattern Recognition and Image Processing Laboratory of Michigan State University, the Biometric Test Center of San Jose State University and, more specifically, in FVC2006 also by the ATVS/Biometric Recognition Group of the Universidad Autonoma de Madrid. In the first competition FVC2000, data consisted of fingerprint images acquired without any special restrictions, and the best system obtained an average Equal Error Rate (EER) of 1.73%. In the 2002 edition, data were also acquired without special restrictions, and average error rates decreased significantly (0.19% EER for the best system). In some sense, these results demonstrated the maturity of fingerprint verification systems. But in the 2004 edition, image quality of the acquired data was artificially corrupted by using an acquisition procedure with exaggerated plastic distortions, artificial dryness and moistness. Surprisingly, the results of FVC2004 were much worse even than those in FVC2000 (an average EER of 2.07% for the best system), thus demonstrating that degradation of quality has a severe impact on the recognition rates.

Recent efforts have also been focused on the standardization of biometric quality information and its incorporation to biometric data structures (Benini, 2007; Benini and et al, 2003, 2006). There are a number of roles regarding a quality measure in the context of biometric systems (Benini, 2007; Grother and Tabassi, 2007): *i*) quality algorithms may be used as a monitoring tool (Ko and Krishnan, 2004) in order to accumulate relevant statistics of the system (e.g. to identify sources experiencing problems and submitting poor quality samples); *ii*) quality of enrolment templates and/or samples acquired during an access transaction can be controlled by acquiring until satisfaction (recapture); and *iii*) some of the steps of the recognition system can be adjusted based on the estimated quality (*quality-based conditional processing*).

A number of recent works have followed this last direction. The algorithm proposed by Fronthaler *et al.* (2008) discards unreliable fingerprint regions from the score decision. Chen *et al.* (2005) proposed a fingerprint matching algorithm in which high quality minutiae contribute more to the computation of the matching score. Quality measures are used as weights for matching distances of an iris recognition system by Chen *et al.* (2006a). Alonso-Fernandez *et al.* (2007c) studied the effect of rejecting low quality samples using a selection of fingerprint quality estimation algorithms and a database acquired with three sensors of different technology. Several works have also taken into account how differences among fingerprint capture devices impact on the quality measure computation (Alonso-Fernandez *et al.*, 2008; Grother *et al.*, 2005; Kang *et al.*, 2003; Sickler and Elliott, 2005).

Quality information has also been incorporated in a number of multimodal fusion approaches. Garcia-Romero *et al.* (2006) adapted the standard SVM fusion approach to take into account the quality information of speech signals. Fierrez-Aguilar *et al.* (2006) used an adaptive score-level fusion approach which exploits differences in behavior of two fingerprint matchers as image quality varies, which can be seen as a particular example of their more general quality-based fusion approach presented in Fierrez-Aguilar *et al.* (2005e). Nandakumar *et al.* (2006) proposed a likelihood ratio-based fusion scheme that takes into account the quality of the biometric samples when estimating the joint densities of the genuine and impostor classes. A novel device-specific quality-dependent score normalization technique is presented by Poh *et al.* (2007). Fronthaler *et al.* (2008) introduced a Bayesian-adaptive cascaded scheme that dynamically switches on different matchers in case of low quality and adapts fusion parameters based on past performance of the matchers. Finally, Kryszczuk and Drygajlo (2008) presented a theoretical framework of credence estimation and error prediction in multibiometric systems, showing how erroneous classification decisions are better handled using quality measures.

1.4 Performance evaluation of biometric systems

In first research works on biometrics conducted over three decades ago, it was common to evaluate biometric products on small custom or proprietary datasets (Atal, 1976; Kanade, 1973) and therefore, experiments were not repeatable and a comparative assessment could not be accomplished. As biometric systems are being deployed, joint efforts have been conducted to perform common experimental protocols and technology benchmarks. Several evaluation procedures (Mansfield and Wayman, 2002), databases and competitions have been settled in the last years, e.g. the NIST Speaker Recognition Evaluations (NIST SRE, 2006), the FERET and FRVT Face Recognition Evaluations (FRVT, 2006), the series of Fingerprint Verification Competitions (FVC) (FVC2006, 2006), the Iris Challenge Evaluation (ICE) (ICE, 2006) or the Signature Verification Competition (SVC) (SVC, 2004).

Different rates can be used to quantify the different properties of biometric systems described in Section 1.1. In this Thesis, we concentrate on performance indicators to compare different systems, and more specifically on the accuracy of the authentication process. We do not consider other performance indicators that are strongly related to particular implementations and hardware/software architectures, as the computational efficiency, resources, speed, etc.

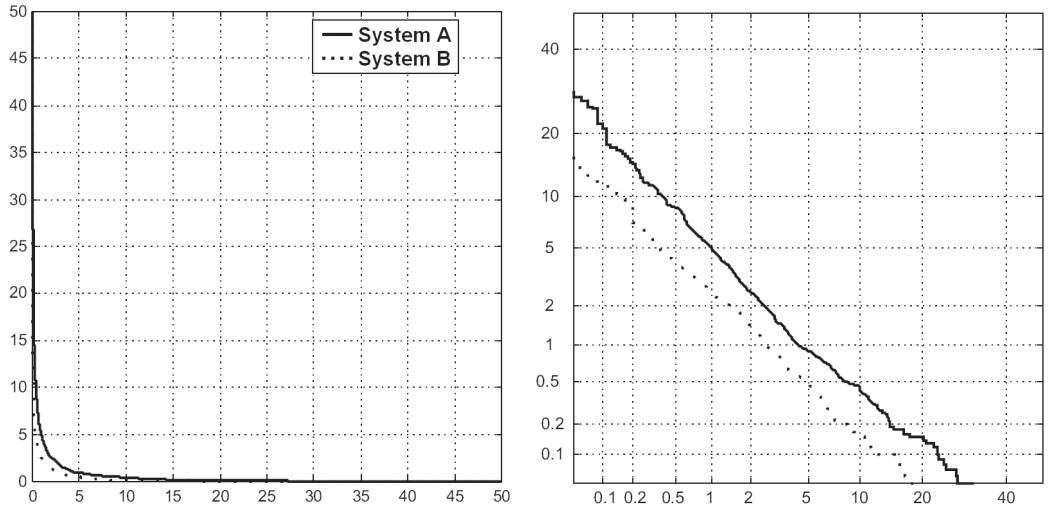


Figure 1.3: **Example of verification performance comparison with ROC (left) and DET (right) curves.**

Biometric authentication can be considered as a detection task, involving a tradeoff between two types of errors (Ortega-Garcia *et al.*, 2004): *i*) Type I error, also named *False Rejection Rate* (FRR) or miss (detection), occurring when a client, target, genuine or authorized user is rejected by the system, and *ii*) Type II error, known as *False Acceptance Rate* (FAR) or false alarm, taking place when an unauthorized or impostor user is accepted as being a true user. Although each type of error can be computed for a given decision threshold, a single performance level is inadequate to represent the full capabilities of the system and, as such a system has many possible operating points, it is best represented by a complete performance curve. These total performance capabilities have been traditionally shown in form of ROC (Receiver - or also Relative - Operating Characteristic) plot, in which FAR versus FRR is depicted for all the possible decision thresholds. A variant of the ROC curve, the so-called DET (Detection Error Tradeoff) plot, is used in this work (Martin *et al.*, 1997). In the DET curve, the use of a normal deviate scale makes the comparison of competing systems easier. A comparison between ROC and DET curves for two hypothetical competing verification systems A and B is given in Figure 1.3.

A specific point is attained when FAR and FRR coincide, the so-called EER (Equal Error Rate). The global EER of a system can be easily detected by the intersection between the DET curve of the system and the diagonal line $y = x$. Nevertheless, and because of the step-like nature of FAR and FRR plots, EER calculation may be ambiguous according to the above-mentioned definition, so an operational procedure

for computing the EER must be followed. In this work, the procedure for computing the EER described by Maio *et al.* (2002) has been applied.

1.4.1 Statistical significance of experimental results

In the work presented by Guyon *et al.* (1998), the minimum size of the test data set, N, that guarantees statistical significance in a pattern recognition task is derived. The goal was to estimate N so that it is guaranteed, with a risk α of being wrong, that the probability of error P does not exceed the estimated error rate from the test set, $\widehat{P}$, by an amount larger than $\varepsilon(N, \alpha)$, that is

$$\Pr\left\{P > \widehat{P} + \varepsilon(N, \alpha)\right\} < \alpha. \tag{1.2}$$

Letting $\varepsilon(N, \alpha) = \beta P$, and supposing recognition errors as Bernouilli trials (Papoulis, 1984), we can derive the following relation:

$$N \approx \frac{-\ln \alpha}{\beta^2 P}. \tag{1.3}$$

For a typical configuration ($\alpha = 0.05$ and $\beta = 0.2$), the following simplified criterion is obtained:

$$N \approx 100/P. \tag{1.4}$$

If the samples in the test data set are not independent (due to correlation factors including the recording conditions, some types of sensors, certain groups of users, etc.) then N must be further increased. The reader is referred to Guyon *et al.* (1998) for a detailed analysis.

1.5 Motivation of the Thesis

Provided that the performance of a biometric system is heavily affected by the quality of biometric signals, this Thesis is focused on the biometric quality assessment problem, and its application in multimodal biometric systems. The research carried out in this Thesis is motivated by the following observations from the state-of-the-art:

- Prior work on quality evaluation and sample quality analysis is limited (Grother and Tabassi, 2007). Biometric quality measurement is an operationally important and difficult step that is nevertheless massively under-researched in comparison to the primary feature extraction and pattern recognition task. Although many

quality assessment algorithms have been developed, mainly for fingerprint images, they have been tested under limited and heterogenous frameworks. It has not been until the last years when the concept of sample quality has been formalized and a framework for evaluating biometric quality measures has been proposed (Grother and Tabassi, 2007; Youmaran and Adler, 2006). Thus, there are no comparative studies of biometric quality algorithms under a common framework, using the same dataset and the same protocol.

- Previous studies have shown that the performance of biometric systems is heavily affected by the quality of biometric signals. For the case of fingerprints, the two most popular approaches for fingerprint recognition are found to behave differently as image quality varies (Fierrez-Aguilar *et al.*, 2006). Some works have also taken into account how differences among fingerprint capture devices impact on the quality measure computation (Grother *et al.*, 2005; Kang *et al.*, 2003; Sickler and Elliott, 2005). However, results are based on an specific quality assessment algorithm and/or databases acquired with a single sensor. It can be hypothesized that using other quality assessment algorithms or fingerprint sensors may lead to different results.

- In behavioral biometric traits such as signature, it is harder to define what quality is. There are studies that relate performance with signature complexity or variability (Allgrove and Fairhurst, 2000; Fierrez-Aguilar *et al.*, 2005d). The effect of different features extracted automatically from online signatures is also studied by Muller and Henniger (2007). There are also works focused on speech quality (Garcia-Romero *et al.*, 2006). However, prior work on sample quality analysis for behavioral traits is quite limited.

- Additional problems may arise when a biometric device is replaced without reacquiring the corresponding template (Poh *et al.*, 2007), or when a biometric template is matched against a template generated using a different algorithm (Grother *et al.*, 2005). These are common *interoperability* problems, which typically are not specifically overcome by biometric systems, and thus lower the recognition performance, sometimes dramatically (Alonso-Fernandez *et al.*, 2005c, 2006c; Grother *et al.*, 2005; Ross and Jain, 2004). Unfortunately, as biometric technology is extensively deployed, it will be a common situation to replace parts of operational systems as they are damaged or newer designs appear, or to exchange information among several applications involving systems developed by different vendors (Poh *et al.*, 2007). Examples are the necessity of all ePassports issued by each

country to be readable by readers placed at borders of other countries, or individuals remotely accessing to a system using their own sensor (e.g. a PDA or mobile telephone with biometric signal acquisition capabilities).

- Incorporating biometric quality information in multibiometric systems is currently a research challenge (BMEC, 2007; BQW, 2007). Multibiometric systems integrate the evidence presented by multiple biometric systems (Jain *et al.*, 2006). Such systems are more robust to variations in the sample quality as shown in several studies (Fierrez-Aguilar *et al.*, 2006; Nandakumar *et al.*, 2006). Incorporation of quality information in biometric systems can also provide additional improvement (BQW, 2007; Fierrez-Aguilar *et al.*, 2005e; Grother and Tabassi, 2007). For example, dynamically assigning weights to the outputs of individual matchers based on the quality of the samples presented at the input (quality-based fusion) can improve the overall recognition performance. Other works (Chen *et al.*, 2005) are focused on adapting the steps of the recognition system based on the quality of the samples (quality-based conditional processing).

These observations will be discussed in Chapter 2, in which the biometric quality assessment problem is analyzed in depth.

1.6 The Thesis

The Thesis developed in this Dissertation can be stated as follows:

> *The incorporation of quality information in biometric systems can provide significant benefits in their performance. Examples of quality-based approaches in biometrics include the adaptation of parts of the system to the quality of the sample at hand, and the reacquisition of samples that do not satisfy certain quality criteria.*

To incorporate quality information in a biometric system, we first should assess how the system performance is affected by the quality of biometric signals. This task is addressed in Chapters 3 and 4 for fingerprints and signature, respectively. An experimental study of system adaptation to the quality of biometric signals is carried out in Chapter 5, in which we propose a multibiometric system architecture generalizable to biometric systems working with heterogeneous sources of information.

1.7 Outline of the Dissertation

The main objectives of this PhD Thesis are as follows:

1. Review and study of the problem of biometric quality analysis.
2. Definition of a framework for evaluating biometric quality measures.
3. Review of existing fingerprint quality assessment algorithms, including the implementation of a representative set and a comparative evaluation.
4. Review of existing signature quality assessment algorithms, including the proposal of new quality measures and a comparative evaluation.
5. Incorporation of biometric quality measures in multibiometric systems, including quality-based fusion and quality-based conditional processing.

This Dissertation is structured according to a *traditional complex* type (Paltridge, 2002) with literature review, theoretical and practical methods and three experimental studies in which the methods are applied. The chapter structure is as follows:

- Chapter 1 introduces the topic of biometric systems and gives the motivation, outline and contributions of this PhD Thesis.
- Chapter 2 summarizes related works and details the motivations for this Thesis based on these previous works.
- Chapter 3 studies the problem of quality assessment of fingerprint images. The taxonomy of existing approaches for fingerprint image quality assessment is a contribution of this PhD Thesis, therefore they will be presented in some detail.
- Chapter 4 studies the problem of quality assessment of signature images. Several measures to predict the performance of signature systems are proposed as contribution. Also, one of the three verification systems used is a contribution of this PhD Thesis.
- Chapter 5 conducts a study of system adaptation to the quality of biometric signals. We contribute with a quality-based multibiometric architecture that is generalizable to biometric systems working with heterogeneous sources of information.

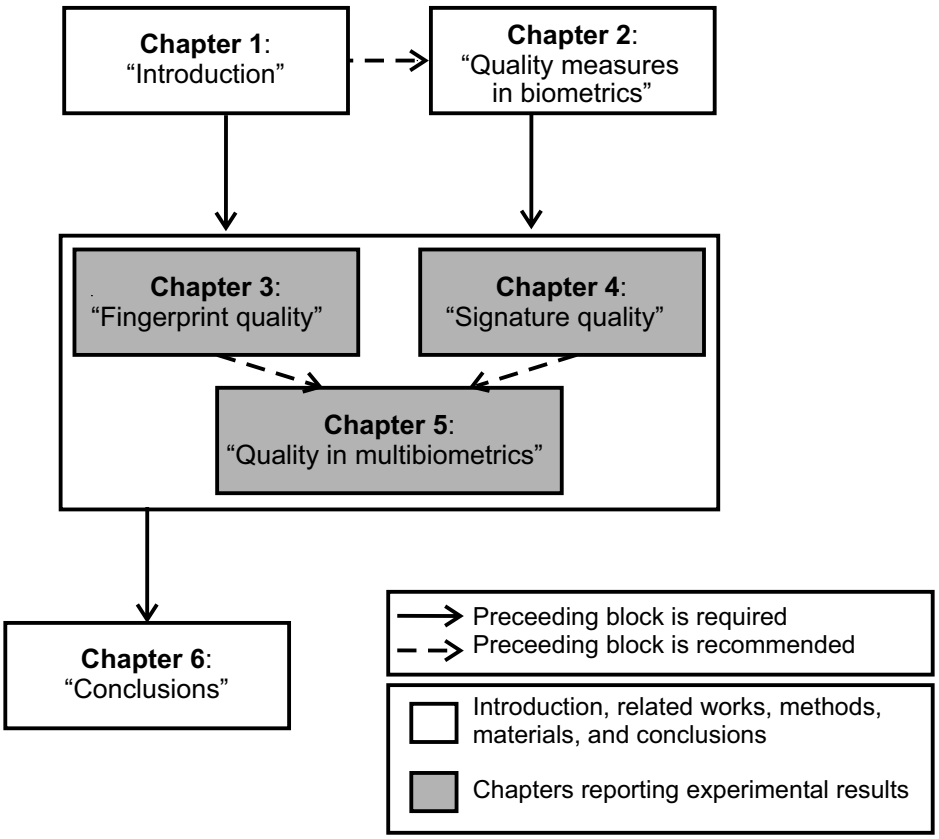


Figure 1.4: **Dependence among Dissertation chapters.**

- Chapter 6 concludes the Dissertation summarizing the main results obtained and outlining future research lines.

The dependence among the chapters is illustrated in Figure 1.4. In order to properly follow the experimental chapters, a background in biometric systems and multibiometrics is desirable. We refer the reader to introductory readings in these topics (Jain and Ross, 2004; Jain *et al.*, 2006, 2004b). For a deeper view, we refer to Jain *et al.* (2008); Ross *et al.* (2006).

Some methods developed in this PhD Thesis are strongly based on popular approaches from the pattern recognition literature. The reader is referred to standard texts for a background on the topic (Duda *et al.*, 2004; Jain *et al.*, 2000; Theodoridis and Koutroumbas, 2003). Chapters 3 and 4 assume a knowledge of the fundamentals of image processing (Gonzalez and Woods, 2002). Chapter 3 also assumes knowledge of the fundamentals of computer vision (Bigun, 2006).

1.8 Research contributions

The research contributions of this PhD Thesis are the following (some publications appear in several items of the list):

- **Literature reviews**.
  1. A taxonomy of fingerprint image quality assessment algorithms (Alonso-Fernandez *et al.*, 2007c, 2005b).
  2. State of the art in fingerprint verification (Alonso-Fernandez *et al.*, 2008a).
- **Novel methods**.
  1. Novel methods for signature quality assessment and performance prediction (Alonso-Fernandez *et al.*, 2007a,b).
  2. Novel methods for quality-based multimodal verification generalizable to biometric systems working with multiple sources of information (Alonso-Fernandez *et al.*, 2008b).
- **New biometric systems**.
  1. A new off-line signature verification system based on contour features (Gilperez *et al.*, 2008), developed jointly with Pecharroman-Balbas (2007).

- **New experimental studies**.

  1. Comparative evaluation of fingerprint quality measures depending on sensor technology using a minutiae- and a ridge-based matcher (Alonso-Fernandez *et al.*, 2007c, 2008; Fierrez-Aguilar *et al.*, 2005b).
  2. Evaluation of impact of signature legibility and signature type in the performance of three off-line signature verification systems (Alonso-Fernandez *et al.*, 2007b).
  3. Evaluation of performance of off-line signature verification systems in terms of two new proposed measures aimed to estimate signature stability/variability (Alonso-Fernandez *et al.*, 2007a).
  4. Study of combination of different contour features for off-line signature verification (Gilperez *et al.*, 2008).
  5. Study of system adaptation to the quality of biometric signals coming from different sources, including quality-based fusion and quality-based conditional processing (Alonso-Fernandez *et al.*, 2008b).

- **New biometric data**.

  1. A new multimodal database including face, speech, signature, fingerprint, hand and iris data modalities from more than 650 subjects acquired within the framework of the BioSecure Network of Excellence (Alonso-Fernandez *et al.*, 2008b). This new database is unique in its class, in the sense that it includes three scenarios in which the subjects have been simultaneously acquired (over the Internet, in an office environment with a PC, and in indoor/outdoor environments with mobile devices). Part of this database is used in the experimental section of Chapter 5.

Other research contributions by the author during his PhD studies that fall outside of the scope of his Ph.D. Thesis include:

- **Literature reviews**.

  1. State of the art in on-line signature verification in the framework of the BioSecure Network of Excellence (Garcia-Salicetti *et al.*, 2008).
  2. Review of fingerprint and signature databases and evaluations (Alonso-Fernandez and Fierrez, 2008; Garcia-Salicetti *et al.*, 2008).

3. Review of biometrics and its applications (Alonso Fernandez *et al.*, 2008).

- **New biometric systems**.

1. An iris verification system based on Gabor features, developed jointly with Tome-Gonzalez (2008).

- **New biometric applications**.

1. Application of signature verification to portable Tablet PC and PDA devices (Alonso-Fernandez *et al.*, 2005a, 2006a; Martinez-Diaz *et al.*, 2007).

- **Novel methods**.

1. New multialgorithm fingerprint adaptive fusion schemes based on image quality (Fronthaler *et al.*, 2008).
2. New user-dependent score normalization scheme that exploits quality information (Alonso-Fernandez *et al.*, 2006b).

- **New experimental studies**.

1. Multi-algorithm fingerprint and signature verification in the framework of the BioSecure Network of Excellence (Alonso-Fernandez *et al.*, 2008a, 2007d; Garcia-Salicetti *et al.*, 2007, 2008).
2. Study of the capability of fingerprint quality measures to discriminate between images of different quality (Alonso-Fernandez *et al.*, 2005b, 2007e, 2008).
3. Attacks to fingerprint recognition systems (Galbally-Herrero *et al.*, 2006; Martinez-Diaz *et al.*, 2006) and iris recognition systems (Ruiz-Albacete *et al.*, 2008).
4. Study of sensor interoperability and sensor fusion in fingerprint and on-line signature verification (Alonso-Fernandez *et al.*, 2005c, 2006c).
5. Study of effects of image quality in the performance of individual users with a multisensor database on a minutiae-based fingerprint verification approach (Alonso-Fernandez *et al.*, 2006b).
6. Study of effects of time variability in iris recognition (Tome-Gonzalez *et al.*, 2008).

- **New biometric data**.

  1. A new on-line signature database of 53 subjects acquired with Tablet PC (Alonso-Fernandez *et al.*, 2005a).
  2. A new multimodal database including speech, iris, face, signature, fingerprints, hand and keystroking modalities from 400 subjects acquired within the framework of the BiosecurID project funded by the Spanish MEC (Galbally *et al.*, 2007).

- **Public technical reports**.

  1. Activities carried out within the BioSecure Network of Excellence, available at BioSecure (2004): 1) acquisition of a new multimodal database, to be released soon, activity in which the author has been actively involved (Allano *et al.*, 2007; Ortega-Garcia and Alonso-Fernandez, 2005a; Ortega-Garcia *et al.*, 2006b,c, 2007), 2) legal issues regarding biometric data (Ortega-Garcia *et al.*, 2006a), 3) reports on existing biometric databases and tools (Ortega-Garcia and Alonso-Fernandez, 2005b; Ortega-Garcia *et al.*, 2006d), 4) reports on activities carried out on specific fields of interest for the author (Veldhuis *et al.*, 2006, 2007).

Chapter 2

Quality Measures in Biometric Systems

Biometric quality measurement is an operationally important step that is nevertheless under-researched in comparison to the primary feature extraction and pattern recognition task. Recently, quality measurement has emerged in the biometric community as an important concern after the poor performance observed in biometric systems on certain pathological samples (Grother and Tabassi, 2007). There are a number of factors that can affect the quality of biometric signals, and there are numerous roles of a quality measure in the context of biometric systems. Standardization bodies are also developing standards that incorporate quality measures in existing standardized biometric data storage and exchange formats.

Since 2006, it is celebrated a new Workshop sponsored by the National Institute of Standards and Technology (NIST) that is dedicated to Biometric Quality Measurements (BQW, 2007). Also, independent evaluations of commercial and research prototypes conducted during the last decade include in each edition new scenarios and conditions that are progressively more difficult in nature. We observe that, in many cases, this results in a performance worsening, and it is not until the next edition that the algorithms show progress under the new challenging conditions. For instance, in the 2000 and 2002 editions of the International Fingerprint Verification Competition, FVC (Cappelli *et al.*, 2006b), the fingerprint samples used were acquired without any special restriction, resulting in a decrease of one order of magnitude in the error rates (see Table 2.1). However, in the 2004 edition, fingerprint samples were intentionally corrupted (e.g. by asking people to exaggeratedly rotate or press the finger against

database	2000	2002	2004	2006
DB1	0.67%	0.10%	1.97%	5.56%
DB2	0.61%	0.14%	1.58%	0.02%
DB3	3.64%	0.37%	1.18%	1.53%
DB4	1.99%	0.10%	0.61%	0.27%
average	1.73%	0.19%	2.07%	2.16%

Table 2.1: **Results in terms of Equal Error Rate (EER) of the best performing algorithm in each of the four databases of the FVC competitions (Cappelli *et al.*, 2006b).**

the sensor, or by artificially drying or moisturizing the skin with water or alcohol). The result was that the error rates of the best systems were much worse (an order of magnitude) than those of previous editions, although the technology improvement for good quality images. This result shows the significant impact that the degradation of quality can have on the recognition performance, and highlights the importance of measuring and dealing with it in biometric systems.

This chapter summarizes the state-of-the-art in the biometric quality problem, giving an overall framework of the different factors related to it. It is structured as follows. We first define what sample quality is from the point of view of biometric systems. Next, we present the factors influencing biometric quality and the strategies to ensure the best possible quality of acquired biometric samples. Next, we present existing frameworks for evaluation of the performance of biometric quality measures. The relationship between human and automatic quality assessment, as well as the role of quality measures within biometric systems is then analyzed. Lastly, we summarize standardization efforts related to biometric quality and we point out further issues and challenges of the quality problem.

Original contributions in this chapter include a taxonomy of factors affecting biometric quality, a taxonomy of strategies to ensure good quality in acquired biometric samples, and a taxonomy of roles of quality measures in the context of biometric systems.

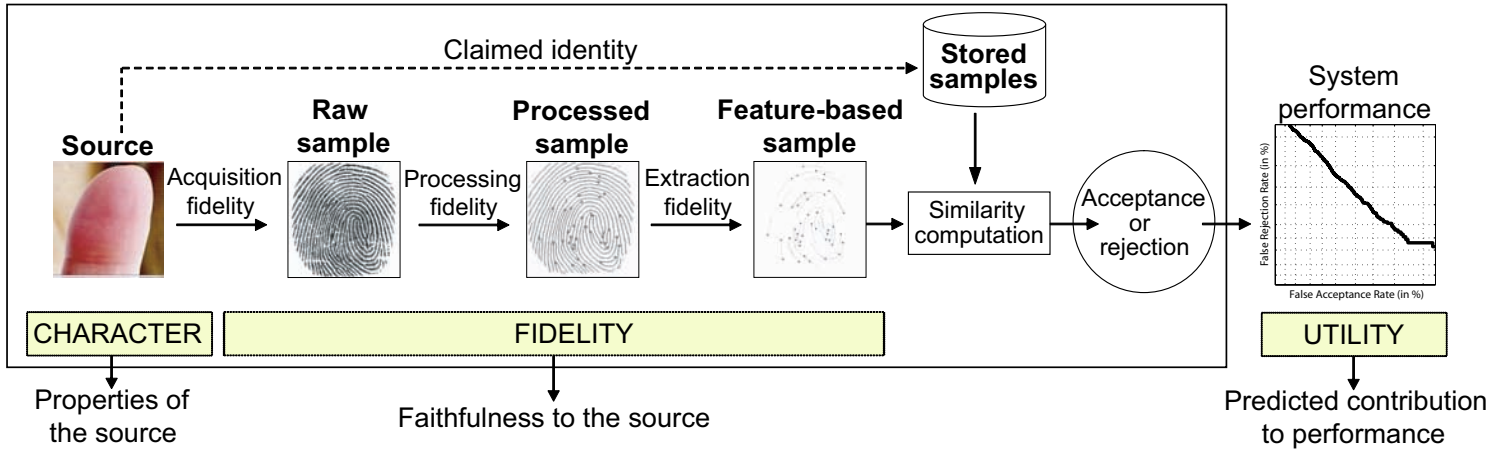


Figure 2.1: **Definition of biometric quality from three different points of view: character, fidelity or utility.**

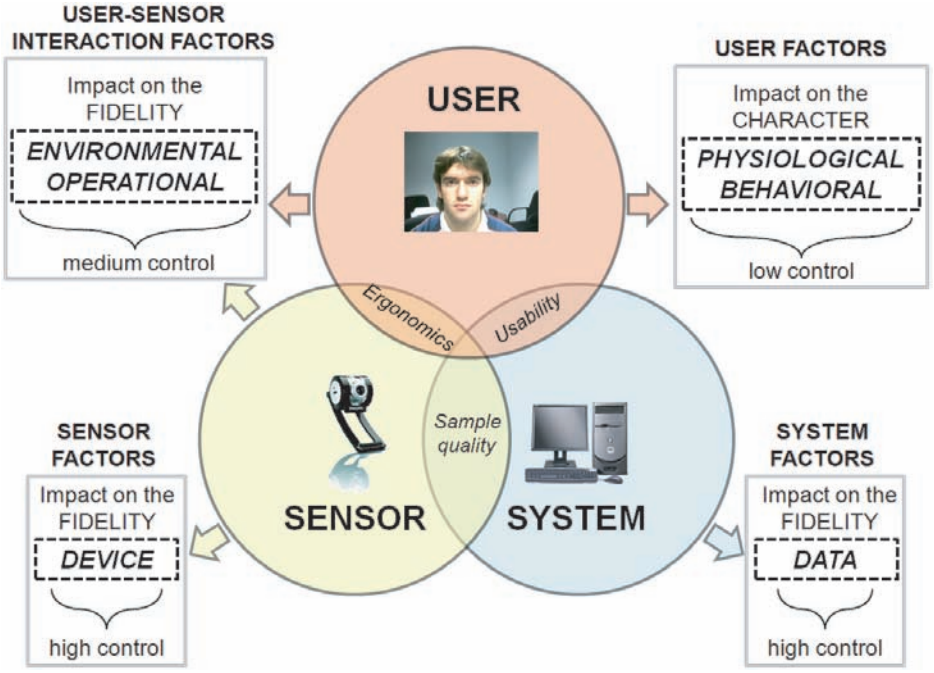


Figure 2.2: **Factors affecting the quality of biometric signals.**

2.1 Definition of biometric sample quality

It has not been until the last years that there is consensus about what biometric sample quality is. Broadly, a sample is of good quality if it is suitable for personal recognition. Recent standardization efforts (Benini and et al, 2006) have established that biometric sample quality can be considered from three different points of view, see Figure 2.1: *i*) *character*, which refers to the quality attributable to inherent physical features of the subject; *ii*) *fidelity*, which is the degree of similarity between a biometric sample and its source, attributable to each step through which the sample is processed; and *iii*) *utility*, which refers to the impact of the individual biometric sample on the overall performance of a biometric system. The *character* of the sample source and the *fidelity* of the processed sample contribute to, or similarly detract from, the *utility* of the sample.

It is generally accepted that a quality metric should most importantly mirror the *utility* of the sample (Grother and Tabassi, 2007), so that samples assigned higher quality lead to better identification of individuals. Thus, quality should be predictive of the recognition performance. This statement, however, is largely subjective: not

FACTOR	Fingerprint	Iris	Face	Speech	Signature	Hand	EFFECTS	AVOIDABLE
Age *	X	X	X	X	X	X	Variability	No
Gender			X	X				
Race		X	X					
Amputation	X				X	X	Lack of data	
Skin condition **	X					X	Lack of data or invalid data	
Diseases	X	X	X	X	X	X		
Injuries	X	X	X	X	X	X		

* **Age**: although iris pigmentation and fingerprint characteristics are highly stable, they change until the adolescence and during the old age. The other traits are subject to natural evolution throughout our life.

** **Skin condition**: it refers to factors like dryness/wetness, sweat, cuts, bruises, etc., which can have impact on traits involving analysis of skin properties (fingerprint and hand).

Table 2.2: **Physiological factors that can have impact on biometric quality.**

all the automatic recognition algorithms work equally, and their performance is not affected by the same factors. Therefore, an adequate quality measure will be largely dependent on the type of automatic recognition algorithm considered. As the recognition performance of different algorithms may not be affected by the same signal quality factors, the efficacy of a quality estimation algorithm will be usually linked to a particular recognition algorithm, or a particular class of algorithms. As a result, a quality measure capable of predicting the performance of a given system may not be useful when considering other systems.

2.2 Factors influencing biometric quality

There are a number of factors affecting the quality of biometric signals. Unfortunately, some of them fall out of our control. For this reason, it is important upon capture of a biometric sample to assess its quality in order to perform appropriate corrective actions. We summarize in Figure 2.2 the different factors that can have impact on the quality of acquired signals. They are classified depending on their relationship with the different parts of the system. We can distinguish among four different classes: factors related entirely to the user, factors that have to do with the user-sensor interaction process, factors related to the acquisition device, and factors related with the processing system:

- **User-related factors.** Here we have ***physiological*** and ***behavioral*** factors. As they have to do entirely with the "user side", they are the most difficult to control. We give a summary of the most important ones in Tables 2.2 and 2.3, together

FACTOR	Fingerprint	Iris	Face	Speech	Signature	Hand	EFFECTS	AVOIDABLE
Tiredness	X	X	X	X	X	X	Invalid data	Difficult
Distraction	X	X	X	X	X	X		Yes
Cooperativity	X	X	X	X	X	X		Depending on
Motivation	X	X	X	X	X	X		
Nervousness	X	X	X	X	X	X		the application
Distance		X	X	X				Yes, recapture
Frontalness		X	X					
Blink, eyes closed		X	X					
Pressure against sensor	X				X	X		
Inconsistent contact	X					X		
Pose, gaze		X	X					
Illiteracy				X	X		Lack of data or invalid data	No
Manual work *	X					X		
Facial expression			X				Variability	Yes, recapture
Ethnic origin **		X	X	X	X			No
Hairstyle, beard, make-up			X					
Clothes			X					Difficult, except coat/sweater
Hat			X					Yes, take off and recapture
Jewelry	X		X			X		
Glasses/contact lenses			X					
		X					Invalid data	

* Manual work: it may affect the skin condition (dryness, cuts, bruises, dirt, diseases, etc.), in some cases irreversibly.

** Ethnic origin: it affects to iris (pigmentation is different in some ethnic groups), face (physical features, hairstyle, beard, jewelry, etc.), speech (language, lexicon, intonation, etc.) and signature (American signatures typically consist of a readable written name, European signatures normally include flourish Oriental signatures consist of independent symbols, etc.).

Table 2.3: **Behavioral factors that can have impact on biometric quality.**

FACTOR	Fingerprint	Iris	Face	Speech	Signature	Hand	EFFECTS	AVOIDABLE
Indoor/outdoor	X	X	X	X	X	X	Variability (light, noise, skin, sensor)	Yes
Background			X				Variability	
Temperature	X					X	Variability (skin properties)	
Humidity	X					X		
Illumination	X	X	X				Variability, invalid data	
Light reflection		X	X				Invalid data	
Ambient noise				X				
Object occlusion			X					
Season	X		X				Variability (clothing, skin properties)	Yes

Table 2.4: **Environmental factors that can have impact on biometric quality.**

with an indication of what biometric trait is affected by each one, their effects, and to what degree we can control them. Notice that most *physiological* factors fall out of our control (e.g. age, gender, race, etc.). A number of them do not necessarily produce degradation on the biometric data, but additional biometric intra-variability (e.g. face or speech characteristics are different in males and females, faces change as we grow up, etc.). These additional variability factors, if not properly considered by the recognition algorithm, may lead to degraded performance. Other factors, like diseases or injuries, may alter a part of our body, our skin, our voice, our ability to sign, etc., resulting in invalid data. In some cases, the alteration may be irreversible, making the affected biometric trait infeasible for recognition. On the contrary, *behavioral* factors are easier to alleviate than *physiological* ones, although it is not always possible or convenient, as we would have to *modify* the people's behavior or habits. People may not be motivated to provide their biometric data at a certain moment or for certain applications. Or they may be tired, distracted or nervous. In other situations, as for the case of criminals, we expect them to be non-cooperative. Note that when dealing with many behavioral factors, one solution is just to recapture after taking corrective actions (e.g. "put off your hat/coat/ring/glasses" or "keep your eyes opened"), but this is not always possible or appropriate.

- **Factors related to the user-sensor interaction.** Two types of factors are included here: ***environmental*** and ***operational***, which we summarize respectively in Tables 2.4 and 2.5. In principle, they are easier to control than user-related factors, although users still play a part in them. For instance, impact of *environmental* factors will be low if we can control the environment. The quality of face images or videos depends on illumination, background, object occlusion, etc., and fingerprint images are affected by modifications of the properties of the skin due to humidity or temperature. Also, illumination and light reflections have great impact on iris images due to the reflective properties of the eye, whereas the quality of speech is highly dependent of factors affecting background noise. Outdoor operation is specially problematic, as we can lose control on many factors affecting not only the biometric trait but also the sensor itself: temperature, humidity, weather, noise, illumination, etc. Outdoor operation demands additional actions to us regarding sensor conditions and its maintenance. Unfortunately, in certain applications, we cannot control the environment, as in the case of modern applications that make use of handheld devices with acquisition capabilities of biometric samples (e.g. PDA, mobile phone, etc.) and/or the Internet.

FACTOR	Fingerprint	Iris	Face	Speech	Signature	Hand	EFFECTS	AVOIDABLE
User familiarity	X	X				X	Invalid data, variability	Yes
Feedback of acquired data	X	X	X		X			
Supervision by an operator	X	X	X	X	X	X		Depending on the application
Sensor cleaning	X					X		
Physical guides *	X	X	X			X		
Ergonomics **	X	X	X		X	X		
Time between acquisitions ***	X	X	X	X	X	X	Variability	

* Physical guides: In some cases, they are incorporated in some sensors to facilitate the acquisition (e.g. hand, finger).

** Ergonomics: it refers to how the design of the acquisition device facilitates the interaction with the user.

*** Time between acquisitions: it is also known as ageing. The biometric data acquired from an individual at two different moments may be very different, having great impact on the system performance.

Table 2.5: **Operational factors that can have impact on biometric quality.**

As in the case of *environmental* factors, *operational* ones (Table 2.5) can be controlled if we have influence on the acquisition act itself. Again, if the acquisition is not done physically in our premises, we will not be able to provide help or supervision to the user, we will not know if the sensor is cleaned periodically, or we will not be able to guarantee the ergonomics of the acquisition kiosk. An important factor that has to do with the operation of the system is the time passed between acquisitions, also known as ageing. There is an intrinsic variability in biometric data characteristics as time passes, not only in the long-term (e.g. changes of our face, voice, etc. or differences in the way we interact with the system) but also in the short-term (e.g. clothes, temporary diseases). The most important consequence is that biometric data acquired from an individual at two different moments may be very different. This affects to any biometric trait, although some of them are more sensitive than others (Jain *et al.*, 2008), as it is the case of signature, face or voice. Another *operational* factor that we should consider is if the user receives feedback of the acquired data via display or similar, which leads to better acquired samples.

- **Factors related to the acquisition sensor.** A number of sensor features can affect the quality of acquired biometric data: its ease of use and maintenance, the size of its acquisition area, the resolution or the acquisition noise, its reliability and physical robustness, its dynamic range or the time it needs to acquire a sample. It is important that these factors be compliant with existing standards,

so we will be able to replace the sensor without degrading the reliability of the acquisition process. This is specially important, because replacing the sensor is very common in operational situations as it is damaged or newer designs appear. Standards compliance also guarantees that we can use different sensors to interact with the system, as in the case of people with their own personal devices.

- **Factors related to the processing system.** Here we find the factors that are easiest to control, which are related to how we process a biometric sample once it has been acquired by the sensor. Factors affecting here are the data format we use for exchange or storage and the algorithms we apply for data processing. If there are storage or exchange speed constraints, we may need to use data compression techniques, which may degrade the sample or template quality.

As can be seen in Figure 2.2, the user-related factors have impact on the *character* of the biometric sample, that is, the quality attributable to the inherent physical features. In this sense, the control we have on these factors is low, as the inherent features of a person are difficult or impossible to modify. The remaining factors affect the *fidelity*, or in other words, the faithfulness between a biometric sample and its source. Their degree of control is, as discussed before, higher than user-related factors.

2.3 Ensuring good quality in biometric samples

In the previous section, we have summarized the usual factors affecting the quality of biometric signals. We will now report some helpful guidelines to control these factors. For that purpose, we identify three points of action, as it can be observed in Figure 2.3: *i*) the capture point, *ii*) the quality assessment algorithm itself, and *iii*) the system that performs the recognition process.

Most of the factors affecting the quality of biometric signals are related with the "user side", as we have discussed before. For this reason, there are many things that can be done at the capture point:

- Supervision of the acquisition by an operator, ensuring that he is well trained, works in an adequate environment, and has enough time to capture good quality signals. Note that this is a repetitive task that may cause tiredness, boredom or lack of motivation in the operator, factors that we must try to control.

- Use of adequate sensors, with enough capabilities for our application (size, resolution, etc.) and with enhanced features allowing the acquisition of bad quality sources (e.g. touchless fingerprint sensors, 3D cameras).

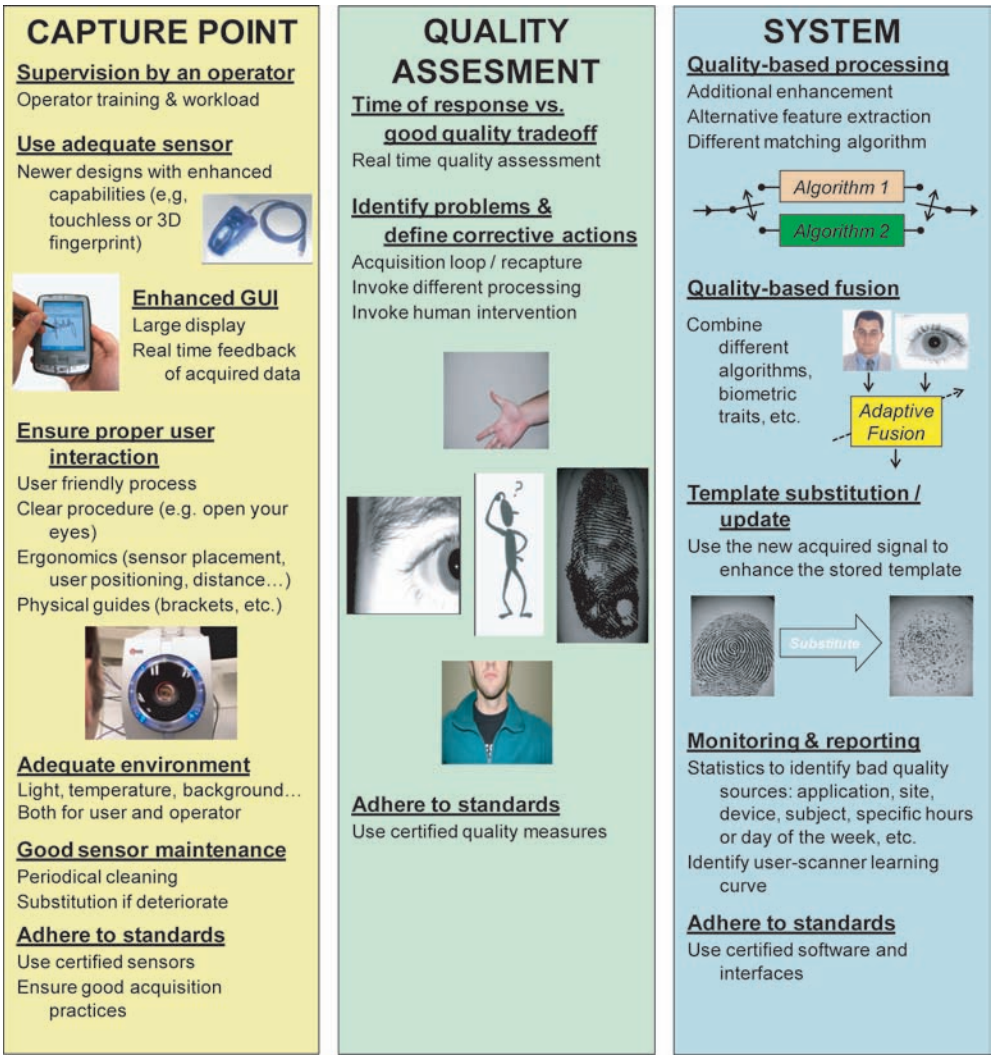


Figure 2.3: **Biometric quality assurance process.**

- Use of an adequate Graphical User Interface (GUI), with a large display providing real time feedback of acquired data, as it has been demonstrated that users tend to provide better signals over time and to habituate faster to the system if they have feedback of their acquisitions.

- To ensure an adequate acquisition environment (light, temperature, background, noise, etc.), with a clear acquisition procedure (e.g. "gaze at the camera" or "place your finger here"), being at the same time ergonomic and user-friendly.

- To ensure a good maintenance of the sensor and of the acquisition kiosk in general, with periodical cleaning and substitution of damaged parts.

Unfortunately, sometimes these guidelines are not possible to put into practice. As we have pointed out in the previous section, a number of uncontrolled situations exist in the "user side", specially as new deployments making use of portable devices and/or remote access appear. This is a challenge that should encourage the biometric community to define a set of best capture practices, and to work towards a common working criteria.

Regarding the "system side" (right part of Figure 2.3), the most important action to ensure good quality of biometric samples is to perform quality-dependent processing and/or quality-dependent fusion. In brief words, it means to invoke different algorithms and to combine them with different weighting depending on the quality of the signal at hand. This approach enables to integrate specific developments for poor quality signals into established recognition strategies. It is also important that the system monitors the quality of biometric signals, generating periodic reports (Ko and Krishnan, 2004). This is useful to identify sudden problems (e.g. a damaged sensor) and to carry out trend analysis that helps to determine if there is a hidden systematic problem that needs corrective action (e.g. is the quality between two terminals of the same application different and why? is there an specific scanner working worse that the others? is there an specific hour when the quality of acquired signals is worse?). Specially important is to identify if there is a user-scanner learning curve, i.e. if once the users get more familiar with the interaction with the acquisition device, their acquired biometric signals exhibit better quality. This allows us to avoid the "first time user" syndrome, specially for elder people or people who is not used to interact with machines. Another quality-corrective action, which is still under-researched, is known as template adaptation or update (Uludag *et al.*, 2004). It is typical for the stored template data to be significantly different to the processed biometric data obtained during an authentication access due to natural variations across time. In this case, storing multiple templates that represent

the variability associated with a user's biometric data and to update/substitute them with new acquisitions is an efficient way to deal with this problem, ensuring at the same time the best possible quality of stored biometric data.

Between the "user side" and the "system side" (see Figure 2.3), we position the quality assessment algorithm. Since the quality of the acquired signal conditions subsequent actions, it is very important that the quality of biometric samples be computed in real-time. The assessment algorithm should be able to identify which factor is degrading the quality of acquired signals and based on it, start the appropriate corrective action. In some cases, we will be able to reacquire until satisfaction, but in others we will not have the opportunity of ask for a new sample, so we will have to deal with the "bad" sample at hand. Based on the assessed quality, we can invoke different processing algorithms, or we can reject the acquired signal. In this case, we should have defined an exception procedure for users whose samples are rejected by the quality assessment algorithm (e.g. invoke human intervention for an alternative recognition procedure). The cost of this last option, as well as the inconvenience to the user, is a good reason to highlight the importance of having a good quality assessment module in any biometric system.

We should note that adhesion to standards is recommended throughout the quality assurance process: for sensors, software, interfaces, etc. With the use of standards, we obtain great flexibility and modularity, fast technology interchange, sensor and system interoperability, and proper interaction with external security systems.

2.4 Performance of quality assessment algorithms

2.4.1 Previous works

We can find many quality assessment algorithms in the literature (NIST-BQH, 2007). Quality assessment algorithms have been developed mainly for fingerprint images (Alonso-Fernandez *et al.*, 2007c) and recently, for iris (Chen *et al.*, 2006a; Kalka *et al.*, 2005), voice, (Garcia-Romero *et al.*, 2006; Richiardi and Drygajlo, 2008; Richiardi *et al.*, 2007), face (Kryszczuk and Drygajlo, 2007) and signature signals (Alonso-Fernandez *et al.*, 2007a,b; Muller and Henniger, 2007).

In spite of the number of existing quality assessment algorithms, almost all of them have been tested under limited and heterogenous frameworks (Grother and Tabassi, 2007). Biometric quality measurement is an operationally important difficult to benchmark, mainly because it has not been until the last years when the biometric community has formalized the concept of sample quality and has developed several frameworks for

evaluating biometric quality measures.

As shown in Figure 2.1, we can consider biometric sample quality from the point of view of *character* (inherent properties of the source), *fidelity* (faithfulness of the biometric sample to the source), or *utility* (predicted contribution to performance). Youmaran and Adler (2006) have developed a theoretical framework for measuring biometric sample *fidelity*. They relate biometric sample quality with the amount of identifiable information that the sample contains, and suggest that this amount decreases with a reduction in quality. They measure the amount of identifiable information for a person as the relative entropy $D(p||q)$ between the population feature distribution q and the person's feature distribution p. Based on this, we can measure the information loss due to a degradation in sample quality as the relative change in the entropy.

Quality measurement algorithms are increasingly deployed in operational biometric systems (Grother and Tabassi, 2007) and there is now international consensus in industry (Benini and et al, 2006), academia (Chen *et al.*, 2005) and government (Tabassi *et al.*, 2004) that a statement of a biometric sample's quality should be related to its recognition performance. That is, a quality measurement algorithm takes a signal or image, x, and produces a scalar, $q = Q(x)$, which is predictive of error rates associated with that sample. In other words, most of the operational schemes for quality estimation of biometric signals are focused on the *utility* of the signal. A framework for evaluating and comparing quality measures in terms of their capability of predicting the system performance is presented by Grother and Tabassi (2007). We adhere to this framework to report the experimental results of this Ph.D. Thesis.

We should note that, although biometric matching involves at least two samples, they are not acquired at the same time (we store samples in the system database that are later compared with the new ones provided for recognition). Therefore, a quality algorithm should be able to work with individual samples, even though its ultimate intention is to improve recognition performance when matching two (or more) samples. We should also note that the efficacy of a quality algorithm is usually related to a particular recognition algorithm, or to a particular class of algorithms (Grother and Tabassi, 2007). Can vendor A's quality measure be used with vendor B's recognition algorithm? To cope with this problem, there are recent efforts focused on the use of quality vectors instead of quality scalars, where each component of the vector is focused on a specific quality factor (Mansfield, 2007). However, this approach still needs the consensus of researchers and standardization bodies to decide which are the key factors for a given technology and how to provide universal quality measures interpretable by different algorithms. We will later discuss this issue in Section 2.7,

related to standardization efforts.

2.4.2 A framework for evaluating biometric quality measures

Broadly, a sample should be of good quality if it is suitable for automated matching. "Bad" quality in this context refers to any property or defect associated with a sample that would cause performance degradation. We then formalize the concept of sample quality as a scalar quantity that is related monotonically to the performance of biometric matchers (Grother and Tabassi, 2007). Throughout this work, we use low quality values to indicate poor sample properties.

Consider a data set D containing two samples, $d_i^{(1)}$ and $d_i^{(2)}$ collected from each of $i = 1, ..., N$ individuals. The first sample can be regarded as an enrollment sample, the second as a user sample collected later for verification or identification purposes. Consider that a quality algorithm Q can be run on the enrollment sample to produce a quality value

$$q_i^{(1)} = Q(d_i^{(1)}) \tag{2.1}$$

and likewise for the authentication (use-phase) sample

$$q_i^{(2)} = Q(d_i^{(2)}) \tag{2.2}$$

Consider K verification algorithms, V_k, that compare pairs of samples (or templates derived from them) to produce match (i.e., genuine) similarity scores,

$$s_{ii}^{(k)} = V_k(d_i^{(1)}, d_i^{(2)}), \tag{2.3}$$

and, similarly, nonmatch (impostor) scores,

$$\mathrm{s}_{ij}^{(k)} = V_k\left(d_i^{(1)}, d_j^{(2)}\right) \quad i \neq j \tag{2.4}$$

Assume now that the two quality values involved in a matching can be used to produce an estimate of the genuine similarity score

$$s_{ii}^{(k)} = P(q_i^{(1)}, q_i^{(2)}) + \epsilon_{ii}^{(k)}, \tag{2.5}$$

where the function P is some predictor of a matcher k's similarity scores, and ϵ_{ii} is the

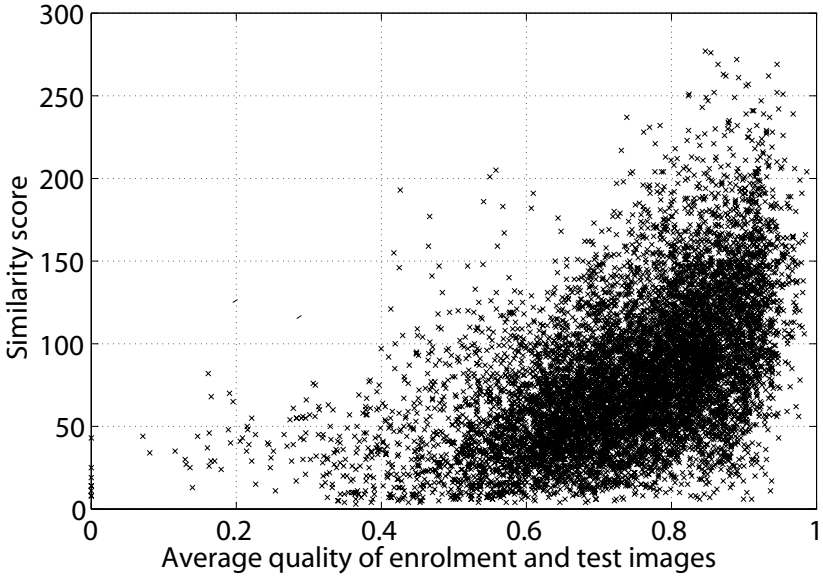


Figure 2.4: **Raw similarity scores from a fingerprint matcher versus the average quality of the enrolment and the test images.**

error in doing so for the ith score. Then substituting Equation (2.1) gives

$$s_{ii}^{(k)} = P(Q(d_i^{(1)}), Q(d_i^{(2)})) + \epsilon_{ii}^{(k)}, \tag{2.6}$$

and it becomes clear that, together, P and Q would be perfect imitators of the matcher V_k in Equation (2.3) if it was not necessary to apply Q to the samples separately. This separation is usually a necessary condition for a quality algorithm to be useful because, at least half of the time (i.e., enrollment), only one sample is available. Thus, the quality problem is complex, first, because Q is considered to produce a scalar and, second, because it is applied separately to the samples. The obvious consequence of this formulation is that it is inevitable that quality values will imprecisely map to similarity scores, i.e., there will be a scatter of the known scores, s_{ii}, for the known qualities $q_i^{(1)}$ and $q_i^{(2)}$. For example, Figure 2.4 shows the raw similarity scores of a fingerprint matcher versus the average quality of the enrolment and the test images. They trend in the correct direction: worse quality gives lower similarity scores. However, it is inappropriate to require quality measures to be linear predictors of the similarity scores; instead, the scores should be a monotonic function (higher quality samples give higher scores) (Grother and Tabassi, 2007).

Quality algorithms should be targeted to application-specific performance variables, i.e., false match and non-match rates. *Verification* applications are positive applica-

tions, which means that samples are captured overtly from users who are motivated to submit high quality samples. For this scenario, the relevant performance metric is the False Rejection Rate (FRR) because two high quality samples from the same individual should produce a high score. Regarding the False Acceptance Rate (FAR), high quality images should give very low impostor scores, but low quality images should also produce low scores (Grother and Tabassi, 2007). Indeed, it is undesirable that a matching algorithm produces high impostor scores from low quality samples.

Biometric matching involves at least two samples. We are then faced with relating performance to two quality values $q_i^{(1)}$ and $q_i^{(2)}$. To simplify the analysis, the two qualities are combined:

$$q_i = H(q_i^{(1)}, q_i^{(2)}) \tag{2.7}$$

Enrolment is usually a supervised process, and it is common to improve the quality of the final stored sample by acquiring as many samples as needed. Subsequent authentication samples gathered in the use-phase of a system can be supervised or unsupervised, thus having samples of less controlled quality. To capture this concept, we can consider $H(x, y) = \min(x, y)$, i.e., the worse of the two samples drives the similarity score. Another utilized functions $H(x, y)$ are (Fierrez-Aguilar *et al.*, 2005b; Grother and Tabassi, 2007): the arithmetic and geometric means, $H(x, y) = (x + y)/2$ and $H(x, y) = \sqrt{xy}$.

2.4.3 Evaluation of quality algorithms

The primary choice for evaluation of quality algorithms in several existing studies is the DET curve (Chen *et al.*, 2005; Fierrez-Aguilar *et al.*, 2005b; Tabassi and Wilson, 2005). DET curves are widely used in the biometric field to report performance capabilities of a system (Martin *et al.*, 1997). Data is partitioned in L levels according to some quality criteria and L rank-ordered DET curves are plotted. However, because DET curves combine the effect of quality on both genuine and impostor performance, we lose sight of the separate effects of quality on FAR and FRR. Three methods for partitioning the data are given by Grother and Tabassi (2007). The simplest case uses scores obtained by comparing authentication and enrolment samples whose qualities are both k. Although common, this method is not representative of an operational use of quality. Instead, by computing performance from scores obtained by comparing authentication samples of quality k with enrolment samples of quality greater than or equal to k, we model the situation in which the enrolment samples are at least as good as the authentication

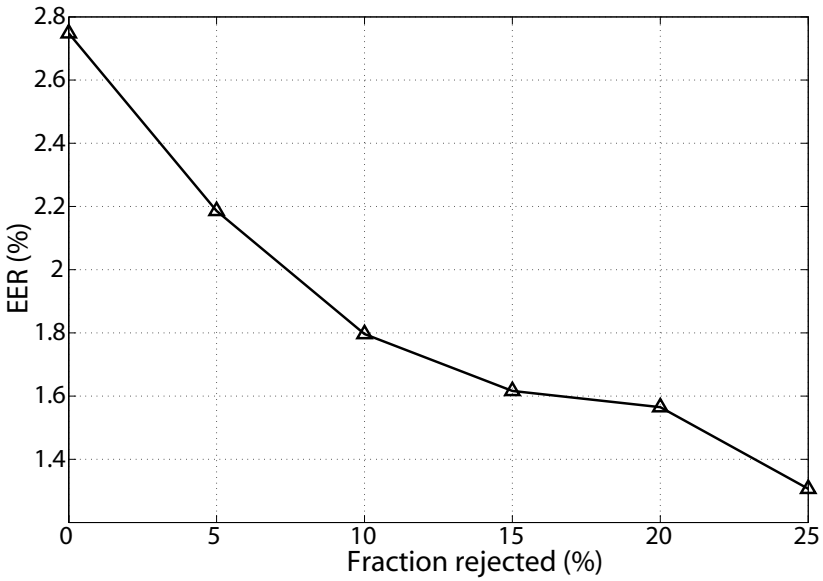


Figure 2.5: **Verification performance of a fingerprint matcher as samples with the lowest quality value are rejected.**

samples. Such use of a quality would lead to failures to acquire for the low quality levels. On the contrary, if we compare performance across all authentication samples against enrolment samples of quality greater than or equal to k, we model the situation where quality control is applied only during enrolment. Although some differences are found, experiments reported by Grother and Tabassi (2007) show that the ranked separation of the DETs is maintained with the three methods.

An alternative approach to the DET curve is the error-vs-reject curve. This curve models the operational case in which quality is used to reject low quality samples with the purpose of improving performance. Similarity scores with associated samples having a quality value lower than a predefined threshold are not included in the computation of the error rates. Note that this procedure involves the combination of quality from two samples (see Equation 2.7). For a good quality algorithm, error rates should decrease quickly with the fraction rejected. An example is shown in Figure 2.5.

2.5 Human vs. automatic quality assessment

It is often assumed that human assessment of biometric quality is the gold standard against which automatic quality measures should be measured. There is an established community of human experts in recognizing biometric signals for certain applications

(e.g. signatures in cheques or fingerprints in the forensic field) and the use of manual quality verification is included in the workflow of some biometric applications such as immigration screening and passport generation (Adler and Dembinsky, 2006).

Many authors make use of datasets with manually labeled quality measures to optimize and test their quality assessment algorithms (e.g. see Alonso-Fernandez *et al.* (2007c) and the references therein). On the other hand, there are some studies that test the relationship between human and algorithm based quality measures (Adler and Dembinsky, 2006). From these studies, it is evident that human and computer processing are not always functionally comparable. For instance, if a human judges a face or iris image to be good because of its sharpness, but a recognition algorithm works in low frequencies, then the human statement of quality is inappropriate. We can improve the judgement of human inspectors by adequate training on the limitations of the recognition system, but this could be prohibitively expensive and time consuming. In addition, if we decide to incorporate a human quality checker, we must consider the human factors such as tiredness, boredom or lack of motivation that a repetitive task like this may cause in the operator.

2.6 Incorporating quality measures in biometric systems

Different uses of sample quality measures in the context of biometric systems have been identified throughout this chapter. These possible uses are represented in Figure 2.6. We should note that these roles are not mutually exclusive. Indeed, the ideal situation would be to include all of them in our application. We can distinguish among:

- **Recapture loop** or **conditional reacquisition**. If an acquired sample does not satisfy our quality criteria, we can implement for instance an "up to three attempts" policy. This depends on the applications constraints, which may require to process the first acquired sample regardless of the quality. Also it is very important to know the reasons for poor quality samples, so we can improve the process, for example: giving feedback to the user including corrective behavior that would improve the quality of the reacquisition, using another sensor, collecting additional samples, invoking different processing, etc. To avoid reacquisition, some systems select the best signal in a stream captured while the user is interacting with the sensor, such as iris or face images from a video.

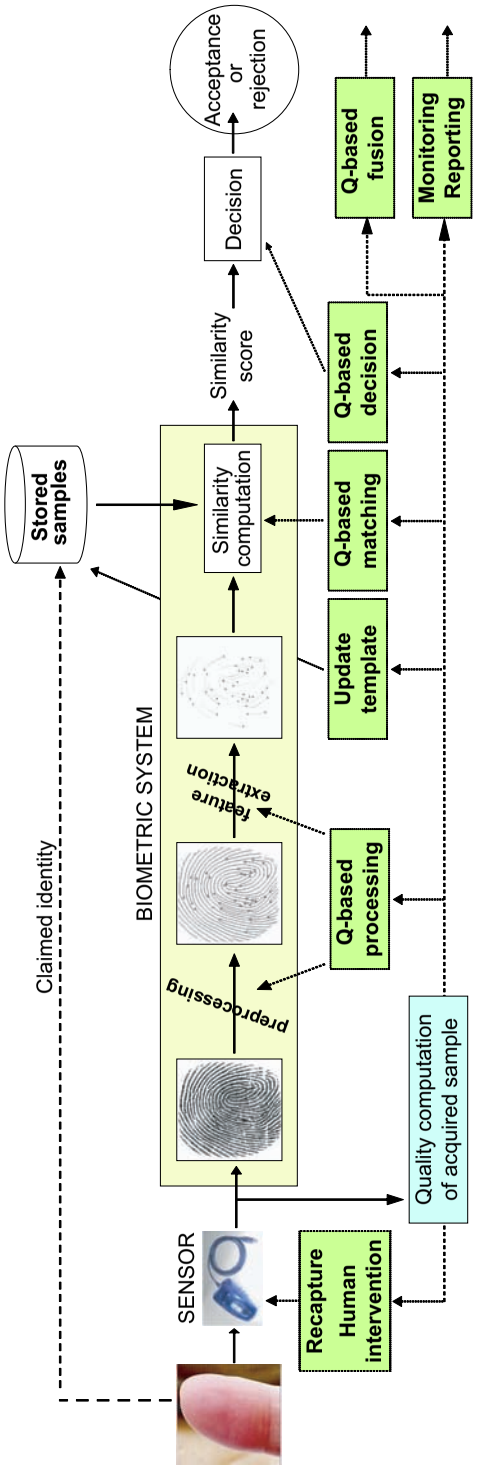


Figure 2.6: **Roles of a sample quality measure in the context of biometric systems.**

- **Invoke human intervention.** In the undesirable case that the biometric data of a user does not meet the quality requirements, we can either deny the access to this person, or (more friendly) invoke human intervention for an alternative recognition procedure. Human intervention is certainly time and cost consuming, and inconvenient for users. Therefore, it is important to capture the best possible input signals.

- **Quality-based processing.** In biometric systems, once a signal has been acquired, two steps are typically performed before the signal is matched against the templates stored in the system database: *i*) *pre-processing*, in which the input signal is enhanced to simplify the task of feature extraction, and *ii*) *feature extraction*, in which we further process the signal to generate a discriminative and compact representation. Depending on the quality of the acquired signal, we can adapt these two steps accordingly. If the quality of the sample is low, we can invoke special enhancement algorithms. Also, we can extract features robust to the kind of degradation that the biometric signal is suffering. In some cases there will be useless parts of the biometric signal (e.g., damaged fingerprint regions). Local quality measures can help to extract features only from the useful regions (Fronthaler *et al.*, 2008), taking into account that a minimum amount of information is needed to reliably using the biometric signal for recognition. It is also possible to rank the extracted features depending on the quality of local regions of the biometric signal, and exploit that information afterwards during the matching.

- **Update of enrolment data.** Biometric data is subject to natural variations across time. To cope with this problem, multiple templates representing the variability associated with the user can be stored in the database, which can be updated with new acquisitions (Ko and Krishnan, 2004; Uludag *et al.*, 2004). To improve the overall quality of the biometric database over time, we can also update the currently enrolled samples of a subject with better quality samples captured during the operation of the system, thereby improving the overall system match accuracy.

- **Quality-based matching and decision.** Once we extract the feature representation of the input biometric signal, it is compared against one (verification) or more (identification) templates stored in the system database. This comparison process is also called *matching*. The result of the comparison is a *similarity* or *matching score*, which in verification systems is then compared to a *decision*

threshold in order to accept or reject an input identity claim. Depending on the quality of acquired templates, we can use different matching algorithms (which also depend on the kind of features extracted in the previous step) (Fierrez-Aguilar *et al.*, 2005e). Also, we can adjust the sensitivity of the matcher or the decision threshold to the quality of the signals under comparison (Chen *et al.*, 2006a). We can discard features with low quality from the matching or give more weight to high quality features (Chen *et al.*, 2005).

- **Quality based-fusion.** Multibiometric systems integrate the evidence presented by multiple sources with the purpose of overcoming some of the limitations shown by the individual sources. The most widely used approach is integrating the matching scores provided by different systems due to the ease in accessing and processing outputs generated by different matchers (Ross *et al.*, 2006). Quality information has been incorporated in a number of fusion approaches, for instance weighting results from the multiple sources depending on the quality (Fierrez-Aguilar *et al.*, 2005e), or using only sources with a minimum quality. There are systems that implement a cascade scheme (e.g. Fronthaler *et al.* (2008)) by dynamically switching on the different sources in case of uncertainty (low quality) with the available ones. Other works that incorporate quality information in the fusion are Fierrez-Aguilar *et al.* (2006); Garcia-Romero *et al.* (2006); Kryszczuk and Drygajlo (2008); Nandakumar *et al.* (2006).

- **Monitoring and reporting.** We can use quality measures to monitor quality across the different parts of our system with the objective of identifying problems that lead to poor quality signals. Ko and Krishnan (2004) have documented a methodology for this purpose. They identify different aspects related to biometric signal quality that can be monitored and reported:

  1. Signal quality by *application*. Different application scenarios may require different scanners, capture software, environment configuration and settings, and these differences may have different impact on the overall quality of captured signals. Therefore, it is important to monitor the signal quality distribution for different applications to find application-specific problems.
  2. Signal quality by *site/terminal*. This helps to identify abnormal sites or terminals due to operator training, site configuration, operational conditions, damaged sensor, environment, etc.
  3. Signal quality by *capture device*. There can be variations in the quality of

captured signals between devices due to differences in the physical acquisition principle (Alonso-Fernandez *et al.*, 2008), mechanical design, etc. Reporting quality distributions by scanner type identifies device-specific problems, helping us to initiate corrective actions.

4. Signal quality by *subject*. It is known that once the users get more familiar with the interaction with the acquisition device, and with the system in general, their acquired biometric signals exhibit better quality. Identifying the interaction learning curve helps us to better train new users, specially elder people or people who is not used to interact with machines, alleviating the "first time user" syndrome.

5. Signal quality by *template*. As we have discussed before, template substitution/updating is a good strategy to deal with the variability of biometric data across time and to improve the quality of stored templates. Periodic quality distribution reports of stored biometric data allows us to detect how the quality of the database is varying, helping us to improve the template substitution/updating algorithm.

6. Signal quality by *biometric input*. In multibiometric systems, where multiple sources of biometric information are combined (Ross *et al.*, 2006), this kind of report is aimed to examine the quality distributions of these different sources. It allows us to detect, for instance, if an specific source is experiencing problems, or if the way we are combining the different sources can be improved.

7. Signal quality *trend analysis*. This provides the quality statistics of all applications, sites, etc., allowing us to identify trends in signal quality or sudden changes that need further investigation.

2.7 Standardizing biometric quality

Standards compliance allows us to replace parts of deployed systems with various technological options coming from open markets. Also, as biometric technology is extensively deployed, a common situation is the exchange of information between several applications, involving diverse biometric systems developed by different vendors. This interoperable scenario is also enabled by the adoption of standards. Examples of interoperable scenarios are the use of ePassports readable by different countries, or the exchange of lists of criminals among Security Forces.

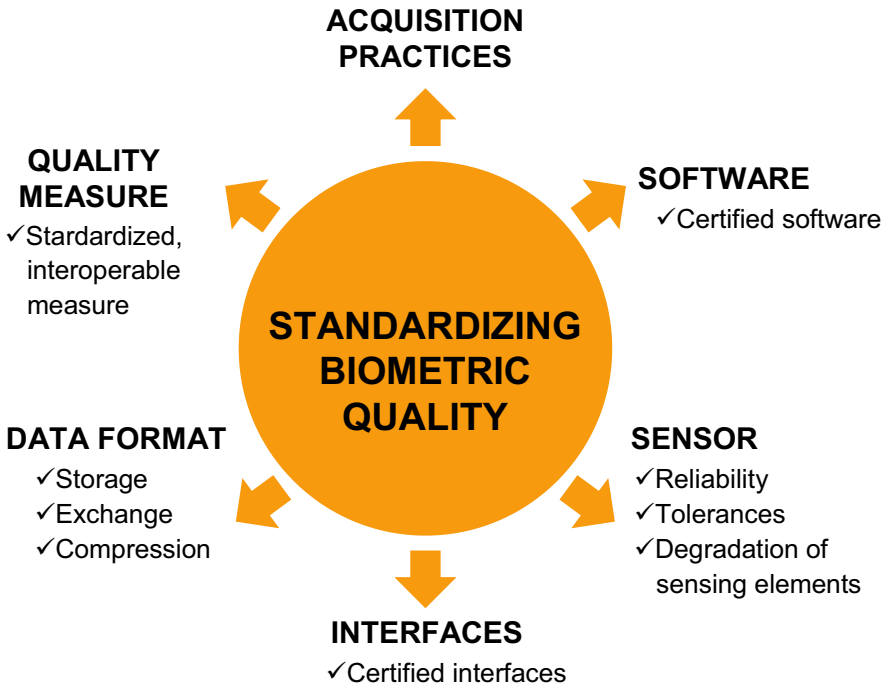


Figure 2.7: **Use of standards in biometric systems to ensure good quality.**

During the last decade, standardization bodies have launched important efforts focused on developing standards for biometric systems. Among the most important international standardization bodies with published biometric standards, or currently under development, we find:

- The International Organization for Standardization (ISO), with the Subcommittee 37 for Biometrics (SC37) of the Joint Technical Committee on Information Technology (JTC1), known as ISO/IEC JTC1/SC37 (ISO/IEC JTC1 SC37, 2002).
- The InterNational Committee for Information Technology Standards (INCITS), with the Technical Committee M1 on Biometrics, known as INCITS M1 (INCITS M1, 2007).
- The Information Technology Laboratory (ITL) of the American National Institute of Standards and Technology (NIST) (NIST-ITL, 2007).

Other international bodies driving or collaborating on biometric initiatives are: the Biometrics Consortium (BC), the International Biometrics Group (IBG), the Biometrics

Management Office of the American Department of Defense (DoD), the Federal Bureau of Investigation (FBI), the European Biometrics Forum (EBF), the International Civil Aviation Organization (ICAO), the International Biometric Industry Association (IBIA), or the American National Standards Institute (ANSI).

We summarize in Figure 2.7 which parts of a biometric system can be standardized. As a result of the efforts carried out by these standardization bodies, we find that international standards relating to biometrics are maturing quickly:

- Standards for *interfaces* between modules, as the BioApi Specification (BioAPI, 1998), sponsored in 1999 by the NIST-ITL and the US Biometric Consortium, and adopted by ISO/IEC and INCITS as the ISO/IEC 19784-1:2005 and ANSI INCITS 358-2002 standards, respectively.

- Standards for *data formats*, as: *i*) the Common Biometric Exchange Formats Framework (CBEFF), sponsored by the NIST-ITL and the Biometric Consortium in 2001/2004, *ii*) the FBI Wavelet Scalar Quantization (WSQ) image compression algorithm for fingerprint images, developed to archive the large FBI fingerprint database, *iii*) the Electronic Fingerprint Transmission Specification (EFTS) (FBI Biometric Specifications (BioSpecs)) of the FBI, initially developed for electronically encoding and transmitting fingerprint images, identification and arrest data, and recently expanded to include additional biometric modalities (palmprint, facial, and iris), or *iv*) the ANSI/NIST-ITL 1-2000 that specifies a common format for exchanging fingerprint, facial, scar, mark, and tattoo identification data between law enforcement and related criminal justice agencies.

- Standards for *acquisition practices*, as: *i*) the ISO-19794-5/ICAO requirements and best practices for facial portraits, with recommendations about the deployment of biometrics in machine readable travel documents, or *ii*) the best practices Annex to ISO 19794-5 standard regarding conditions for taking photographs for face image data, with indications about lighting and camera arrangement, and head positioning.

Most of the biometric existing standards define a quality score field aimed to incorporate *quality measures*. Nevertheless, the content of this field is not explicitly defined or is somewhat subjective (Benini, 2007). The reason for this vagueness is that traditionally there has not been consensus on how to provide universal quality measures interpretable by different algorithms, or which are the key factors that define

quality in a given biometric trait. These problems are being the source of many research works nowadays, and have led to the multipart standardization effort ISO/IEC 29794-1/4/5 on biometric sample quality (Benini, 2007). The goals of this standard are to enable harmonized interpretation of quality scores from different vendors, algorithms and versions. Ongoing works within this standardization project include: *i*) standardizing quality scoring algorithms by setting the key factors that define quality in different biometric traits (e.g., for face recognition, they would be metrics like eyes closed/obstructed, lighting uniformity on face, image focus, face rotation, etc.), *ii*) achieving normalization of scores, with different algorithms expressing quality scores on the same scale, *iii*) building a database of samples and assigned quality scores that would serve as reference for vendors, and *iv*) incorporating fields to existing data interchange format standards to identify the algorithm used to generate the quality scores. The latter approach, known as Quality Algorithm ID (QAID), incorporates standardized data fields (International Biometric Industry Association (IBIA)) that uniquely identifies a quality algorithm, including its vendor, product code and version. It enables to differentiate between quality scores generated by different algorithms/vendors and to adjust them for any differences in processing or analysis as necessary. QAID fields can be easily added to existing data interchange formats such as CBEFF, enabling a modular multi-vendor environment that accomodates samples scored by different quality algorithms. It should noted that this approach does not attempt to define what is good/bad quality or to set how quality measures should be computed, it just provides means to interchange and interpret biometric sample quality scores via existing data interchange formats.

2.8 Issues and challenges

The increasing development of biometrics in the last decade, related to the number of important applications where a correct assessment of identity is a crucial point, has not been followed by extensive research on the biometric quality measurement problem (Grother and Tabassi, 2007). Biometric data quality is a key factor in the performance of identification systems, as the biometric community has realized that biometric systems fail on certain pathological samples. Now that there is international consensus that a statement of a biometric sample's quality should be related to its recognition performance, efforts are going towards an harmonized and universal interpretation of quality measures by defining the key factors that need to be assessed in each biometric trait, and by setting good acquisition practices. This will enable a competitive multi-

vendor marketplace, allowing interoperability of multiple vendors quality assessment algorithms.

A biometric system has to be resilient in processing data with heterogeneous quality yet providing good recognition performance. Although there are several corrective actions that can be performed to improve the quality of acquired signals, some factors fall out of our control or cannot be avoided. In this respect, specially challenging scenarios for biometrics are the ones based on portable devices and/or remote access through Internet, which are expected to work in an unsupervised environment, with no control on the ambient noise, on the user-sensor interaction process, or on the sensor maintenance. Therefore, it is very important upon capture of biometric samples to assess their quality as well as having specific developments for poor quality signals.

Quality is intrinsically multi-dimensional, with factors of very different nature affecting it. A biometric system must adequately address this multifactor nature of the sample quality. There are a number of things that quality measures can do for us in the context of our system to improve the overall performance, such as altering the sample processing/comparison process, or weighting the results from different systems depending on the quality. Some research works have dealt with these matters, but much work is still to be done in this area. Recent independent evaluations of commercial and research prototypes are also starting to include quality studies in their scenarios, as the Minutiae Interoperability Exchange Test in 2005 (Grother *et al.*, 2005) or the BioSecure Multimodal Evaluation Campaign in 2007 (BMEC, 2007).

2.9 Chapter summary and conclusions

Since the establishment of biometric research as an specific research area in late 90s (Jain *et al.*, 2008), the biometric community has focused its efforts in the development of accurate recognition algorithms. Nowadays, biometric recognition is a mature technology that is used in many applications (e.g. e-Passports, ID cards or border control (US-VISIT Program of the U.S. Department of Homeland Security)). However, we can notice recent studies that demonstrate how performance of biometric systems is heavily affected by the quality of biometric signals. The problem of biometric quality measurement has arisen in the last years and at this moment, it is a current research challenge within the biometric community (Grother and Tabassi, 2007).

In this chapter, we present an overall framework of the different issues that make up the biometric quality problem. Issues like the factors influencing biometric quality, the strategies to ensure the best possible quality of acquired biometric samples, or the

role of quality measures within biometric systems are addressed here. We also present a framework for evaluation of the performance of biometric quality measures, as well as existing standardization efforts related to biometric quality.

This chapter includes novel contributions regarding the taxonomy of factors affecting biometric quality, the taxonomy of strategies to ensure good quality in acquired biometric samples, and the taxonomy of roles of quality measures in the context of biometric systems.

Chapter 3

Quality Assessment of Fingerprint Images

Due to its permanence and uniqueness, fingerprint recognition is the most widely deployed biometric technology (Maltoni *et al.*, 2003). Fingerprints are used in forensic investigations since the XIX century by Security Forces worldwide. Nowadays, a large number of convenience applications such as access control or on-line identification also make use of fingerprints (Jain *et al.*, 2006). Nearly half of invests in the biometric market go to the fingerprint technology (IBG, 2007).

This chapter compares several representative fingerprint quality measures by studying both their correlation and their *utility*. We evaluate the impact of the selected image quality measures in the performance of a minutiae- and a ridge-based matcher, which are the two most popular approaches for fingerprint verification (Maltoni *et al.*, 2003). We use for our experiments a multi-session database (Fierrez *et al.*, 2007) acquired with three sensors of different technology. High correlation is found between quality measures in most cases, however, some differences are observed depending on the sensor. Regarding the utility of the selected measures, it has been found that for the approach based on minutiae, the highest performance improvement is obtained in the False Rejection Rate, whereas for the ridge-based approach the highest improvement is observed in the False Acceptance Rate. We also contribute in this chapter with a comprehensive survey of existing fingerprint quality algorithms. We provide basic algorithmic descriptions of each quality estimation measure and the rationale behind, including visual examples that show the behavior of the measures with fingerprint images of different quality.

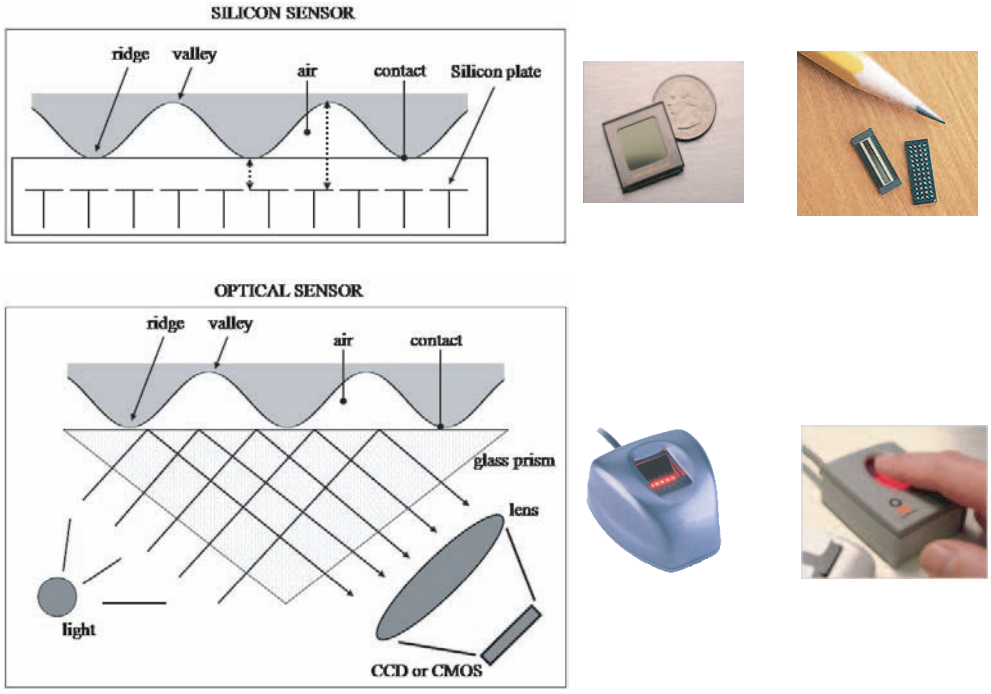


Figure 3.1: **Acquisition principles of silicon and optical sensors.**

This chapter is structured as follows. We first present the basics of fingerprint recognition systems, including its different phases and the most common used algorithms. We next give a comprehensive description of existing approaches for fingerprint image quality assessment. After that, we outline the fingerprint matching systems and the experimental framework used. Results are then described and finally, a summary and some conclusions are given.

The minutiae-based matcher used in this Chapter is the one released by the National Institute of Standards and Technology (Watson *et al.*, 2004), and the ridge-based one is a proprietary system developed at the Biometric Recognition Group - ATVS (Fierrez-Aguilar *et al.*, 2005b), therefore they are not contributions of this Thesis. Similarly, quality measures used in this Chapter are not original, although they have been implemented and optimized in the framework of this Ph.D. Thesis. Original contributions in this chapter are related to the taxonomy of fingerprint image quality assessment algorithms, the implementation of a representative set of them, the study of correlation between the selected quality algorithms, and the study of utility of the quality measures for two different matchers with sensors of different technology.

This chapter is based on the publications: Alonso-Fernandez *et al.* (2008a, 2007c, 2005b, 2008); Fierrez-Aguilar *et al.* (2005b).


Figure 3.2: **Solid-state sensors embedded in portable devices.**

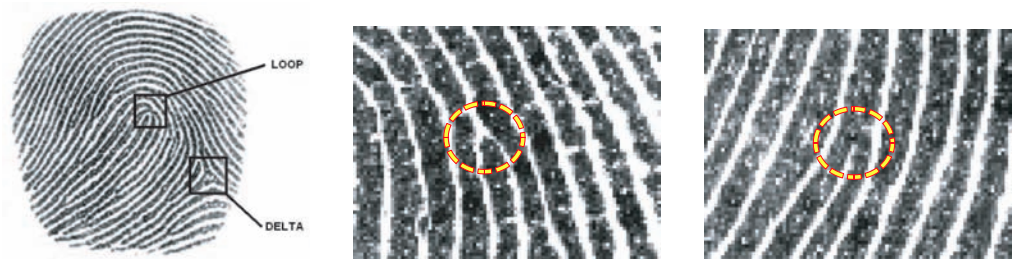
3.1 Automatic fingerprint recognition

A fingerprint verification system follows the general architecture of a biometric system presented in Chapter 1. We now describe the most popular strategies for the different phases, namely: *i*) *fingerprint sensing*, in which the fingerprint of an individual is acquired by a fingerprint scanner to produce a raw digital representation; *ii*) *pre-processing*, in which the input fingerprint is enhanced and adapted to simplify the task of feature extraction; *iii*) *feature extraction*, in which the fingerprint is further processed to generate discriminative properties, also called feature vectors; and *iv*) *matching*, in which the feature vector of the input fingerprint is compared against the template (feature vector) of a single user.

3.1.1 Fingerprint Sensing

The acquisition of fingerprint images has been historically carried out by spreading the finger with ink and pressing it against a paper card. The paper card is then scanned, resulting in a digital representation. This process is known as *off-line* acquisition and is still used in law enforcement applications. Nowadays, it is possible to acquire the fingerprint image by pressing the finger against the flat surface of an electronic fingerprint sensor. This process is known as *on-line* acquisition. There are three families of electronic fingerprint sensors based on the sensing technology (Maltoni *et al.*, 2003):

- *Optical* (right part of Figure 3.1): The finger touches a glass prism and the prism is illuminated with diffused light. The light is reflected at the valleys and absorbed at the ridges. The reflected light is focused onto a CCD or CMOS sensor. Optical



(a) (b) (c)

Figure 3.3: **(a) loop and delta singularities, (b) ridge ending, (c) ridge bifurcation.**

fingerprint sensors provide good image quality and large sensing area but they cannot be miniaturized because as the distance between the prism and the image sensor is reduced, more optical distortion is introduced in the acquired image.

- *Solid-state* or silicon sensors (left part of Figure 3.1): they consist of an array of pixels, each pixel being a sensor itself. Users place the finger on the surface of the silicon, and four techniques are typically used to convert the ridge/valley information into an electrical signal: capacitive, thermal, electric field and piezoelectric. Since solid-state sensors do not use optical components, their size is considerably smaller and can be easily embedded for instance in PDAs or laptops as seen in Figure 3.2, but silicon sensors are expensive, so their sensing area is typically small.

  The large-scale deployment of small and low cost sensors also makes possible its incorporation in portable hand-held devices like PDAs or laptops.

- *Ultrasound*: Acoustic signals are sent, capturing the echo signals that are reflected in the fingerprint surface. Acoustic signals are able to cross dirt and oil that may be present in the finger, thus giving good quality images. On the other hand, ultrasound scanners are large and expensive, and take some seconds to acquire an image.

A new generation of touchless live scan devices that generate a 3D representation of fingerprints is appearing (Chen *et al.*, 2006b). Several images of the finger are acquired from different views using a multi-camera system, and a contact-free 3D representation of the fingerprint is then constructed. This new sensing technology overcomes some of the problems that intrinsically appear in contact-based sensors such as improper finger placement, skin deformation, sensor noise or dirt.

3.1.2 Preprocessing and Feature Extraction

A fingerprint is composed of a pattern of interleaved *ridges* and *valley*. They smoothly flow in parallel and sometimes terminate or bifurcate. At a global level, this pattern sometimes exhibits a number of particular shapes called *singularities* which can be classified into three types: *loop*, *delta* and *whorl*. In Figure 3.3a we can see an example of loop and delta singularities (the whorl singularity can be defined as two opposing loops). Singularities at the global level are commonly used for fingerprint classification, which simplifies search and retrieval across a large database of fingerprint images. At the local level, the ridges and valleys pattern can exhibit a particular shape called *minutia*. There are several types of minutiae but for practical reasons, only two types of minutiae are considered: ridge ending (Figure 3.3b) and ridge bifurcation (Figure 3.3c).

The gray-scale representation of a fingerprint image is known to be unstable for fingerprint recognition (Maltoni *et al.*, 2003). Although there are fingerprint matching techniques that directly compare gray images using correlation-based methods, most of the fingerprint matching algorithms use features which are extracted from the gray-scale image. To make this extraction easy and reliable, a set of preprocessing steps is commonly performed, namely: *i*) computation of local ridge orientation and *ii*) local ridge frequency, *iii*) enhancement of the fingerprint image, and *iv*) segmentation of the fingerprint area from the background.

- The *local ridge orientation* at a pixel level is defined as the angle that the fingerprint ridges form with the horizontal axis. Most of the algorithms do not compute the local ridge orientation at each pixel, but over a square-meshed grid (Figure 3.4). The simplest approach for local ridge orientation estimation is based on the gray-scale gradient. Since the gradient phase angle denotes the direction of the maximum pixel-intensity change, the ridge orientation is orthogonal to this phase angle. There are essentially two orientation estimation techniques: the direction tensor sampling, (Bigun and Granlund, 1987) and spectral tensor discretization (Knutsson, 1982) using Gabor filters. For its computational efficiency the method independently suggested by Bigun and Granlund (1987) is the most commonly utilized in fingerprint applications because the spectral approach needs more filtering. We refer to Bigun (2006) for a detailed treatment of both approaches.

- The *local ridge frequency* at a pixel level is defined as the number of ridges per unit length along a hypothetical segment centered at this pixel and orthogonal to

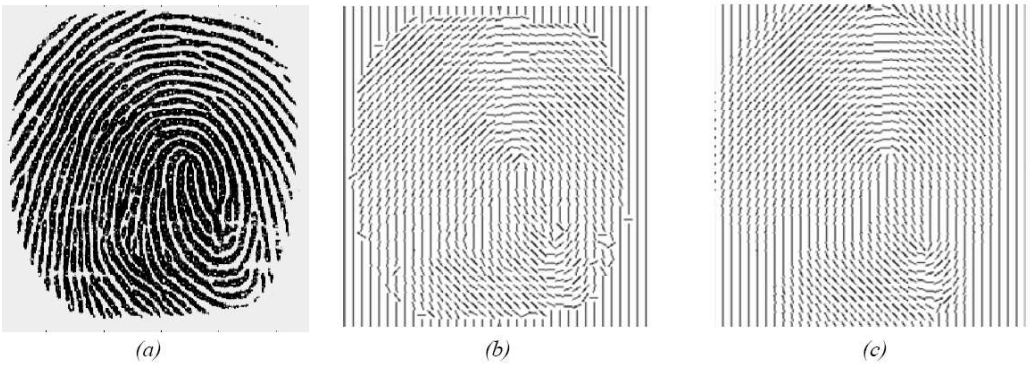


Figure 3.4: **Local ridge orientation of a fingerprint image computed over a square-meshed grid: (a) original image, (b) orientation image, (c) smoothed orientation image. Each element of (b) and (c) denotes the local orientation of the ridges. Figure extracted from Simon-Zorita (2003).**

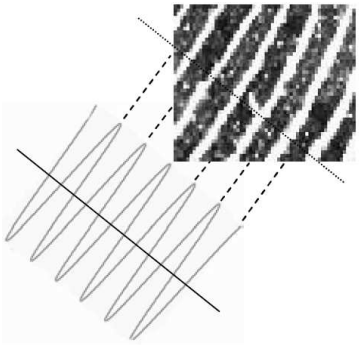


Figure 3.5: **Modeling of ridges and valleys as a sinusoidal-shaped wave.**

the local ridge orientation (Maltoni *et al.*, 2003). As in the case of the local ridge orientation, the local ridge frequency is computed over a square-meshed grid. Existing methods (Hong *et al.*, 1998; Kovacs-Vajna *et al.*, 2000; Maio and Maltoni, 1998) usually model the ridge-valley structure as a sinusoidal-shaped wave (Figure 3.5), where the ridge frequency is set as the frequency of this sinusoid, and the orientation is used to angle the wave.

- Ideally, in a fingerprint image, ridges and valleys flow smoothly in a locally constant direction. In practice, however, there are factors that affect the quality of a fingerprint image: wetness or dryness of the skin, noise of the sensor, temporary or permanent cuts and bruises in the skin, variability in the pressure against the sensor, etc. Several *enhancement* algorithms have been proposed in literature

Figure 3.6: **Enhancement of fingerprint images.**

Figure 3.7: **Segmentation of fingerprint images. Left: original image. Right: segmentation mask.**

with the aim of improving the clarity of ridges and valleys. The most widely used fingerprint enhancement techniques utilize *contextual filters*, which means changing the filter parameters according to the local characteristics (context) of the image. Filters are tuned to the local ridge orientation and/or frequency, thus removing the imperfections and preserving ridges and valleys (Figure 3.6).

- Fingerprint *segmentation* consists in the separation of the fingerprint area (foreground) from the background. This is useful to avoid subsequent extraction of fingerprint features in the background, which is the noisy area. Global and local thresholding segmentation methods are not very effective and more robust segmentation techniques are commonly used (Bazen and Gerez, 2001; Jain *et al.*, 1997b; Maio and Maltoni, 1997; Mehtre, 1993; Nilsson, 2005; Shen *et al.*, 2001). These techniques exploit the existence of an oriented periodical pattern in the foreground, and a nonoriented isotropic pattern in the background (Figure 3.7).

Once the fingerprint image has been preprocessed, a feature extraction step is performed. Most of the existing fingerprint recognition systems are based on minutiae

Figure 3.8: **Binarization and thinning of fingerprint images using contextual filters. Figure extracted from Simon-Zorita *et al.* (2003).**

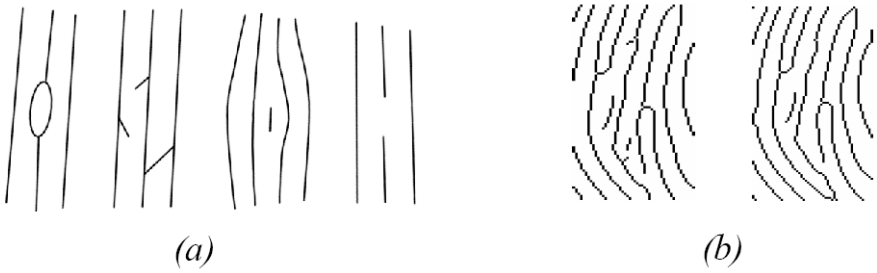


Figure 3.9: **Thinning step: (a) typical imperfections appeared during the thinning step, (b) a thinned fingerprint structure before and after removing imperfections.**

matching, so that reliable minutiae extraction is needed. Usually, the preprocessed fingerprint image is converted into a binary image which is then thinned using morphology (Figure 3.8). The thinning step reduces the ridge thickness to one pixel, allowing straightforward minutiae detection. During the thinning step, a number of spurious imperfections may appear (Figure 3.9a) and thus, a postprocessing step is sometimes performed (Figure 3.9b) in order to remove the imperfections from the thinned image. Several approaches for binarization, thinning and minutiae detection have been proposed in the literature (Maltoni *et al.*, 2003). However, binarization and thinning suffer from several problems: *i*) spurious imperfections, as mentioned; *b*) loss of structural information; *c*) computational cost; and *d*) lack of robustness in low quality fingerprint images. Because of that, other approaches that extract minutiae directly from the gray-scale image have been also proposed (Bolle *et al.*, 2002; Chang and Fan, 2001; Fronthaler *et al.*, 2006; Jiang *et al.*, 2001; Liu *et al.*, 2000; Maio and Maltoni, 1997).

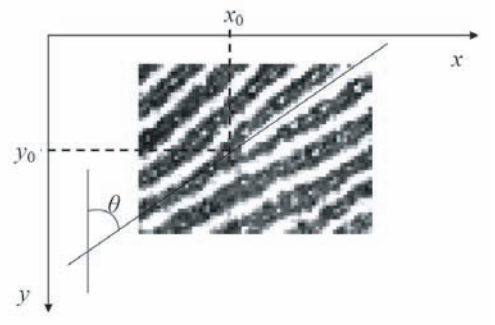


Figure 3.10: **Minutia represented by its spatial coordinates and angle.**

3.1.3 Fingerprint Matching

In the matching step, features extracted from the input fingerprint are compared against those in a template, which represents a single user (retrieved from the system database based on the claimed identity). The result of such a procedure is either a degree of similarity (also called matching score) or an acceptance/rejection decision. There are fingerprint matching techniques that directly compare gray-scale images (or sub-images) using correlation-based methods, so that the fingerprint template coincides with the gray-scale image. However, most of the fingerprint matching algorithms use features which are extracted from the gray-scale image, as mentioned in Section 3.1.2.

A large number of approaches for fingerprint matching can be found in literature. They can be classified into: *i*) correlation-based approaches, *ii*) minutiae-based approaches, and *iii*) ridge or texture-based approaches.

- In the *correlation-based approaches*, the fingerprint images are superimposed and the gray-scale images are directly compared using a measure of correlation. Due to non-linear distortion, different impressions of the same finger may result in differences of the global structure, making the comparison unreliable. In addition, computing the correlation between two fingerprint images is computationally expensive. To deal with these problems, correlation can be computed only in certain local regions of the image which can be selected following several criteria. Also, to speed up the process, correlation can be computed in the Fourier domain or using heuristic approaches which allow to reduce the number of computational operations.

- *Minutiae-based approaches* are the most popular and widely used methods for fingerprint matching, since they are analogous with the way that forensic experts

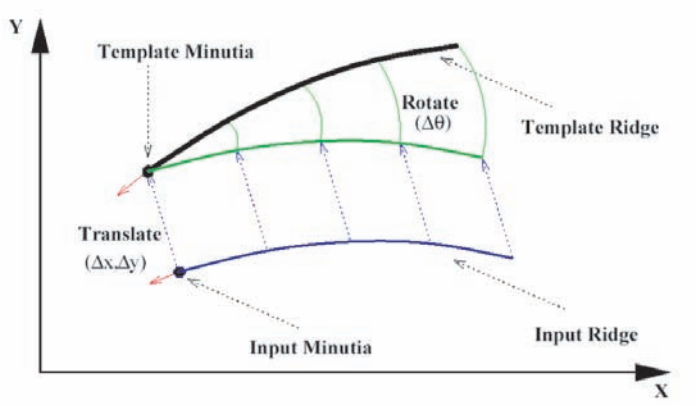


Figure 3.11: **Alignment between minutiae of two fingerprints. Figure extracted from Jain *et al.* (1997a).**

compare fingerprints. A fingerprint is modeled as a set of minutiae, which are usually represented by its spatial coordinates and the angle between the tangent to the ridge line at the minutiae position and the horizontal or vertical axis (Figure 3.10). The minutiae sets of the two fingerprints to be compared are first aligned, requiring displacement and rotation to be computed, as depicted in Figure 3.11 (some approaches also compute scaling and other distortion-tolerant transformations). This involves a minimization problem, the complexity of which can be reduced in various ways (Chikkerur and Ratha, 2005). Once aligned, corresponding minutiae at similar positions in both fingerprints are looked for. A *region of tolerance* around the minutiae position is defined in order to compensate for the variations that may appear in the minutiae position due to noise and distortion. Likewise, differences in angle between corresponding minutia points are tolerated. Other approaches use *local minutia matching*, which means combining comparisons of local minutia configurations. These kind of techniques relax global spatial relationships which are highly distinctive (Maltoni *et al.*, 2003) but naturally more vulnerable to nonlinear deformations. Some matching approaches combine both techniques by first carrying out a fast local matching and then, if the two fingerprints match at local level, consolidating the matching at global level.

- Unfortunately, minutiae are known to be unreliably extracted in low image quality conditions. For this and other reasons, alternative features have been proposed in literature as an alternative to minutiae (or to be used in conjunction with

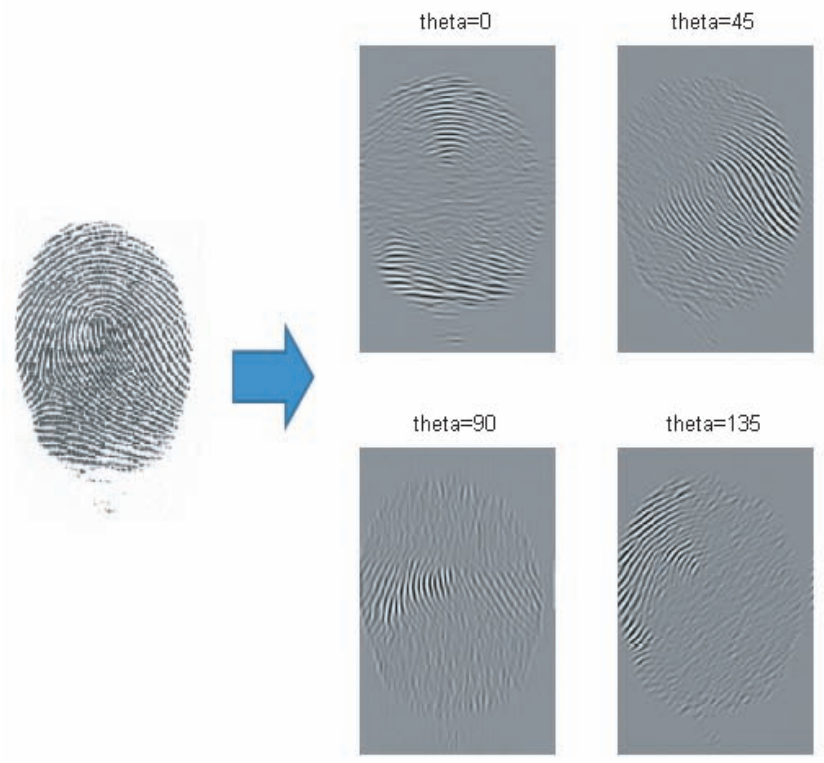


Figure 3.12: **Texture information based on local orientation. Figure extracted from Munoz-Serrano (2004).**

minutiae) (Maltoni *et al.*, 2003). The alternative feature most widely studied for fingerprint matching is the *texture information*. The fingerprint structure consists of periodical repetitions of a pattern of ridges and valleys that can be characterized by its local orientation, frequency, symmetry, etc. In Figure 3.12, ridges with different local orientations are extracted from a fingerprint image. Texture information is less discriminative than minutiae, but more reliable under low quality conditions (Fierrez-Aguilar *et al.*, 2005b).

3.1.4 Issues and Challenges

One of the biggest challenges of fingerprint recognition is the high variability commonly found between different impressions of the same finger. This variability is known as *intra-class* variability and is caused by factors like displacement or rotation between different acquisitions, partial overlap (specially in sensors of small area), noise in the sensor (for example, residues from previous acquisitions), etc. Some examples are shown

(a) Partial overlap (b) Rotation or displacement

Figure 3.13: **Examples of intra-class variability in fingerprints. Figure extracted from Simon-Zorita (2003).**

in Figure 3.13. Fingerprint matching remains as a challenging pattern recognition problem due to the difficulty in matching fingerprints affected by one or several of the mentioned factors (Maltoni *et al.*, 2003).

A successful approach to enhance the performance of a fingerprint verification system is to combine the results of different recognition algorithms. A number of simple fusion rules and complex trained fusion rules have been proposed in the literature (Bigun *et al.*, 1997; Kittler *et al.*, 1998; Snelick *et al.*, 2005). Examples for combining minutia- and texture-based approaches are to be found in Alonso-Fernandez *et al.* (2008a); Fierrez-Aguilar *et al.* (2006); Marcialis and Roli (2005); Ross *et al.* (2003). Also, a comprehensive study of the combination of different fingerprint recognition systems is done in Fierrez-Aguilar *et al.* (2005c). However, it has been found that simple fusion approaches are not always outperformed by more complex fusion approaches, calling for further studies of the subject.

Another recent issue in fingerprint recognition is the use of multiple sensors, either for sensor fusion (Marcialis and Roli, 2004) or for sensor interoperability (Alonso-Fernandez *et al.*, 2006c; Ross and Jain, 2004). Fusion of sensors offers some important potentialities (Marcialis and Roli, 2004): *i*) the overall performance can be improved substantially, *ii*) population coverage can be improved by reducing enrollment and verification failures, and *iii*) it may naturally resist spoofing attempts against biometric systems. Regarding sensor interoperability, most biometric systems are designed under the assumption that the data to be compared is obtained uniquely and the same for every sensor, thus being restricted in their ability to match or compare biometric data originating from different sensors in practise. As a result, changing the sensor may affect the performance of the system. Recent progress has been made in the development

of common data-exchange formats to facilitate the exchange of feature sets between vendors (CBEFF, 2001). However, little effort has been invested in the development of algorithms to alleviate the problem of sensor interoperability. Some approaches to handle this problem are given in Ross and Jain (2004), one example of which is the normalization of raw data and extracted features. Interoperability studies have been included in vendor and algorithm competitions, as in BMEC (2007); Grother *et al.* (2005).

Due to the low cost and reduced size of new fingerprint sensors, several devices of daily use already include fingerprint sensors embedded (e.g. mobile telephones, PC peripherals, PDAs, etc., see Figure 3.2). However, using small-area sensors implies having less information available from a fingerprint and little overlap between different acquisitions of the same finger, which has great impact on the performance of the recognition system (Maltoni *et al.*, 2003). Some fingerprint sensors are equipped with mechanical guides in order to constrain the finger position. Another alternative is to perform several acquisitions of a finger, gathering (partially) overlapping information during the enrollment, and reconstruct a full fingerprint image.

Biometric systems are also vulnerable to attacks (Uludag and Jain, 2004). Recent studies have shown the vulnerability of fingerprint systems to fake fingerprints (Galbally-Herrero *et al.*, 2006; Matsumoto *et al.*, 2002; Putte and Keuning, 2000; Ratha *et al.*, 2001a). Surprisingly, fake biometric input to the sensor is shown to be quite successful. Liveness detection could be a solution and it is receiving great attention (Antonelli *et al.*, 2006; Derakhshani *et al.*, 2003; Schuckers *et al.*, 2004). It has been also shown that the matching score is a valuable information for the attacker (Martinez-Diaz *et al.*, 2006; Ratha *et al.*, 2001b; Uludag and Jain, 2004). Using the feedback provided by this score, signals in the channels of the verification system can be modified iteratively and the system is compromised in a number of iterations. A solution could be given by concealing the matching score and just releasing an acceptance/rejection decision, but this may not be suitable in certain biometric systems (Uludag and Jain, 2004).

With the advances in fingerprint sensing technology, new high resolution sensors are able to acquire ridge pores and even perspiration activities of the pores. These features can provide additional discriminative information to existing fingerprint recognition systems, as studied in Chen and Jain (2007); Jain *et al.* (2007). In addition, acquiring perspiration activities of the pores can be used to detect spoofing attacks.

3.2 Literature review of algorithms for fingerprint image quality estimation

3.2.1 Assessing the quality of fingerprint images

Fingerprint quality can be defined as a measure of the clarity of ridges and valleys and the "extractability" of the features used for identification (such as minutiae) (Chen *et al.*, 2005). In good quality images, ridges and valleys flow smoothly in a locally constant direction (Hong *et al.*, 1998).

Yao *et al.* (2004) define a number of factors that contribute to poor fingerprint quality images (some examples are shown in Figure 3.14):

- *Inconsistent contact* caused by the 3D-2D mapping performed in fingerprint acquisition, which is typically uncontrolled and thus, it results in different mapped regions across different impressions due to variability in fingerprint placement, rotation and pressure.

- *Nonuniform contact* of the ridge-valley structure due to factors like dryness (too little ridge contact), humidity (neighboring ridges touching each other), sweat, dirt, etc., resulting in "noisy" images and feature extraction artifacts.

- *Irreproducible contact* due to injuries of the finger that change the ridge structure either temporarily or permanently, for example caused by manual works, accidents, etc.

- Noise introduced by the act of sensing due to residual dirt or fingerprints on the sensor surface, shadows in optical sensors, electrical noise in capacitive sensors, etc.

- Distortion of the sensed finger due to imperfect imaging conditions.

These factors are caused by a number of reasons (Joun *et al.*, 2003) that sometimes cannot be avoided and/or vary along time, as mentioned in Section 2.2. For the case of fingerprints they are:

- *Physiological reasons:* age, amputation, diseases, injuries, skin dryness, etc.

- *Behavioral reasons:* occupation (manual work), stress, motivation, cooperativity, hobbies, fingernails, rings, false nails, finger positioning, etc.

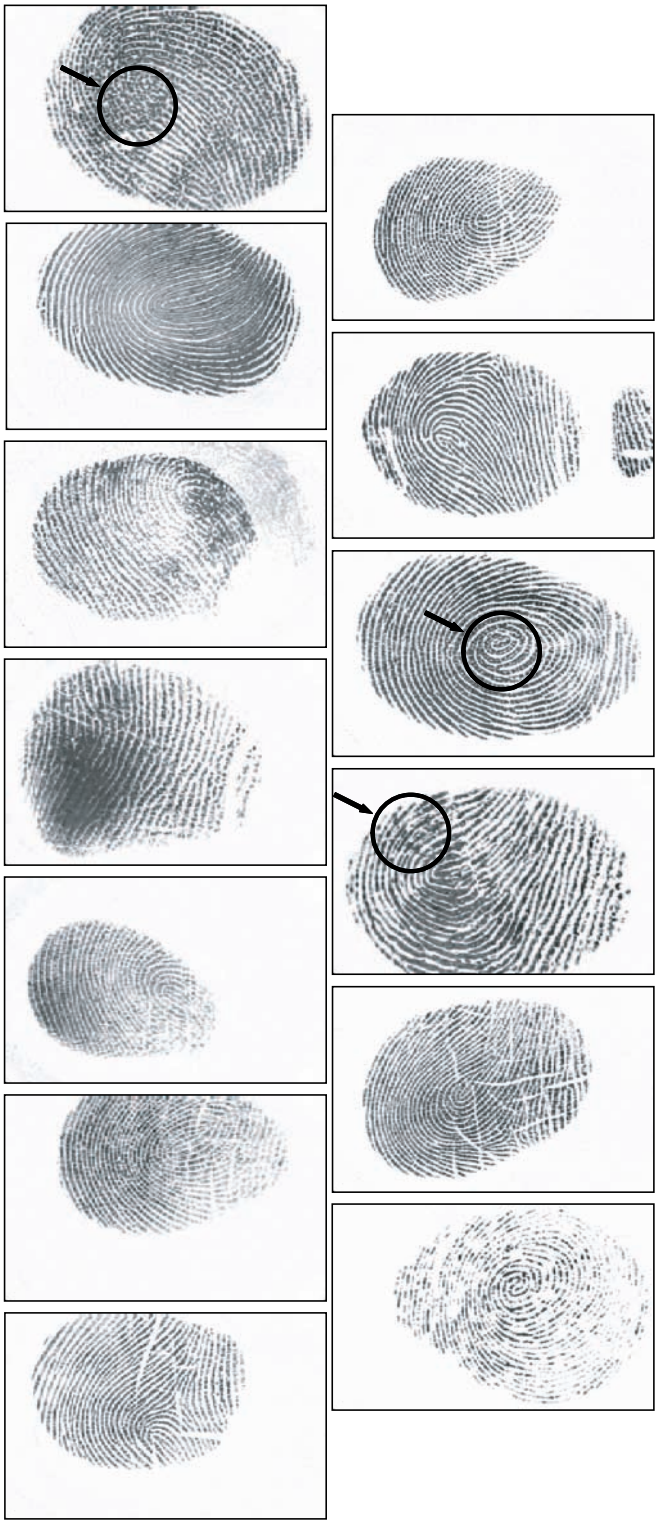


Figure 3.14: **Sample images of poor quality due to different factors: (a) displacement with respect to the center, (b) incomplete fingerprint (out of the scanning area), (c) incomplete fingerprint (low pressure), (d) blurring, (e) ghost effects (non-zero background), (f) non-homogeneous gray-scale, (g) ridge structure not well defined, (h) lack of ridge structure in some zones, (i) broken ridge structure due to chaps, (j) artifacts in ridge structure, (k) visible pores, (l) fingerprint divided in two parts, and (m) fingerprint size. Figure extracted from Simon-Zorita (2003).**

- *Environmental reasons:* light level, weather, humidity, etc.
- *Operational reasons:* sensor dirt, residual prints, feedback, ease of use, ergonomics, user familiarity, time ageing, etc.
- *Sensor and hardware reasons:* type and quality of sensor (size, noise, etc.)

Once the quality of a given fingerprint image is assessed, a number of strategies can be adopted to overcome the impact of low quality fingerprints as we described in Section 2.6. For instance, asking the user for a new sample (Grother *et al.*, 2005). Other strategy is to compensate for the image quality effects in the feature extraction/matching steps of the recognition system. This is followed by a number of studies, for example exploiting the signal quality in the segmentation step (Shi *et al.*, 2004), in the matching step (Chen *et al.*, 2005), or performing quality-based fusion of different matchers and/or traits at the match score level (Baker and Maurer, 2005; Bigun *et al.*, 1997; Fierrez-Aguilar *et al.*, 2006, 2005e; Nandakumar *et al.*, 2006; Toh *et al.*, 2004) so as the weights for the fusion are selected to allow better quality samples to dominate the fusion.

3.2.2 Fingerprint image quality estimation methods

A number of approaches for fingerprint image quality computation have been described in the literature. Existing methods assess fingerprint image quality by measuring one or more of the following properties, see Figure 3.15: ridge strength or directionality, ridge continuity, ridge clarity, integrity of the ridge-valley structure, or estimated verification performance when using the image at hand. A number of sources of information are used to measure these properties: *i*) angle information provided by the direction field, *ii*) Gabor filters, which represent another implementation of the direction angle (Bigun, 2006), *iii*) pixel intensity of the gray-scale image, *iv*) power spectrum, and *v*) Neural Networks.

Existing approaches for fingerprint image quality estimation can be divided into: *i*) those that use *local* features of the image extracted from non-overlapped blocks; *ii*) those that use *global* features of the image, analyzing it in a holistic manner; and *iii*) those that address the problem of quality assessment as a *classification* problem. They are described in Sections 3.2.3, 3.2.4 and 3.2.5, respectively. Also, a summary of existing local and global fingerprint quality measures, including a brief description, is shown in Tables 3.1 and 3.2, respectively.

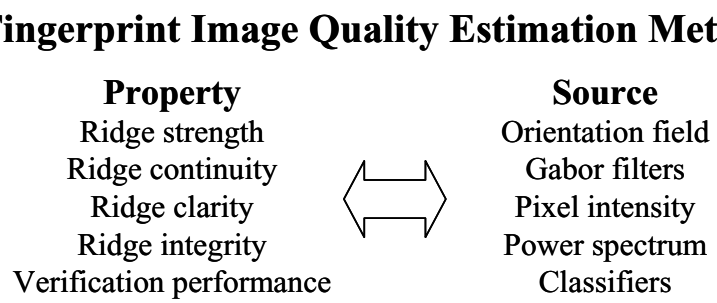


Figure 3.15: **Taxonomy of existing fingerprint image quality estimation methods.**

The quality measures presented here are aimed to evaluate the *utility* of fingerprint images. There are also works aimed to study their *fidelity*, which is not considered in this Ph.D. Thesis. The fidelity of quality metrics is studied by Cappelli *et al.* (2006a); Van der Weken *et al.* (2007); Wilson *et al.* (2000). Wilson *et al.* (2000) have studied the effects of image resolution in the matching accuracy, whereas Cappelli *et al.* (2006a) have studied the correlation between the quality characteristics of a fingerprint scanner with the performance they can assure when the acquired images are matched by a recognition algorithm. In Van der Weken *et al.* (2007), we can find a number of quality metrics aimed at objectively assess the quality of an image in terms of the similarity between a reference image and a degraded version of it.

3.2.3 Methods based on local features

Methods that rely on local features usually divide the image into non-overlapped square blocks and extract features from each block. Blocks are then classified into groups of different quality. A *local measure of quality* is finally generated. This local measure can be the percentage of blocks classified with "high" or "low" quality, or an elaborated combination. Some methods assign a relative weight to each block based on its distance from the centroid of the fingerprint image, since blocks near the centroid are supposed to provide more reliable information (Chen *et al.*, 2005; Ratha and Bolle, 2004).

3.2.3.1 Based on the local direction

This group of methods use the local direction information provided by the direction field (Bigun and Granlund, 1987) to compute several local features in each block. For a comprehensive introduction of the theory and applications of direction fields we refer the reader to Bigun (2006).

SOURCE: LOCAL DIRECTION

Orientation Certainty Level (Lim *et al.*, 2002)
Orientation strength measure computed from the gradient of the gray level image

Ridge frequency, ridge thickness, ridge-to-valley thickness (Lim *et al.*, 2002)
Computed from the sinusoid that models ridges/valleys in the direction normal to ridge flow

Local Orientation (Chen *et al.*, 2004)
Average absolute difference of local orientation with the surrounding blocks

Spatial Coherence (Chen *et al.*, 2005)
Direction coherence measure computed from the gradient of the gray level image

Symmetry features (Fronthaler *et al.*, 2006)
Correlation between linear and parabolic symmetry in a fingerprint image

SOURCE: GABOR FILTERS

Gabor features (Shen *et al.*, 2001)
Standard deviation of m filter responses with different directions

SOURCE: PIXEL INTENSITY

Directionality (Ratha and Bolle, 2004)
Minimum sum of intensity differences between a pixel (i, j) and l pixels selected along a line segment centered at (i, j), computed for n different directions of the line segment

Variance and local contrast (Joun *et al.*, 2003)

Mean, variation, contrast and eccentric moment (Shi *et al.*, 2004)

Clustering Factor (Lim *et al.*, 2004)
Degree to which similar pixels (i.e. ridges or valleys) cluster in the nearby region

Local Clarity (Chen *et al.*, 2004)
Overlapping area of the gray level distributions of segmented ridges and valleys

SOURCE: POWER SPECTRUM

DFT of the sinusoid that models ridges and valleys (Lim *et al.*, 2004)

SOURCE: COMBINATION OF LOCAL FEATURES

Amplitude, frequency and variance of the sinusoid that models ridges and valleys (Hong *et al.*, 1998)

Direction map, low contrast map, low flow map and high curve map (Watson *et al.*, 2004)

Table 3.1: **Summary of existing fingerprint quality measures based on local features.**

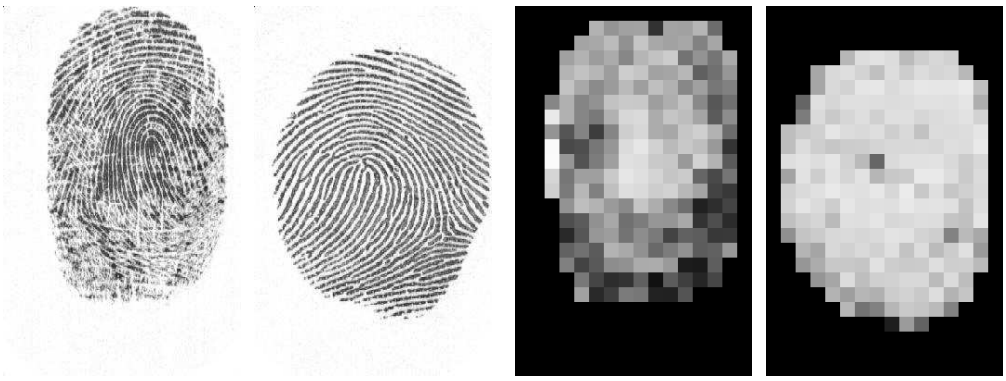
SOURCE: DIRECTION FIELD
Continuity of the direction field (Lim *et al.*, 2002) Detection of abrupt direction changes between blocks
Uniformity of the frequency field (Lim *et al.*, 2002) Standard deviation of the ridge-to-valley thickness ratio
SOURCE: POWER SPECTRUM
Energy concentration in ring-shaped regions of the spectrum (Chen *et al.*, 2005)

Table 3.2: **Summary of existing fingerprint quality measures based on global features.**

The method presented by Lim *et al.* (2002) computes the following features in each block: Orientation Certainty Level (OCL), ridge frequency, ridge thickness and ridge-to-valley thickness ratio. Blocks are then labeled as "good", "undetermined", "bad" or "blank" by setting thresholds for the four features. A local quality score S_L is finally computed based on the total number of "good", "undetermined" and "bad" quality image blocks in the image. The Orientation Certainty Level measures the energy concentration along the dominant direction of ridges. It is computed as the ratio between the two eigenvalues of the covariance matrix of the gradient vector. Ridge frequency is used to detect abnormal ridges that are too close or too far whereas ridge thickness and ridge-to-valley thickness ratio are used to detect ridges that are unreasonably thick or thin. An example of Orientation Certainty Level computation is shown in Figure 3.16 for two fingerprints of different quality.

The Orientation Certainty Level is also used by Lim *et al.* (2004) to detect high curvature regions of the image. Although high curvature has no direct relationship with the quality of a fingerprint image (e.g. core and delta points), it could help to detect regions with invalid curvature. The curvature of a block is captured by (Lim *et al.*, 2004) by combining the orientations of four quadrants and each of their Certainty Levels. Both measures are used together to distinguish between blocks with core/deltas and blocks with invalid curvature due to low quality.

The method presented by Chen *et al.* (2004) computes the average absolute difference of local orientation with the surrounding blocks, resulting in a Local Orientation Quality measure (LOQ). A Global Orientation Quality Score $GOQS$ is finally computed by averaging all the Local Orientation Quality scores of the image. In high quality images, it is expected that ridge direction changes smoothly across the whole image,



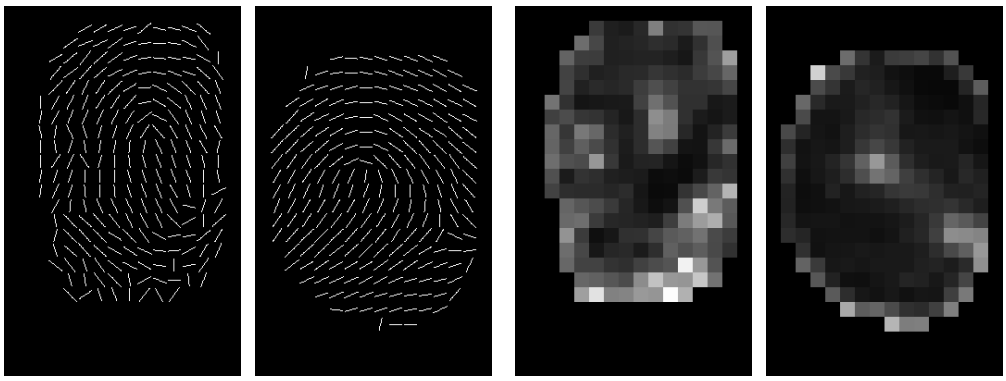
(a) (b)

Figure 3.16: **Computation of the Orientation Certainty Level (OCL) for two fingerprints of different quality. Panel (a) are the input fingerprint images. Panel (b) are the block-wise values of the OCL; blocks with brighter color indicate higher quality in the region.**

thus the $GOQS$ provides information about how smoothly local direction changes from block to block. An example of Local Orientation Quality computation is shown in Figure 3.17 for two fingerprints of different quality.

Recently, Chen *et al.* (2005) proposed a local quality index which measures the local coherence of the intensity gradient, reflecting the clarity of local ridge-valley direction in each block. A local quality score Q_S is finally computed by averaging the coherence of each block.

The method presented by Fronthaler *et al.* (2006) employs symmetry features for fingerprint quality assessment. In this approach, the orientation tensor (Bigun *et al.*, 2004) of a fingerprint image is decomposed into two symmetry representations, allowing to draw conclusions on its quality. On one hand, a coherent ridge flow has linear symmetry and is thus modeled by symmetry features of order 0. On the other hand, points of high curvature like minutia, core and delta points exhibit parabolic symmetry and are therefore represented by symmetry features of order 1. Figure 3.18 depicts these two symmetry representations for two fingerprints of different quality. In a further step, the two symmetries are combined and averaged within small non-overlapped blocks, yielding S_b. To determine the final local quality Q_b, S_b is negatively weighted with the block-wise correlation between the two involved symmetries. A large negative correlation is desirable in terms of quality, because this suggests well separated symmetries. The local quality Q_b is also visualized in the last column of Figure 3.18. An overall quality measure is derived by averaging over the foreground blocks of Q_b.



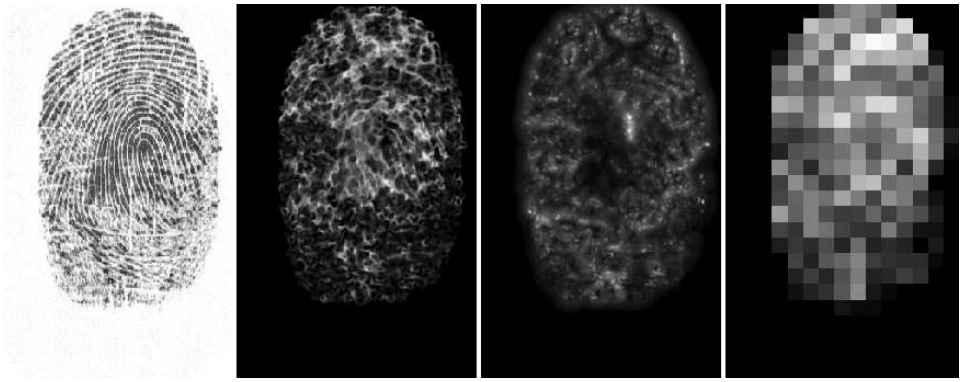
(a) (b)

Figure 3.17: **Computation of the Local Orientation Quality (LOQ) for two fingerprints of different quality. Panel (a) are the direction fields of the images shown in Figure 3.16a. Panel (b) are the block-wise values of the average absolute difference of local orientation with the surrounding blocks; blocks with brighter color indicate higher difference value and thus, lower quality.**

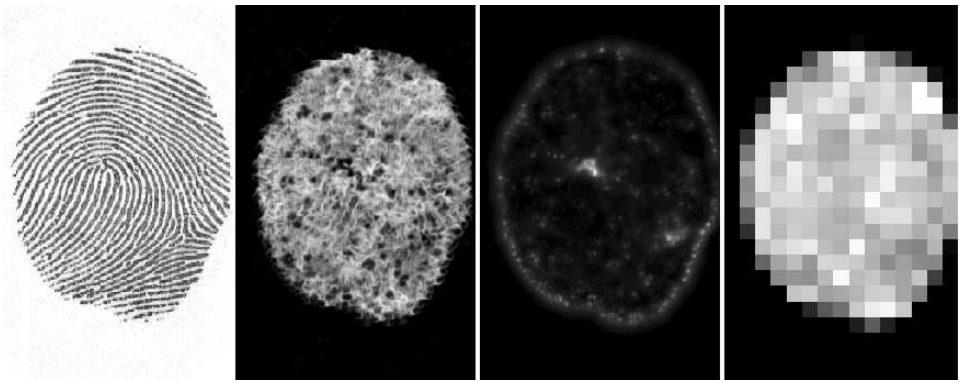
3.2.3.2 Based on Gabor filters

Gabor filters can be viewed as a filter-bank that can represent the local frequencies. Two dimensional quadrature mirror filters are close akins of Gabor filters (Knutsson, 1982). Gabor filters were introduced to image processing by Daugman (1988), and both filter families represent another implementation of the local-direction fields (Bigun, 2006), though they are frequently used stand-alone, without a local-direction field interpretation.

Shen *et al.* (2001) proposed a method based on Gabor features. Each block is filtered using a Gabor filter with m different directions. If a block has high quality (i.e. strong ridge direction), one or several filter responses are larger than the others. In poor quality blocks or background blocks, the m filter responses are similar. The standard deviation of the m filter responses is then used to determine the quality of each block ("good" and "poor"). A quality index QI of the whole image is finally computed as the percentage of foreground blocks marked as "good". If QI is lower than a predefined threshold, the image is rejected. Poor quality images are additionally categorized as "smudged" or "dry". An example of quality estimation using Gabor filters is shown in Figure 3.19 for two fingerprints of different quality.



(a) Low quality fingerprint

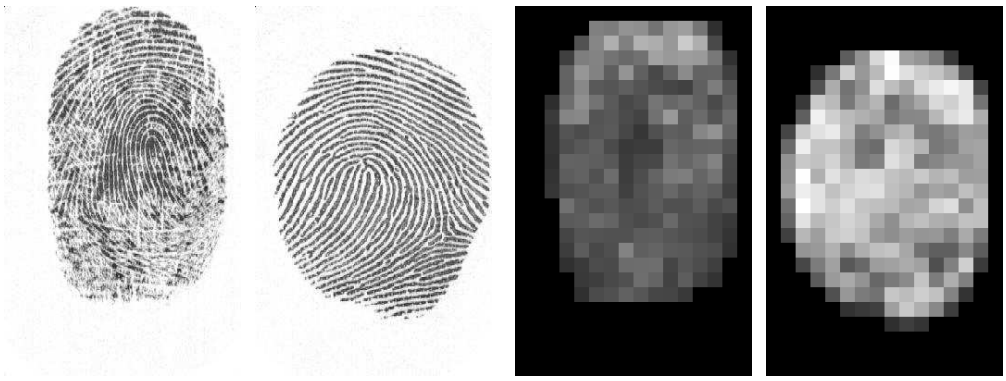


(b) High quality fingerprint

Figure 3.18: **Estimation of fingerprint quality using symmetry features. Figure shows the decomposition of two fingerprints of different quality into linear and parabolic symmetry (second and third column, respectively). The final local quality estimation in blocks is depicted in the fourth column (blocks with brighter color indicate higher quality in the region).**

3.2.3.3 Based on pixel intensity

The method described by Ratha and Bolle (2004) classifies blocks into "directional" and "non-directional" as follows. The sum of intensity differences $D_d(i,j)$ between a pixel (i,j) and l pixels selected along a line segment of direction d centered at (i,j) is computed for n different directions. For each different direction d, the histogram of $D_d(i,j)$ values is obtained for all pixels within a given foreground block. If only one of the n histograms has a maximum value greater than a prominent threshold, the block is marked as "directional". Otherwise, the block is marked as "non-directional". An overall quality score Q is finally computed. A relative weight w_i is assigned to each foreground block based on its distance to the centroid of the foreground. The quality



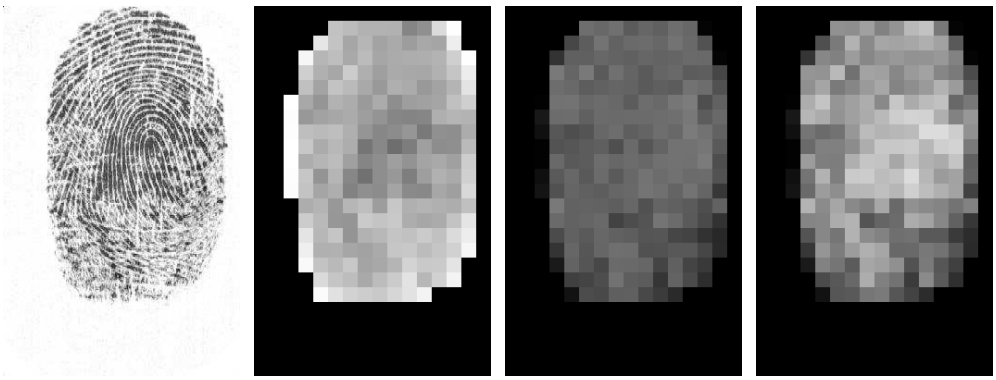
(a) (b)

Figure 3.19: **Estimation of fingerprint quality using Gabor filters. Panel (a) are the input fingerprint images. Panel (b) are the block-wise values of the standard deviation of m filter responses (8 in this example) with different direction. Blocks with brighter color indicate higher standard deviation value and thus, higher quality.**

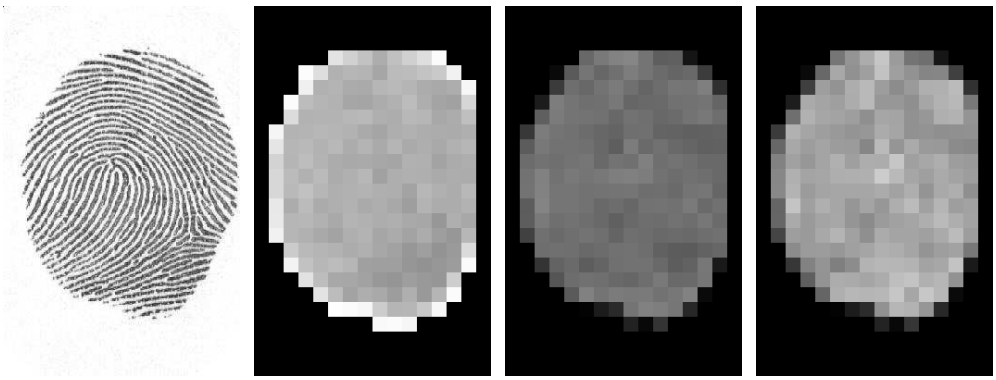
score Q is defined as $Q = \sum_D w_i \ / \ \sum_F w_i$ where D is the set of directional blocks and F is the set of foreground blocks. If Q is lower than a threshold, then the image is considered to be of poor quality. Measures of the smudginess and dryness of poor quality images are also defined by Ratha and Bolle (2004).

Two methods based on pixel intensity are presented by Joun *et al.* (2003). The first one measures the variance in gray levels in overlapped blocks. High quality blocks will have large variance while low quality blocks will have a small one. The second method measures the local contrast of gray values among ridges and valleys along the local direction of the ridge flow. Blocks with high quality will show high contrast, which means that ridges and valleys are well separated on the grayscale. Shi *et al.* (2004) define further features extracted from the gray level image to characterize a block of a fingerprint image: mean, variation, contrast and eccentric moment. They use these four features extracted from the gray level image to improve the fingerprint segmentation in low quality regions. An example of quality estimation using gray level statistics is shown in Figure 3.20 for two fingerprints of different quality.

The method presented by Lim *et al.* (2004) checks the consistency of ridge and valley's gray level as follows. It binarizes image blocks using Otsu's method (Otsu, 1979) to extract ridge and valley regions and then computes a Clustering Factor, defined as the degree to which gray values of ridge/valley pixels are clustered. The more clustered are ridge/valley pixels, the higher the clarity of such structure, and hence its quality.



(a) Low quality fingerprint



(b) High quality fingerprint

Figure 3.20: **Estimation of fingerprint quality using gray level statistics for the two fingerprints of different quality shown in Figure 3.16a. Figure shows (from left to right of each subplot): fingerprint image and block-wise values of mean, standard deviation and contrast value, respectively. Brighter values in the blocks indicate higher values. For the low quality fingerprint we observe more fluctuation of the three measures across the image.**

Chen *et al.* (2004) proposed a measure which computes the clarity of ridges and valleys. For each block, they extract the amplitude of the sinusoidal-shaped wave along the direction normal to the local ridge direction (Hong *et al.*, 1998) (see Figure 3.21). A threshold is then used to separate the ridge region and valley region of the block. The gray level distribution of the segmented ridges and valleys is computed and the overlapping area of the distributions is used as a measure of clarity of ridges and valleys. For ridges/valleys with high clarity, both distributions should have a very small overlapping area. A Global Clarity Score is finally computed by averaging all the local clarity measures of the image. An example of quality estimation using the Local Clarity Score is shown in Figure 3.22 for two fingerprint blocks of different quality.

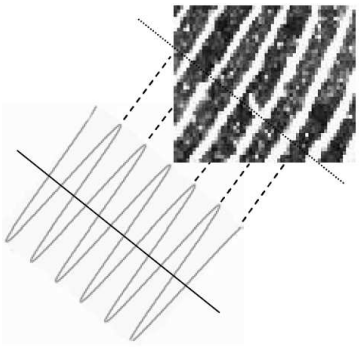


Figure 3.21: **Modeling of ridges and valleys as a sinusoid.**

3.2.3.4 Based on Power Spectrum

The method presented by Lim *et al.* (2004) extracts the sinusoidal-shaped wave along the direction normal to the local ridge direction (Hong *et al.*, 1998) (see Figure 3.21), and then computes its Discrete Fourier Transform. Low quality blocks will not exhibit an obvious dominant frequency, or it will be out of the normal ridge frequency range.

3.2.3.5 Based on a combination of local features

Hong *et al.* (1998) modeled ridges and valleys as a sinusoidal-shaped wave along the direction normal to the local ridge direction (see Figure 3.21) and extracted the amplitude, frequency and variance of the sinusoid. Based on these parameters, they classify blocks as *recoverable* and *unrecoverable*.

The minutia detection (MINDTCT) package of the NIST Fingerprint Image Software (NFIS) (Watson *et al.*, 2004) locally analyzes the fingerprint image and generates an image quality map. The quality of each block is assessed by computing several maps: direction map, low contrast, low flow and high curve. The direction map is indicating areas of the image with sufficient ridge structure. The low contrast map is marking blocks with weak contrast, which are considered as background blocks. The low flow map is representing blocks that could not be assigned a dominant ridge flow. The high curve map is marking blocks that are in high curvature areas, which usually are core and delta regions, but also other low quality regions. These maps are integrated into one quality map, containing 5 levels of quality (an example is shown in Figure 3.23 for two fingerprints of different quality).

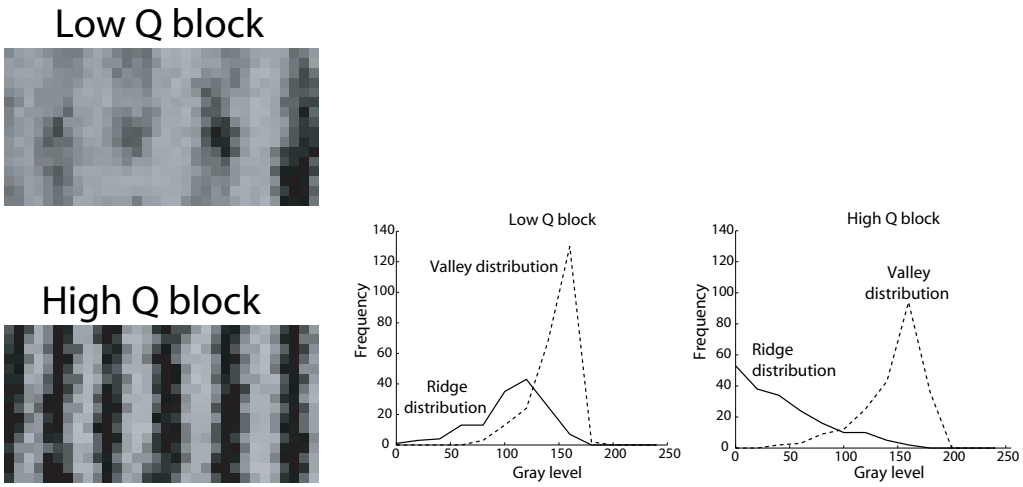


Figure 3.22: **Computation of the Local Clarity Score for two fingerprint blocks of different quality. Panel (a) are the fingerprint blocks. Panel (b) are the gray level distributions of the segmented ridges and valleys. The degree of overlapping for the low and high quality block is** 0.22 **and** 0.10**, respectively.**

3.2.4 Methods based on global features

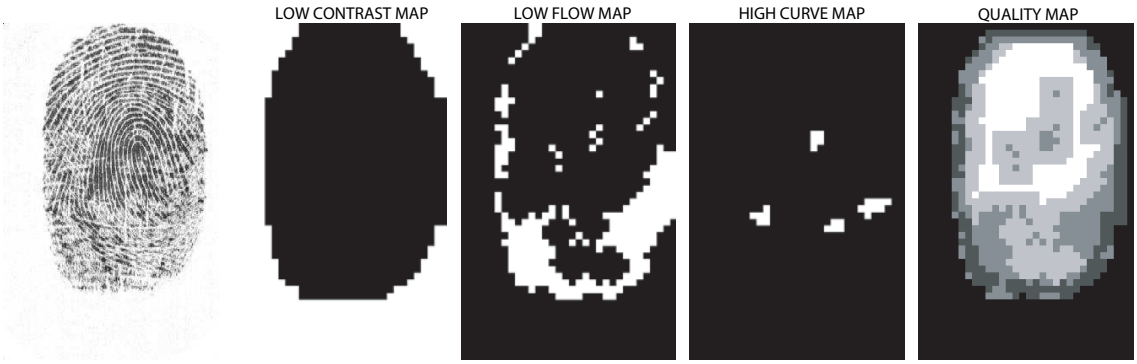
Methods that rely on global features analyze the image in a holistic manner and compute a *global measure of quality* based on the features extracted.

3.2.4.1 Based on the direction field

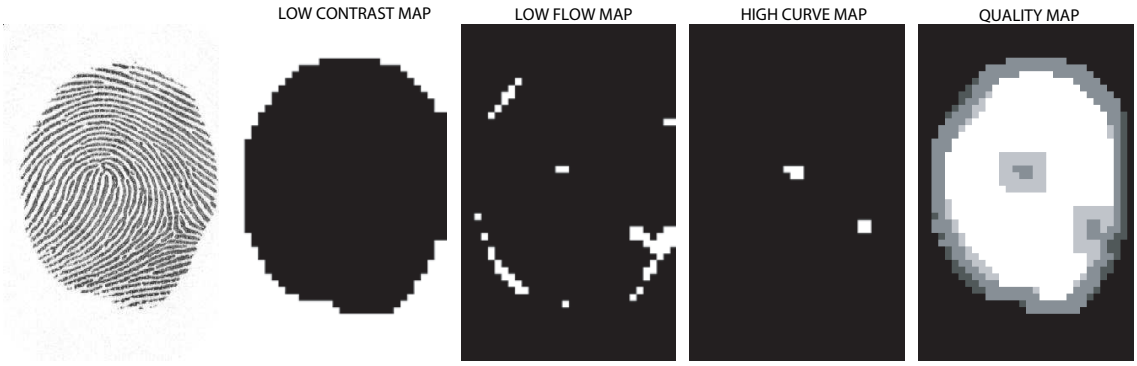
Lim *et al.* (2002) presented two features to analyze the global structure of a fingerprint image. Both of them use the local direction information provided by the direction field, which is estimated in non-overlapping blocks. The first feature checks the continuity of the direction field. Abrupt direction changes between blocks are accumulated and mapped into a global direction score. As we can observe in Figure 3.17, ridge direction changes smoothly across the whole image in case of high quality. The second feature checks the uniformity of the frequency field (Maltoni *et al.*, 2003). This is done by computing the standard deviation of the ridge-to-valley thickness ratio and mapping it into a global score, as large deviation indicates low image quality.

3.2.4.2 Based on Power Spectrum

Global structure is analyzed by Chen *et al.* (2005) by computing the 2D Discrete Fourier Transform (DFT). For a fingerprint image, the ridge frequency values lie within



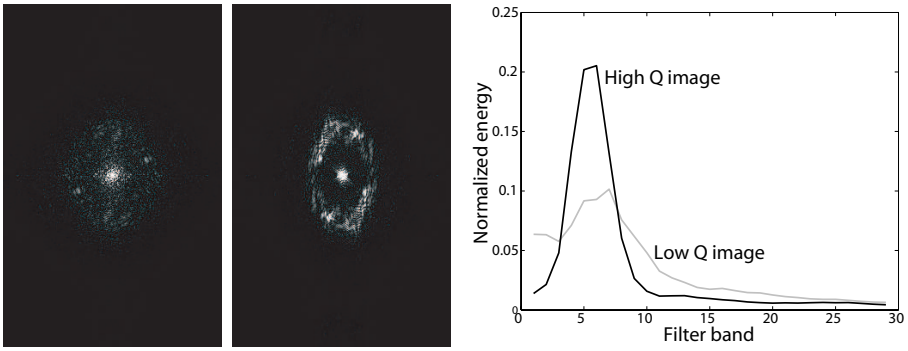
(a) Low quality fingerprint



(b) High quality fingerprint

Figure 3.23: **Fingerprint quality maps provided by the minutia detection package of the NIST Fingerprint Image Software for two fingerprints of different quality.**

a certain range. A region of interest (ROI) of the spectrum is defined as an annular region with radius ranging between the minimum and maximum typical ridge frequency values. As the fingerprint image quality increases, the energy will be more concentrated within the ROI, see Figure 3.24a. The global quality index Q_F defined by Chen *et al.* (2005) is a measure of the energy concentration in ring-shaped regions of the ROI. For this purpose, a set of bandpass filters is employed to extract the energy in each frequency band. High quality images will have the energy concentrated in few bands while poor ones will have a more diffused distribution. The energy concentration is measured using the entropy. An example of quality estimation using the global quality index Q_F is shown in Figure 3.24 for two fingerprints of different quality.



(a) Power spectrum (b) Energy concentration

Figure 3.24: **Computation of the energy concentration in the power spectrum for two fingerprints of different quality. Panel (a) are the power spectra of the images shown in Figure 3.16a. Panel (b) shows the energy distributions in the region of interest. The quality values for the low and high quality image are** 0.35 **and** 0.88 **respectively.**

3.2.5 Methods based on classifiers

The method that uses classifiers (Tabassi and Wilson, 2005; Tabassi *et al.*, 2004) defines the quality measure as a degree of separation between the match and non-match distributions of a given fingerprint. This can be seen as a prediction of the matcher performance. Tabassi et al. Tabassi and Wilson (2005); Tabassi *et al.* (2004) extract the fingerprint features (minutiae in this case) and then compute the quality of each extracted feature to estimate the quality of the fingerprint image, which is defined as stated above.

Let $s(x_{ii})$ be the similarity score of a genuine comparison (*match*) corresponding to the subject i, and $s(x_{ji})$, $i \neq j$ be the similarity score of an impostor comparison (*non-match*) between subject i and impostor j. Quality Q_N of a biometric sample x_{ii} is then defined as the prediction of

$$o(x_{ii}) = \frac{s(x_{ii}) - E[s(x_{ji})]}{\sigma(s(x_{ji}))} \tag{3.1}$$

where $E[.]$ is mathematical expectation and $\sigma(.)$ is standard deviation. Eq. (3.1) is a measure of separation between the *match* and the *non-match* distributions, which is supposed to be higher as image quality increases. The prediction of $o(x_{ii})$ is done by using a neural network. Output of the neural network is a number that classifies the quality of the fingerprint into 5 values: 5 (poor), 4 (fair), 3 (good), 2 (very good) and 1 (excellent).

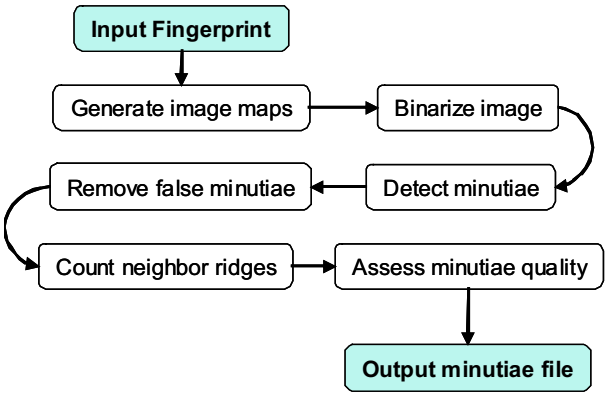


Figure 3.25: **System architecture of the MINDTCT package of the NIST Fingerprint Image Software 2 (NFIS2).**

3.3 Fingerprint matcher based on minutiae

As fingerprint minutiae-based matcher for our study, we use the matcher included in the freely available NIST Fingerprint Image Software 2 - NFIS2 (Watson *et al.*, 2004). NFIS2 contains software technology, developed for the Federal Bureau of Investigation (FBI), designed to facilitate and support the automated manipulation and processing of fingerprint images. Source code for over 50 different utilities or packages and an extensive User's Guide are distributed on CD-ROM free of charge (Watson *et al.*, 2004). For our evaluation and tests with NFIS2, we have used the following packages: MINDTCT for minutiae extraction, and BOZORTH3 for fingerprint matching.

MINDTCT takes a fingerprint image and locates all minutiae in the image, assigning to each minutia point its location, orientation, type, and quality. The architecture of MINDTCT is shown in Figure 3.25 and it can be divided in the following stages:

1. Generation of image quality map.
2. Binarization.
3. Minutiae detection.
4. Removal of false minutiae, including islands, lakes, holes, minutiae in regions of poor image quality, side minutiae, hooks, overlaps, minutiae that are too wide, and minutiae that are too narrow (pores).
5. Counting of ridges between a minutia point and its nearest neighbors.
6. Minutiae quality assessment.

Because of the variation of image quality within a fingerprint, MINDTCT analyzes the image and determines areas that are degraded. Several characteristics are measured, including regions of low contrast, incoherent ridge flow, and high curvature. These three conditions represent unstable areas in the image where minutiae detection is unreliable, and together they are used to represent levels of quality in the image. The image quality map of the stage 1 is generated integrating these three characteristics. Images are divided into non-overlapping blocks, where one out of five levels of quality is assigned to each block.

The minutiae detection step scans the binary image of the fingerprint, identifying local pixel patterns that indicate the ending or splitting of a ridge. A set of minutia patterns is used to detect candidate minutia points. Subsequently, false minutiae are removed and the remaining candidates are considered as the true minutiae of the image. Fingerprint minutiae marchers often use other information in addition to just the points themselves. Apart from minutia's position, direction, and type, MINDTCT computes ridge counts between a minutia point and each of its nearest neighbors.

In the last stage, MINDTCT assigns a quality/reliability measure to each detected minutia point. Even after performing the removal stage, false minutiae potentially remain in the list. Two factors are combined to produce a quality measure for each detected minutia point. The first factor is taken directly from the location of the minutia point within the quality map generated in the stage 1. The second factor is based on simple pixel intensity statistics (mean and standard deviation) within the immediate neighborhood of the minutia point. A high quality region within a fingerprint image is expected to have significant contrast that will cover the full grayscale spectrum (Watson *et al.*, 2004).

The BOZORTH3 matching algorithm computes a match score between the minutiae from any two fingerprints to help determine if they are from the same finger. The BOZORTH3 matcher uses only the location and orientation of the minutia points to match the fingerprints, and it is rotation and translation invariant. For fingerprint matching, compatibility between minutiae pairs of the two images are assessed by comparing the following measures : *i*) distance between the two minutiae and *ii*) angle between each minutia's orientation and the intervening line between both minutiae. This process can be observed in Figure 3.26.

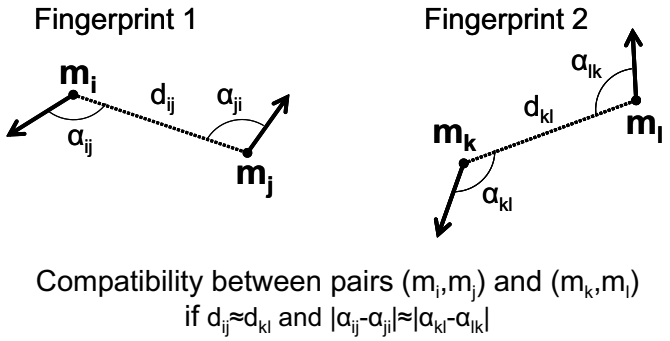


Figure 3.26: **Compatibility between minutiae pairs of two different fingerprints.**

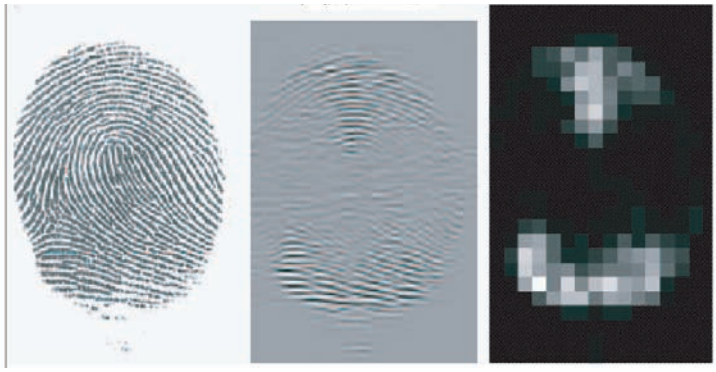


Figure 3.27: **Processing steps of the ridge-based matcher. From left to right: original image, filtered image with filter orientation $\theta = 0$ and FingerCode. Figure extracted from Munoz-Serrano (2004).**

3.4 Fingerprint matcher based on ridge information

The ridge-based matcher (also referred to as texture-based) uses a set of Gabor filters to capture the ridge strength (Fierrez-Aguilar *et al.*, 2005b). The input fingerprint image is tessellated into square cells, and the variance of the filter responses in each cell across all filtered images is used as feature vector. This feature vector is called FingerCode because of the similarity to previous research works (Daugman, 2004; Ross *et al.*, 2003). The automatic alignment is based on the system described in Ross *et al.* (2002), in which the correlation between the two FingerCodes is computed, obtaining the optimal offset. The ridge-based matcher is divided in two phases: *i*) extraction of the FingerCode; and *ii*) matching of the FingerCodes.

No image enhancement is performed since Gabor filters extract information that is in a specific (usually low-pass) band that is not affected from noise, to the same extent

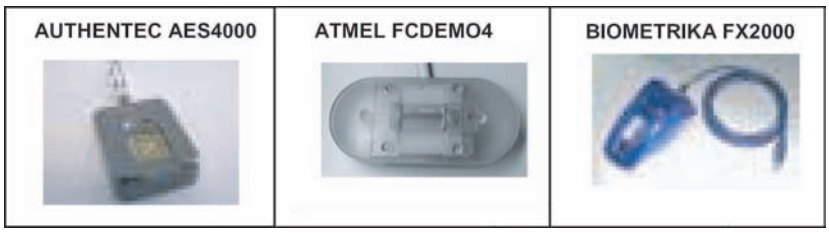


Figure 3.28: **Biosec baseline fingerprint sensors.**

as the original image is. The complete processing for extracting the FingerCode consist in the following three steps:

- Convolution of the input fingerprint image with 8 Gabor filters, obtaining 8 filtered images F_θ.
- Tessellation of the filtered images into equal-sized square disjoint cells.
- Extraction of the FingerCode.

For each cell of each filtered image F_θ, we compute the variance of the pixel intensities. These standard deviation values constitute the FingerCode of a fingerprint image. A sample fingerprint image, the resulting convolved image with a Gabor filter of orientation $\theta = 0°$, and its FingerCode are shown in Figure 3.27.

The sequence of steps for matching of two FingerCodes is: *i*) alignment of the two fingerprints to be compared; and *ii*) similarity computation between the FingerCodes. The matching score is computed as the Euclidean distance between the two FingerCodes. To determine the alignment between two fingerprints, we compute the 2D correlation of the two FingerCodes (Ross *et al.*, 2002). Correlation involves multiplying corresponding entries between the two FingerCodes at all possible translation offsets, and determining the sum, which is computed more efficiently in the Fourier domain. The offset that results in the maximum sum is chosen to be the optimal alignment. Every offset is properly weighted to account for the amount of overlap between the two FingerCodes. It is worth noting that this procedure does not account for rotational offset between the two fingerprints. For the database used in this work, which is acquired under realistic conditions, we have observed that typical rotations between different impressions of the same fingerprint are compensated by using the tessellation.

3.5 Experimental framework

3.5.1 Database and protocol

For the experiments in this chapter, we use the BioSec baseline corpus (Fierrez *et al.*, 2007). Data consists of 19,200 fingerprint images acquired from 200 individuals in 2 acquisition sessions, separated typically by one to four weeks, using 3 different sensors. The fingerprint sensors are:

- Capacitive sensor Authentec AES400, with an image size of 96 pixels width and 96 pixels height.
- Thermal sensor Atmel FCDEM04, with an image size of 400 pixels width and 496 pixels height.
- Optical sensor Biometrika FX2000, with an image size of 400 pixels width and 560 pixels height.

The capacitive sensor has a resolution of 250 dpi[1], whereas the thermal and the optical ones have a resolution of 500 dpi. They are shown in Figure 3.28. A total of 4 captures of the print of 4 fingers (right and left index and middle) were captured with each of the 3 sensors, interleaving fingers between consecutive acquisitions. The total number of fingerprint images is therefore 200 individuals $\times$ 2 sessions $\times$ 4 fingers $\times$ 4 captures $= 6,400$ images per sensor. In Figure 3.29, some fingerprint samples from the BioSec baseline corpus are shown.

The 200 subjects included in BioSec Baseline are further divided into: *i*) the *development set*, including the first 25 and the last 25 individuals of the corpus, totaling 50 individuals; and *ii*) the *test set*, including the remaining 150 individuals. The development set is used to tune the parameters of the different quality assessment algorithms. No training of parameters is done on the test set. We consider the different fingers of the test set as different users enrolled in the system, thus resulting in $150 \times 4 = 600$ users. For evaluation of the verification performance, the following matchings are defined in the test set: *a*) genuine matchings: the 4 samples in the first session to the 4 samples in the second session, resulting in 150 individuals $\times$ 4 fingers $\times$ 4 templates $\times$ 4 test images $= 9,600$ genuine scores per sensor; and *b*) impostor matchings: the first sample in the first session to the same sample of the remaining users, avoiding symmetric matches, resulting in $(150 \times 4) \times (150 \times 4 - 1)/2 = 179,700$ impostor scores per sensor.

[1]The NIST-NFIQ quality measure and the NIST-NFIS2 package are developed for 500 dpi images, thus images from the capacitive sensor are first interpolated using bicubic interpolation.

Figure 3.29: **Example images from the BioSec baseline corpus. Fingerprint images are plotted for the same finger for** (i) **capacitive sensor (top row), optical sensor (medium row), thermal sensor (bottom row), and** (ii) **three different fingerprints, one per column.**

3.5.2 Selected quality measures

Different measures have been selected from the literature in order to have a representative set. We have implemented at least one measure that make use of the different features presented in Tables 3.1 and 3.2: direction information (local direction, Gabor filters or global direction field), pixel intensity information and power spectrum information. The measure that relies on direction information is the *Orientation Certainty Level* (OCL) (Lim *et al.*, 2002), the measure based on pixel intensity information is the *Local Clarity Score* (LCS) (Chen *et al.*, 2004) and the measure based on the power spectrum is the *energy concentration* (Chen *et al.*, 2005). We have also used the ex-

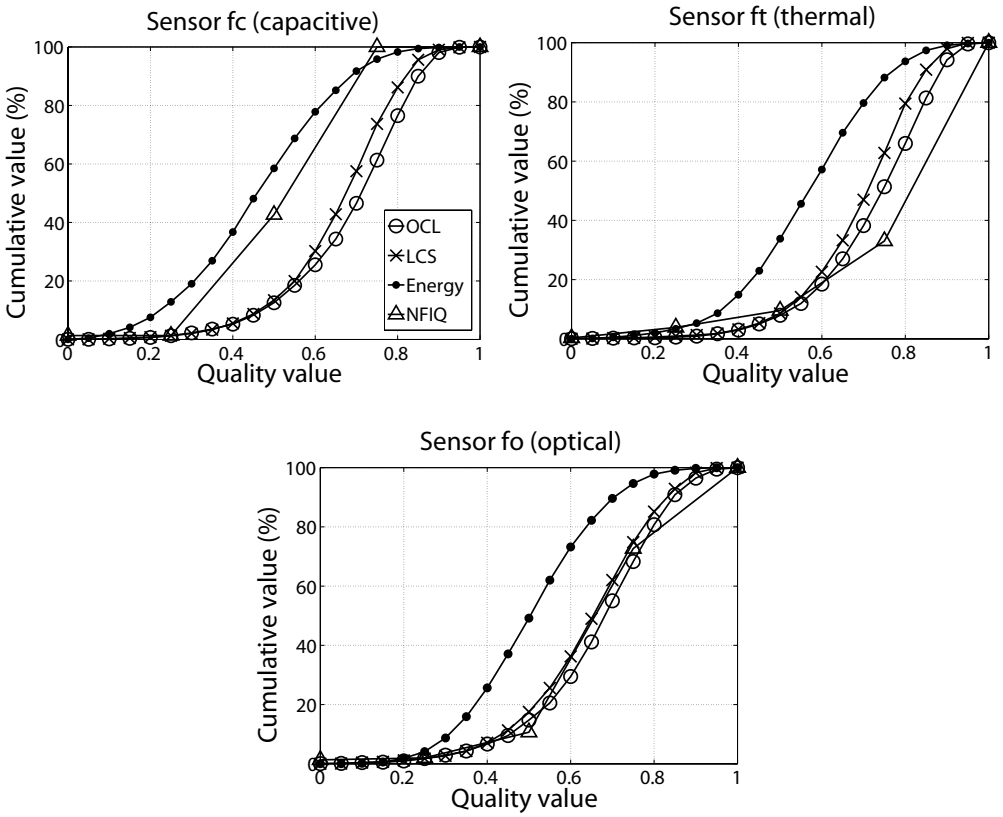
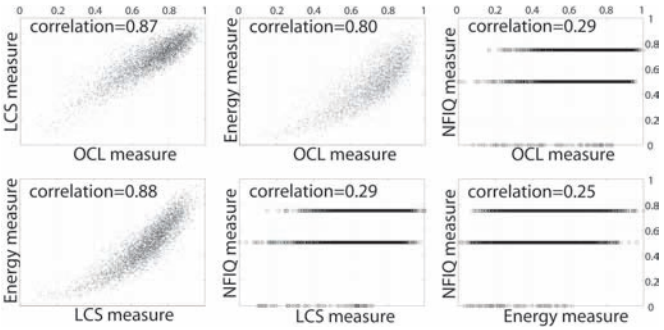


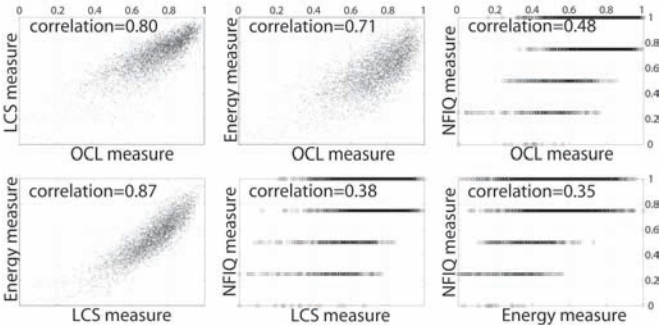
Figure 3.30: **Quality distribution of the images of the BioSec baseline corpus (test set). All image quality values are normalized into the [0-1] range, with 0 corresponding to the worst quality and 1 corresponding to the best quality.**

isting measure based on classifiers, NFIQ, which is included in the NIST Fingerprint Image Software 2 - NFIS2 (Watson *et al.*, 2004).

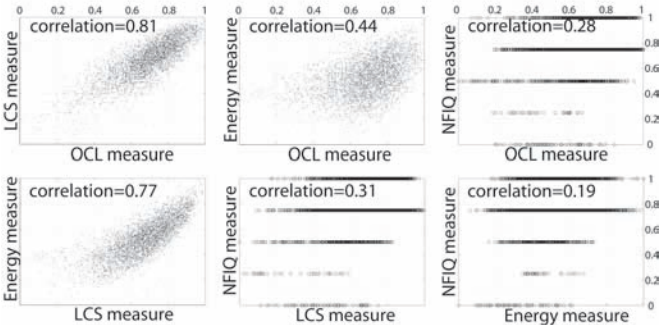
In the experiments carried out in this chapter, all image quality values are normalized into the [0-1] range for better comparison, with 0 corresponding to the worst quality and 1 corresponding to the best quality. In Figure 3.30, it is depicted the image quality distribution of the database used in this chapter for the selected quality measures (test set). Note that the NFIQ measure only have 5 values due to its discrete nature (Watson *et al.*, 2004).



(a) **Capacitive sensor.**



(b) **Thermal sensor.**



(c) **Optical sensor.**

Figure 3.31: **Correlation between the automatic quality assessment algorithms tested in this work (x- and y-axis are the quality values of the two algorithms under comparison). Pearson correlation value between the two algorithms is also shown in each subplot.**

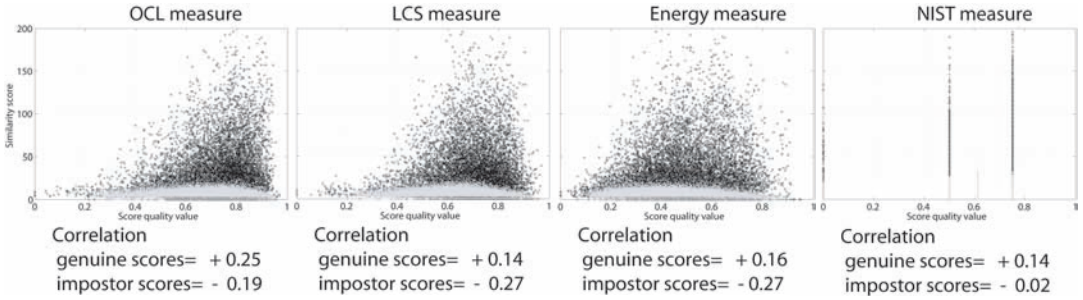
3.6 Results

In Figure 3.31 we plot the correlation among the quality measures tested in this chapter for the test set of the Biosec database. In addition, we show the Neyman-Pearson correlation values (Papoulis, 1984) between them, which are observed to be high, except when the NFIQ measure is involved. This could be due to the finite number of quality labels used by this algorithm (Watson *et al.*, 2004). In spite of the high correlation observed between most of the measures, their values are different depending on the sensor (e.g. correlation between the OCL and energy measures is 0.8, 0.71 and 0.44 for the capacitive, thermal and optical, respectively). This suggest that quality measures work differently with each sensor, which could be due to their different physical acquisition principles. Also worth noting, the lowest correlation values are obtained with the optical sensor.

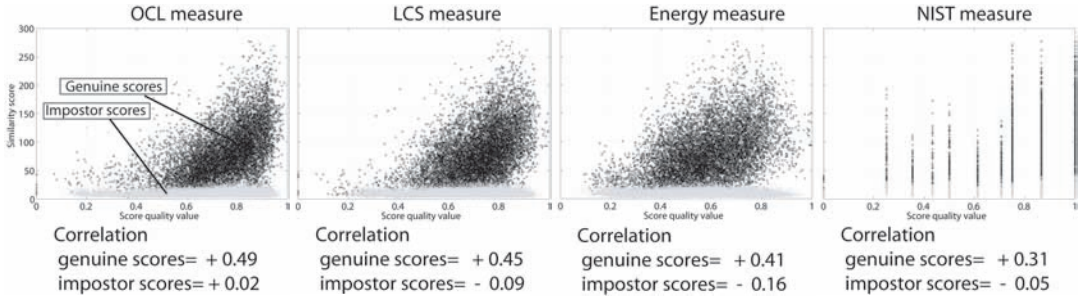
In order to evaluate the *utility* of the compared quality metrics, i.e. their capability to predict the performance of a matcher (Grother and Tabassi, 2007), we plot in Figures 3.32 and 3.33 the similarity scores of the two matchers (minutiae- and ridge-based) against the average quality of the two involved fingerprint images. We assign a quality value to a given score, which is computed as $\sqrt{Q_e \times Q_t}$, where Q_e and Q_t are the quality values of the enrolment and test fingerprint, respectively, corresponding to the matching (note that the NIST-NFIQ quality measure only provides 5 possible values for Q_e and Q_t, and thus, the combined value $\sqrt{Q_e \times Q_t}$ also exhibit a discrete nature but with more than 5 possible values). We also give in Figures 3.32 and 3.33 the Neyman-Pearson correlation between similarity scores and its assigned quality value. In addition, Figures 3.34 and 3.35 depict the error rates of the two verification systems as we reject samples (i.e. matching scores) with the lowest quality value. We report the error rates at three points: the Equal Error Rate (EER), the False Acceptance Rate at 1% FRR, and the False Rejection Rate at 1% FAR.

Minutiae-based matcher.

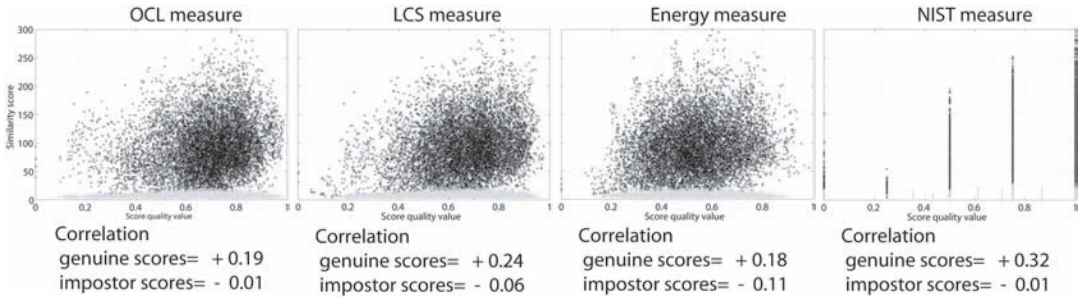
For the minutiae-based matcher, positive correlation values are observed between quality measures and genuine similarity scores, as it is plotted in Figure 3.32. On the other hand, correlation is found to be close to zero for the impostor scores (or even negative, as in the case of the capacitive sensor).



(a) Capacitive sensor.

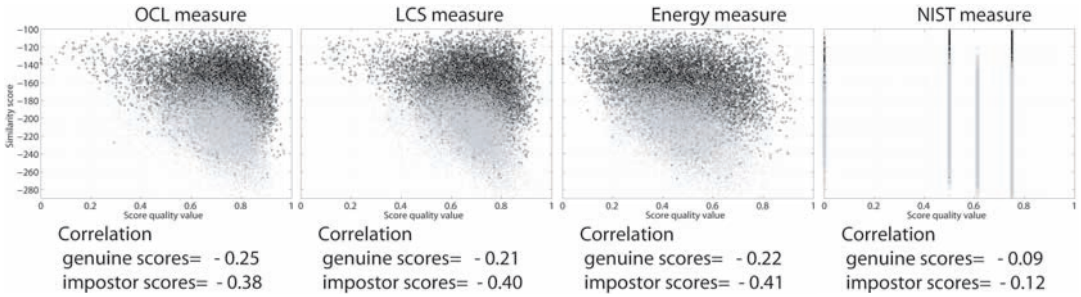


(b) Thermal sensor.

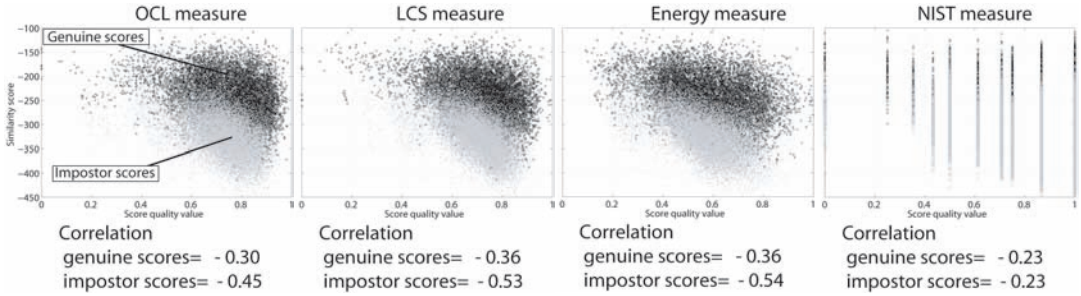


(c) Optical sensor.

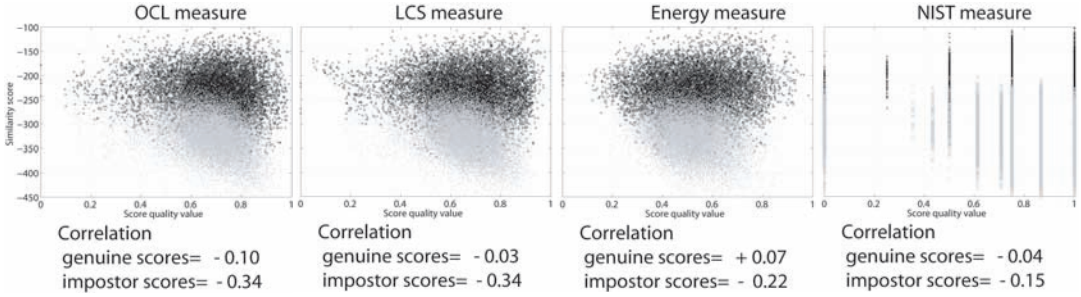
Figure 3.32: ***Minutiae-based matcher.*** **Dependence of similarity scores (y-axis) on the average quality of the template and the input images (x-axis). We assign a quality value to a given score, which is computed as $\sqrt{Q_e \times Q_t}$, where Q_e and Q_t are the quality values of the enrolment and test fingerprint samples, respectively, corresponding to the matching.**



(a) Capacitive sensor.



(b) Thermal sensor.



(c) Optical sensor.

Figure 3.33: ***Ridge-based matcher.*** **Dependence of similarity scores (y-axis) on the average quality of the template and the input images (x-axis). We assign a quality value to a given score, which is computed as $\sqrt{Q_e \times Q_t}$, where Q_e and Q_t are the quality values of the enrolment and test fingerprint samples, respectively, corresponding to the matching.**

As a result of the correlation found between genuine scores and quality values, a remarkable performance improvement is obtained in the FRR, as can be seen in Figure 3.34. After rejection of just 5% of the samples, FRR is improved in the best case about 10%, 30%, and 50% for the capacitive, thermal and optical sensor, respectively. Significant improvement is also obtained in the EER (about 5%, 20% and 45% , respectively). On the contrary, the smallest improvement is obtained for the FAR (about 7% and 3% for the thermal and optical sensor, respectively) or even no improvement, as observed in some cases.

Regarding sensor technology, we observe a clear relationship between the sensor acquisition area and the relative performance improvement: the sensor having the smallest acquisition area (the capacitive) obtains the lowest improvement, whereas the sensor with the biggest area (the optical) always results in the highest improvement of performance. We detail this effect in Table 3.3. It is well known that acquisition surface of fingerprint sensors has impact on the performance due to the amount of discriminative information contained in the acquired biometric data (Maltoni *et al.*, 2003). For a fingerprint matcher based on minutiae features, more acquisition area implies more minutiae acquired from a fingerprint. As a result, with more acquisition surface, higher amount of minutiae is affected by quality degradation.

Ridge-based matcher.

As far as the ridge-based matcher is concerned, negative correlation values between quality measures and similarity scores are found, both for the genuine and impostor ones (see Figure 3.33). Correlation values are higher for the impostor scores, therefore the highest improvement of performance when rejecting low quality scores is observed in the FAR, as can be seen in Figure 3.35. Interestingly enough, no improvement is observed in the FRR.

In addition, sensor technology does not play a primary role with relative performance improvement for the ridge-based matcher, contrarily to what happened with the minutiae-based matcher. The unique relationship between sensor area and performance improvement is observed in the FAR.

3.7 Chapter summary and conclusions

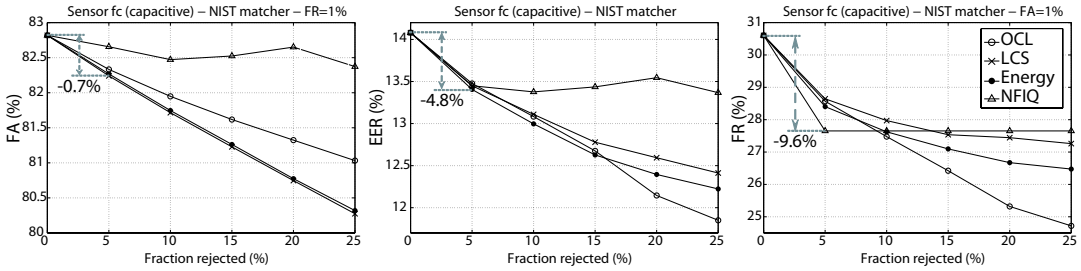
In this chapter we have presented a taxonomy of existing approaches for fingerprint image quality estimation, divided into: *i*) approaches that use local features of the

image; *ii*) approaches that use global features of the image; and *iii*) approaches that address the problem of quality assessment as a classification problem. They make use of different local and global image features that are extracted using several sources: direction field, Gabor filter responses, power spectrum and pixel intensity values.

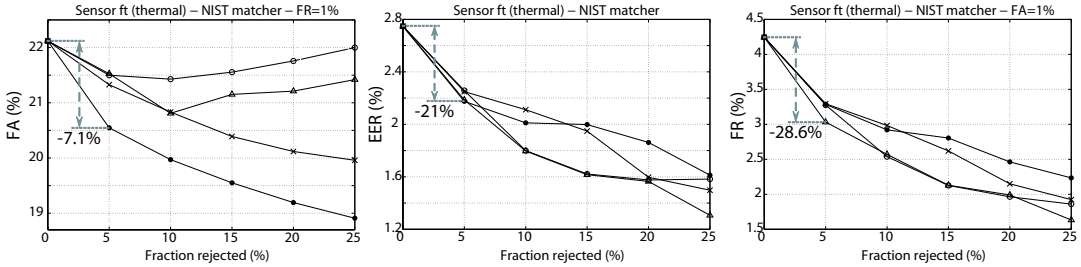
Based on the proposed taxonomy, we have performed comparative experiments using a selection of quality estimation algorithms that includes approaches based on the three classes defined above. We have used for our experiments the Biosec baseline corpus, which includes 19,200 fingerprint images from 200 individuals acquired with three fingerprint sensors based on different acquisition principles. High correlation is found between quality measures in most cases, although different correlation values are obtained depending on the sensor. This suggest that the quality measures work differently with each sensor.

We also have studied the capability of the selected quality algorithms to predict the performance of the two most widely used approaches for fingerprint recognition. It has been found that for the approach based on minutiae, when rejecting low quality samples, the highest performance improvement is obtained in the False Rejection Rate, whereas for the ridge-based approach the highest improvement is observed in the False Acceptance Rate. We have also observed a relationship between sensor acquisition area and the achieved relative performance improvement.

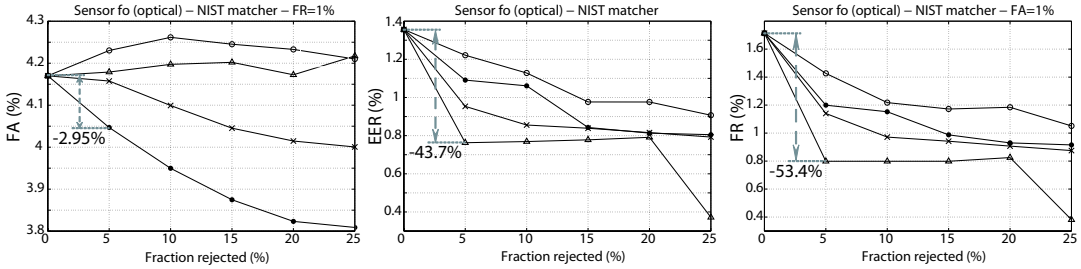
This chapter presents novel contributions regarding the taxonomy of fingerprint quality assessment algorithms, the study of correlation of a representative set of quality measures and their utility for two different matchers with sensors of different technology.



(a) Capacitive sensor.

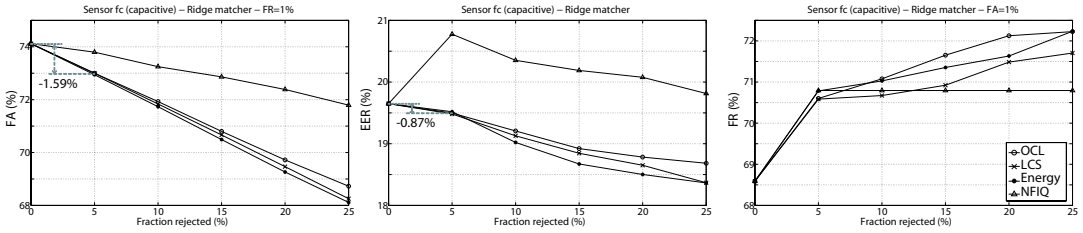


(b) Thermal sensor.

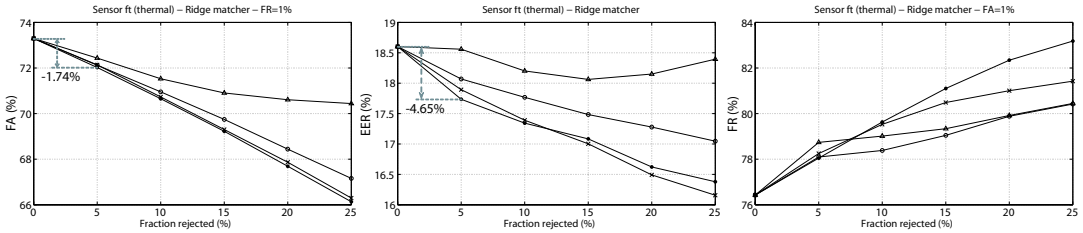


(c) Optical sensor.

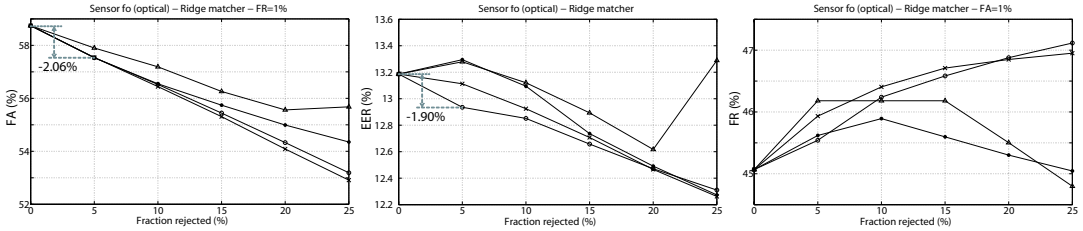
Figure 3.34: ***Minutiae-based matcher.*** **Verification performance as samples with the lowest quality value are rejected. Results are shown for all the quality measures tested in this work in terms of False Acceptance Rate at 1% FRR (first column), Equal Error Rate - EER (second column) and False Rejection Rate at 1% FAR (third column).**



(a) Capacitive sensor.



(b) Thermal sensor.



(c) Optical sensor.

Figure 3.35: ***Ridge-based matcher.*** **Verification performance as samples with the lowest quality value are rejected. Results are shown for all the quality measures tested in this work in terms of False Acceptance Rate at 1% FRR (first column), Equal Error Rate - EER (second column) and False Rejection Rate at 1% FAR (third column).**

		Minutiae matcher			Ridge matcher		
sensor	image size (pixels)	FA	EER	FR	FA	EER	FR
Capacitive	36,864 *	-0.7%	-4.8%	-9.6%	-1.59	-0.87	no improv.
Thermal	198,400	-7.1%	-21%	-28.6%	-1.74	-4.65	no improv.
Optical	224,000	-2.95%	-43.7%	-53.4%	-2.06	-1.90	no improv.

Table 3.3: **Relationship between sensor acquisition area and relative performance improvement obtained after rejection of 5% of the samples (results shown in this table are the best cases of Figures 3.34 and 3.35). It is observed that, in general, bigger acquisition area results in higher performance improvement for the minutiae-based matcher.**
* **Image size of the capacitive sensor is after interpolation to 500 dpi, see Section 3.5.1.**

Chapter 4

Quality Assessment of Signature Images

The handwritten signature is one of the most widely used individual authentication methods due to its acceptance in government, legal and commercial transactions as a method of identity verification (Fairhurst, 1997; Jain *et al.*, 2004b). People are used to sign documents to confirm their identity in cheques, financial transactions, credit card validations, contracts, etc. Moreover, signature capture is a very simple and common process.

This chapter is focused on off-line signature verification, a pattern classification problem with a long history, involving the discrimination of signatures written on a piece of paper (Plamondon and Srihari, 2000). It is worth noting that even professional forensic document examiners perform a correct classification rate of only about 70%, confirming that this a challenging research area.

This chapter presents several measures aimed to predict the performance of off-line signature verification systems. They are used as a measure of *utility* and evaluated on three matchers that use different approaches based on global and local image analysis. The proposed measures, extracted from signature images, assess factors like signature legibility, complexity, stability, duration, etc. Some remarkable findings of this chapter are that better performance is obtained with legible signatures and skilled forgeries, or that performance is worsened with highly variable signatures.

This chapter is structured as follows. We first review the state of the art in off-line signature recognition, describing the most commonly used approaches. Next, we present the measures used to evaluate the utility of the system. After that, we outline

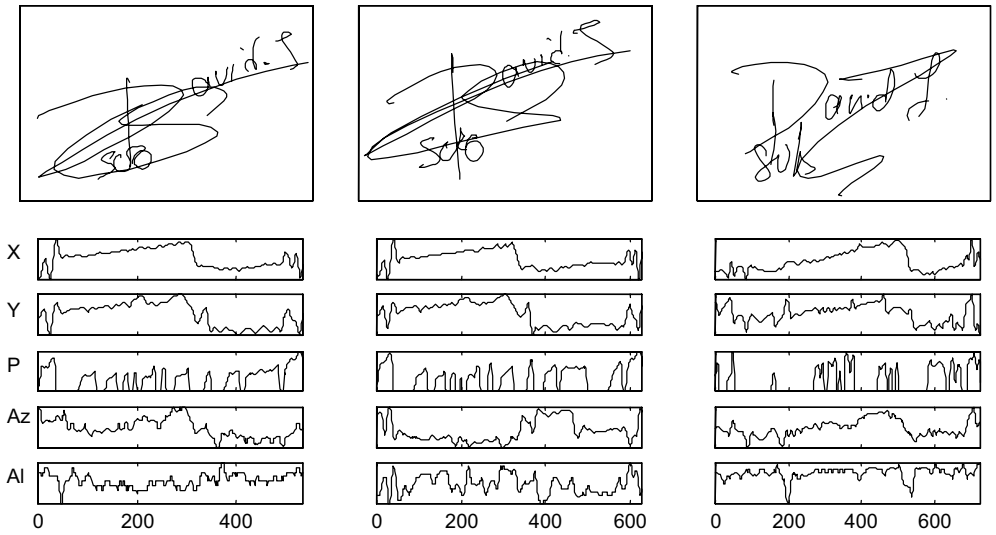


Figure 4.1: **Example of signatures from MCYT database. The two left signatures are genuine and the one on the right is a skilled forgery. Plots below each signature correspond to the available on-line information, namely: position trajectories (horizontal x, and vertical y), pressure (p), and pen inclination (*azimuth* and *altitude* angles).**

the experimental framework and the signature matching systems used. Results are then described and finally, a summary and some conclusions are given.

This chapter present novel contributions in one of the matchers that exploits local information of the signature, which has been developed jointly with Pecharroman-Balbas (2007), the proposal of measures to predict the performance of signature systems, and the study of their utility.

This chapter is based on the publications: Alonso-Fernandez *et al.* (2007a,b); Gilperez *et al.* (2008).

4.1 Automatic off-line signature recognition

There are two main automatic signature recognition approaches (Plamondon and Srihari, 2000): off-line and on-line. Off-line methods consider only the signature image, so only static information is available for the recognition task. On-line systems use pen tablets or digitizers which capture dynamic information such as velocity and acceleration of the signing process, see Figure 4.1. These features are then available for recognition, providing a richer source of information than off-line static images. On-line signature verification systems have traditionally shown to be more reliable as

dynamic features provide in general a higher variability between users and are harder to imitate (Plamondon and Lorette, 1989; Rigoll and Kosmala, 1998). But in spite of the advantages of on-line signature approaches, off-line signature verification has a wide field of implementation. Signature capture in off-line systems is a very simple process and we are used to sign documents to confirm our identity in cheques, financial transactions, credit card validations, contracts, etc. In fact, some authors have tried to extract pseudo-dynamic features from signature images in an attempt to enhance the performance of off-line verification systems (Ammar and Fukumura, 1986; Fang *et al.*, 1999; Lee and Pan, 1992).

Like other biometric systems, signature verification systems are exposed to forgeries, which can be easily performed by direct observation and learning of the signature by the forger. Commonly, two kind of impostors are considered in signature verification tasks: casual impostors, which produce *random forgeries* that are visually distinct (e.g. their own signature) from the target signature, and real impostors, that produce *skilled forgeries* which attempt to imitate the target signature (Justino *et al.*, 2001), as the example shown in the right part of Figure 4.1. A robust system against simple forgeries may be weak against skilled forgeries.

In this section, we describe the main existing approaches for off-line signature recognition. They are presented according to the general architecture of a biometric system presented in Chapter 1, namely: *i*) signature acquisition; *ii*) preprocessing, *iii*) feature extraction and *iv*) matching. This section is based on publication Martinez-Diaz (2007).

4.1.1 Signature acquisition and preprocessing

Due to their specific nature, off-line signatures are acquired after the user has produced its signature. The most common way is by document scanning. After the image has been captured, signature region is segmented from the background (Ammar *et al.*, 1988). In some cases, noise reduction techniques are used to enhance the signature extraction phase. The following steps are commonly performed for these purposes:

1. *Binarization.* Signature images are converted to binary images in most cases in order to use them as input for other stages. This step is commonly performed using classical thresholding techniques, like the Otsu method (Otsu, 1979). An example is shown in Figure 4.2.

2. *Noise reduction.* Noise may appear after the binarization step. These can be deleted using morphological operations such as openings and closings (Gonzalez

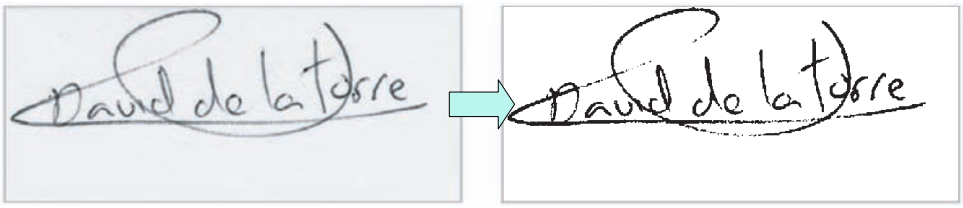


Figure 4.2: **Signature binarization using the Otsu method.**

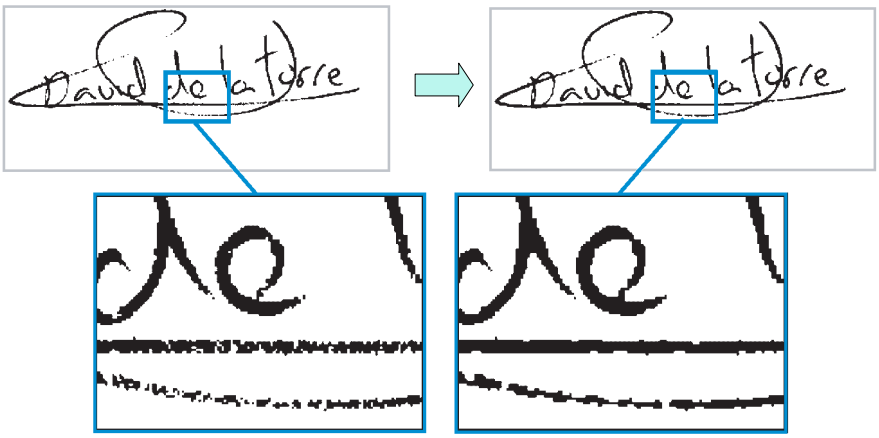


Figure 4.3: **Noise removal using morphological closing.**

and Woods, 2002), as can be seen in Figure 4.3.

3. *Segmentation.* Signature images are segmented by extracting signature strokes from the background in order to process only the signature traces (Lee and Lizarraga, 1996). In the work presented by Fierrez-Aguilar *et al.* (2004), signatures are segmented by locating and eliminating the outermost flourish strokes, considering the signature image only in the inside of a bounding box, as outermost flourish strokes usually present more intra-variability. This process can be seen in Figure 4.4. A sophisticated method for segmenting signature images is presented by Sabourin and Plamondon (1988), where statistics of directional data are used to grow regions using a merging algorithm.

4. *Normalization and centering.* While some authors consider the signature size and position as user-specific (Murshed *et al.*, 1995; Sabourin and Drouhard, 1992), signatures are generally aligned and normalized. In Figure 4.5, an example of size normalization to a fixed width while maintaining the aspect ratio is depicted for two different signatures. By using this process, all signatures from an specific subject are normalized to the same size, as can be observed in Figure 4.6.

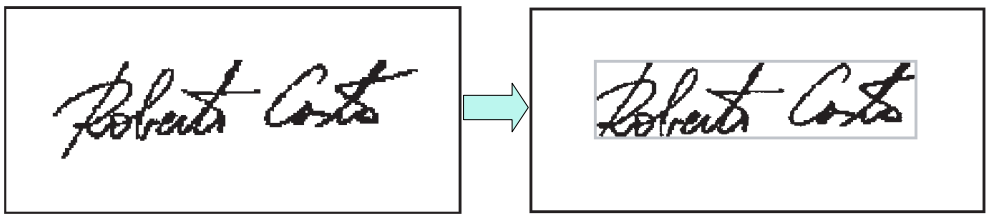


Figure 4.4: **Elimination of signature outermost flourish strokes. Figure extracted from Alonso-Hermira (2003); Moreno-Marquez (2003).**

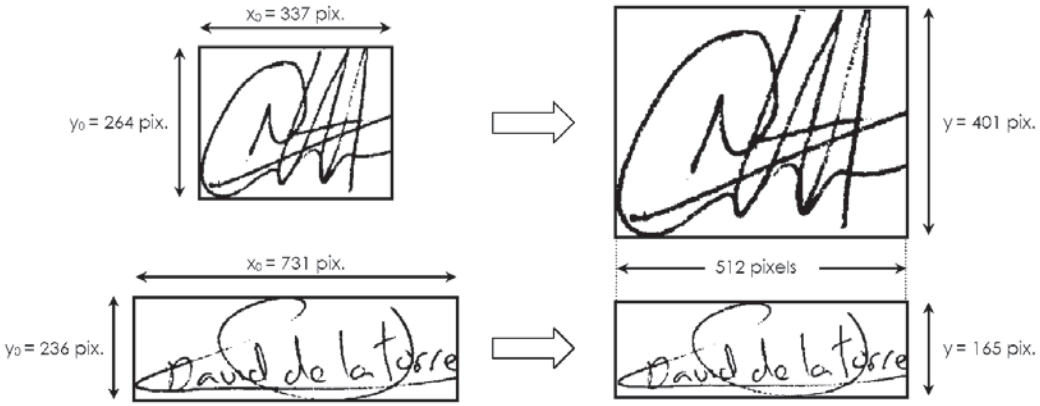


Figure 4.5: **Size normalization to a fixed width. Figure extracted from Alonso-Hermira (2003); Moreno-Marquez (2003).**

Other approaches perform the signature extraction process in different ways, like the approach known as filiformity detection which is presented by Djeziri *et al.* (1998). Some authors perform a thinning process to the signature strokes before the feature extraction phase (Lee and Pan, 1992).

4.1.2 Feature extraction

A vast quantity of approaches have been proposed in the last few years, most of them summarized by Dimauro *et al.* (2004); Hou *et al.* (2004); Leclerc and Plamondon (1994); Plamondon and Lorette (1989); Sabourin (1992). Feature extraction methods can be classified in *global* and *local* approaches.

Global approaches extract feature vectors based on the whole signature image. First works used several classical shape description techniques, such as Fourier descriptors, Hadamard transforms, etc. (Ammar *et al.*, 1988). Some examples of recent approaches include:

Figure 4.6: **Several signatures of two different subjects after size normalization and centering. Figure extracted from Alonso-Hermira (2003); Moreno-Marquez (2003).**

- Directional probability density functions techniques that compute histograms of the direction of the signature strokes (Sabourin and Drouhard, 1992).
- Vertical and horizontal projection moments, computing the amount of pixels from each row and column of the image (Bajaj and Chaudhury, 1997).
- Shape-matrices computed over a pseudo-convex hull of the signature image (Sabourin *et al.*, 1997).
- Slant directions and signature envelope features extracted using morphological image processing (Lee and Lizarraga, 1996).
- Pixel density based techniques that divide the signature image in cells and compute the amount of signature pixels in each cell (Justino *et al.*, 2000; Rigoll and Kosmala, 1998).
- Geometrical features such as contour measures based on polar and cartesian coordinates (Ferrer *et al.*, 2005).
- Simple graphometric features such as signature proportion, space between signature blocks, baseline angle, image area, number of closed loops, number of crossings, maximum horizontal and vertical projections, global slant angle, number of edge points, etc. (Baltzakis and Papamarkos, 2001; Justino *et al.*, 2000).

In *local* approaches, signature images are divided in regions and feature vectors are then computed from each region. Some recent approaches include:

- Structural descriptors which consider the whole signature as a set of hierarchical symbols that can be described at different levels in a tree-form structure (Ammar *et al.*, 1990).

- In Sabourin *et al.* (1993), shadow codes are proposed as features. This technique divides the signature image in cells, and then computes the projection of the pixels in each cell over different directions.
- Granulometric distributions are proposed by Sabourin *et al.* (1996). This approach divides the signature image in cells, which are called retinas, and then computes the pattern spectrum of the pixels from each retina based on different morphological operators.
- Simple features such as curvature, angle and size of isolated strokes (Guo *et al.*, 1997).
- A smoothness index, which allows to compare individual stroke curves based on their smoothness (Fang *et al.*, 1999).
- Slant directions and signature envelope features extracted from local regions of the image using morphological image processing (Lee and Lizarraga, 1996).

There are also approaches that combine local and global features similar to the above-mentioned, as in the works presented by Fierrez-Aguilar *et al.* (2004); Huang and Yan (1997); Sabourin *et al.* (1994).

Features can also been classified in two other types: *static* and *pseudo-dynamic* features. The features presented until now in this section are all static features. Pseudo-dynamic features try to extract dynamic information from the signature image, because, as stated before, dynamic features provide very valuable information to detect skilled forgeries. In the approach proposed by Ammar and Fukumura (1986), pressure information is retrieved from the strokes structure, thus recovering some dynamic information which is used to detect skilled forgeries. Directional stroke tracing from signature images is computed by Lee and Pan (1992); Pan and Lee (1991) by retracing the signature with an heuristical parametric algorithm emulating the way in which a human would retrace the signature.

4.1.3 Signature matching

Several techniques have been proposed for off-line signature matching over the past few decades. They are mainly based on classical pattern classification techniques. Signature matching approaches can be divided in: *minimum distance* classifiers, *Hidden Markov Models* (*HMMs*), *Neural Networks* and *Support Vector Machines* (*SVMs*). Other approaches will be presented at the end of this section.

- *Minimum distance* classifiers. This is the simplest classification technique. It has been widely used as its implementation is completely straightforward. The distance between feature vectors is directly computed in order to test their similarity. Two types of distances are the most commonly used: *Euclidean* (Lee and Lizarraga, 1996; Sabourin *et al.*, 1993, 1997) and *Mahalanobis* (Fang *et al.*, 1999; Lee and Lizarraga, 1996; Nagel and Rosenfeld, 1977) distances. One variant of the previous methods is the *Nearest Neighbor* classifier (Sabourin *et al.*, 1993), which matches the test feature vector to the class of the template that is closer to it.

- *Hidden Markov Models* (*HMMs*). An HMM models a double-stochastic process, governed by a finite-state Markov Chain and a set of random functions. In each instant, the process generates an observation symbol, according to the random function corresponding to the actual state. Each state depends only from previous states. The correct choice of the model topology is crucial when designing an HMM classifier. Choosing correct probability density functions associated with each state is also critical. A brief description of HMMs is done by Rabiner (1989). Hidden Markov Models application examples in off-line signature verification are given by Fierrez-Aguilar *et al.* (2004); Justino *et al.* (2000); Rigoll and Kosmala (1998).

- *Neural Networks.* Neural networks have been widely used in signature verification as they provide a framework adaptable to many kinds of features. Neural networks are a combination of perceptrons or neurons, which are simple classifiers that can be interconnected using as inputs their weighted outputs building in this way multi-layer neural networks. Some examples of systems that use neural networks are: Bajaj and Chaudhury (1997); Baltzakis and Papamarkos (2001); Huang and Yan (1997); Murshed *et al.* (1995); Sabourin and Drouhard (1992).

- *Support Vector Machines* (*SVMs*). SVMs are linear classifiers which compute the optimum hyperplane that maximizes the class separability. One of their main advantages is that they allow to deal with high-dimensional feature vectors. This approach is not common in off-line signature verification systems but it has shown very promising results, as in the work reported by Martinez *et al.* (2004), where an SVM classifier is used with geometric features. A complete description of SVMs implementation is done by Burges (1998). A comparison between SVM and HMM approaches is carried out by Justino *et al.* (2005) showing that, for

the database and features under consideration, the SVM system performs better than the HMM system.

In the work presented by Guo *et al.* (1997), a dynamic programming based approach is used. This technique models the signature as a set of ordered symbols and computes the cost function for transforming the test signature symbol set into the template set. An approach based on relaxation matching is presented by Huang and Yan (2002). This technique uses statistical classifiers that give soft-decisions which are viewed as matching-confidence values and combined to compute the matching scores.

Fusion of the scores obtained with different classifiers has also been proposed (Fierrez-Aguilar *et al.*, 2004). Cordella *et al.* (1999) present a serial multi-expert approach that combines two classifiers, one aimed against random forgeries and the other one against skilled forgeries.

4.1.4 Issues and challenges

Off-line signature verification is a very convenient biometric based validation approach. Unfortunately, none of the approaches given up to date have attained the same reliability as other biometric verification systems based on different traits such as iris, fingerprint, etc. While systems are reasonably robust against simple forgeries, skilled forgeries are still a challenge. Off-line signature verification is still an open issue, with new approaches being proposed constantly. Human expert approaches should also be taken into account. The perceptual influence in human-based signature verification is studied by Fairhurst and Kaplani (2003). The authors study how different amounts and typologies of training data and test data lead to very different error rates. These results are proposed as a path to improve automatic signature verification systems.

Another problem is the scarcity of available signature templates when a user is enrolled in a system. Usually, several templates are needed to obtain a reasonable verification performance, but this is not always possible. Moreover, template signatures should be captured in different sessions in order to obtain a robust model against medium- and long-term intra-variability. This is a challenging problem in signature recognition, as many users tend to have a high variation in their signatures between different realizations or gradually over medium to long periods of time.

The non-existence of publicly available signature databases makes difficult the evaluation of off-line recognition systems. This is normally due to legal issues regarding personal data protection. Verification systems in the literature use proprietary databases, usually from very small populations which make nearly impossible to systematically

compare their results. Furthermore, signatures from different parts of the world tend to be very diverse: European signatures are commonly flourished, Asian signatures use Asian characters, etc. Systems designed to deal with Western signatures may no be valid for Asian ones (Hou *et al.*, 2004). Capturing a database containing samples of each type of signature is a very difficult task.

4.2 Contribution: quality estimation of signature samples

In fingerprint images, we can objectively define quality as the strength, continuity, clarity, uniformity or integrity of the ridge structure. But in behavioral biometric traits such signature, it is harder to clearly define what quality is. There are works (Allgrove and Fairhurst, 2000; Muller and Henniger, 2007) postulating that signature stability can be considered as a measure of signature quality. Signature complexity could be other quality measure suitable for signatures (Brault and Plamondon, 1993). But these two factors, complexity and variability, depend on how a signer decides to sign. It is clear that a blurred image or a weak impression of a fingerprint is not suitable for recognition, thus a sufficient reason to ask a user for a new fingerprint sample. However, signature complexity or variability are weak reasons to reject a signature sample, mainly because subsequent samples provided by the user probably will have the same complexity or variability. In this case, signature recognition systems should be able to deal with these features and to adjust the recognition process based on the estimated complexity or variability. An optimal system could therefore be designed that chooses a feature set which best suits the characteristics of the signature at hand (Guest, 2004).

In this Section, we present several measures aimed to predict the performance of off-line signature verification systems (i.e. quality defined as *utility*). There are also works aimed to study signature quality as a *fidelity* measure, which is not considered in this Ph.D. Thesis, e.g. Vargas *et al.* (2007). The proposed measures, extracted from signature images, include:

- Two manually assessed measures, signature legibility and signature type, aimed at evaluating how the knowledge about letters, syllables or name instances may help in the process of imitating a signature (Section 4.2.1).

- One measure that computes the area of a signature where slants with different directions intersect, which could be considered as a measure of complexity (Section 4.2.2).

Figure 4.7: **Signature examples with different degrees of name legibility (from top to bottom).**

- One measure that computes the intra-variability of a given set of signatures with the aim of estimating its stability (Section 4.2.2).

- Three geometrical measures aimed at evaluating the variance of the pen pressure during the process of signing, the signature duration and the signature area (Section 4.2.3).

4.2.1 Legibility and type of signature

We focus here on *occidental* signatures, which typically consist of connected text (i.e. name) and/or some form of flourish. Sometimes, signatures only consist of a readable written name (e.g. American signatures). In other cases, as frequently happens in European countries, signatures may consist of only an elaborated flourish. In contrast to occidental signatures, oriental signatures consist of independent symbols. Examples of both oriental and occidental signatures can be found in the First International Signature Verification Competition (Yeung *et al.*, 2004).

Signature verification systems have been shown to be sensitive to some extent to signature complexity (Fierrez-Aguilar *et al.*, 2005d). Easy to forge signatures result in increased False Acceptance Rate. Signature variability also has an impact in the verification rates attainable (Allgrove and Fairhurst, 2000). It can be hypothesized that these two factors, complexity and variability, are related in some way with signature legibility and signature type. Moreover, some studies have been concerned with the ability of humans in recognizing handwritten script (Brault and Plamondon, 1993; Fairhurst and Kaplani, 2003). Knowledge about letters, syllables or name instances may help in the process of imitating a signature, which is not the case for an incomprehensible set of strokes that, in principle, are not related to any linguistic knowledge. Therefore, we propose to evaluate the impact of signature legibility and signature type in the recognition rates of verification systems. In this work, signature legibility and type are assessed by a human expert. This is a suitable situation in off-line signature verification environments, where signature acquisition is typically performed by a human operator using a scanner or a camera (Plamondon and Srihari, 2000).

All signers in the database used for our experiments are manually assigned a *legibility* label and a *type* label. One of three different *legibility* labels is assigned: *i*) name not legible or no name; *ii*) uncertain; and *iii*) name clearly legible. Examples are shown in Figure 4.7. Condition *ii*) is used in the case that some characters of the name can be recognized but it is not possible to extract the name completely. In addition, four different *type* labels are assigned based on the following criterion: *a*) simple flourish;

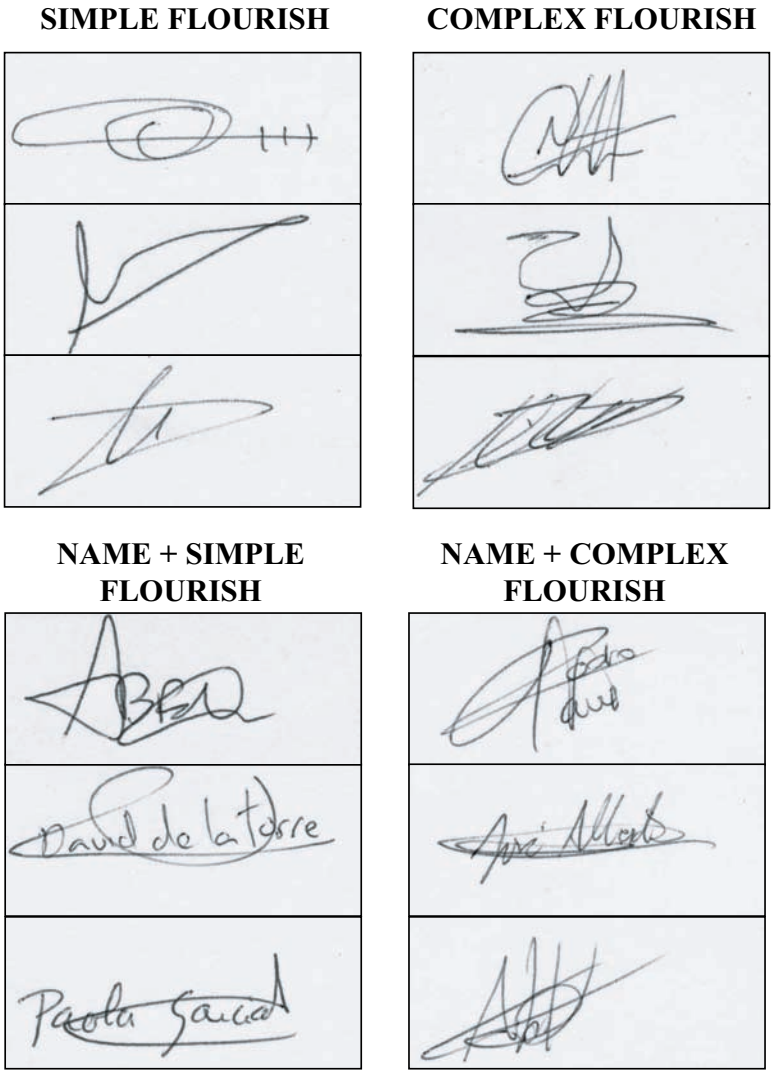


Figure 4.8: **Signature examples of the four types encountered in the MCYT corpus (from left to right).**

Legibility level	Number of users
Non-legible	18 users (24.00%)
Medium	19 users (25.33%)
Legible	38 users (50.67%)

Type	Number of users
Simple flourish	5 users (6.67%)
Complex flourish	13 users (17.33%)
Name + simple flourish	35 users (46.67%)
Name + complex flourish	22 users (29.33%)

Table 4.1: **Distribution of users on the MCYT database (75 users) based on name legibility and signature type.**

b) complex flourish; *c*) name + simple flourish; and *d*) name + complex flourish. Examples are shown in Figure 4.8. It should be noted that signatures of class *a*) and *b*) are those assigned to the non-legible class. Similarly, signatures of class *c*) and *d*) are those assigned to the medium and legible classes. The distributions of signers in the database used in this chapter based on name legibility and signature type are shown in Table 4.1 (the database is described later in Section 4.3).

4.2.2 Slant and variability measures

We have proposed two measures that can be automatically extracted from off-line signature images (Alonso-Fernandez *et al.*, 2007a). The first computes the area of a signature where slants with different directions intersect, which could be considered as a measure of complexity. The second measure computes the intra-variability of a given set of signatures with the aim of estimating its stability.

We first preprocess input signature images by performing the following steps: binarization by global thresholding of the histogram (Otsu, 1979), morphological opening plus closing operations on the binary image for noise removal, segmentation of the signature outer traces, and normalization of the image size to a fixed width while maintaining the aspect ratio. Segmentation of the outer traces is done because signature boundary normally corresponds to flourish, which has high intra-user variability, whereas normalization of the image size is aimed to make the proportions of different realizations of an individual to be the same.

Next, slant directions of the signature strokes and those of the envelopes of the dilated signature images are extracted. For slant direction extraction, the preprocessed

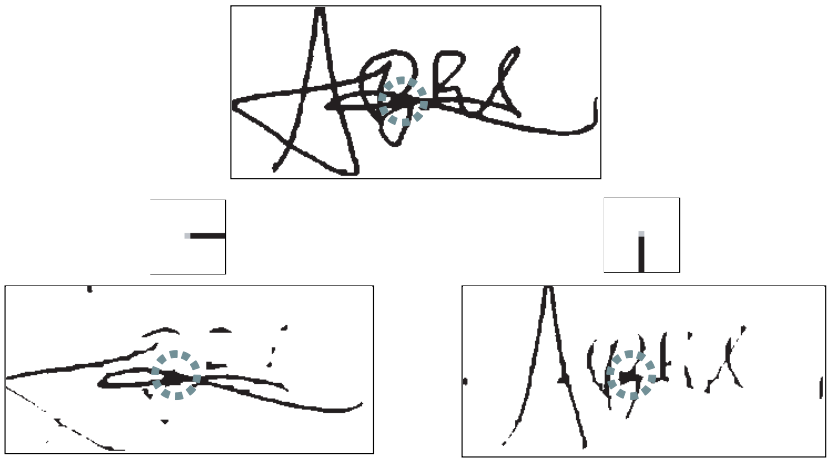


Figure 4.9: ***Slant measure.*** **Example of two eroded images (bottom row) of a given signature image (top row). The middle row shows the two structuring elements used for the erosion. The dotted circle denotes a region of the signature having various strokes crossing in several directions. In this region, no predominant slant direction exists.**

signature image is eroded with 32 structuring elements like the ones presented in the middle row of Figure 4.9, each one having a different orientation regularly distributed between 0 and 360 degrees (Fierrez-Aguilar *et al.*, 2004), thus generating 32 eroded images. A slant direction feature sub-vector of 32 components is then generated, where each component is computed as the signature pixel count in each eroded image. For envelope direction extraction, the preprocessed signature image is successively dilated 5 times with each one of 6 linear structuring elements, whose orientation is also regularly distributed, thus generating 5×6 dilated images. An envelope direction feature sub-vector of 5×6 components is then generated, where each component is computed as the signature pixel count in the difference image between successive dilations. The preprocessed signature is finally parameterized as a vector $\mathbf{o}$ with 62 components by concatenating the slant and envelope feature sub-vectors. For additional details of these steps, including the structuring elements used for erosion and dilation, we refer the reader to Fierrez-Aguilar *et al.* (2004) and the references therein.

4.2.2.1 Slant Measure

The area of a signature where slants with different directions intersect is measured as follows. Given the 32 eroded images generated as explained above, a small degree of overlap is expected among them (i.e. any pixel should be marked in as few eroded

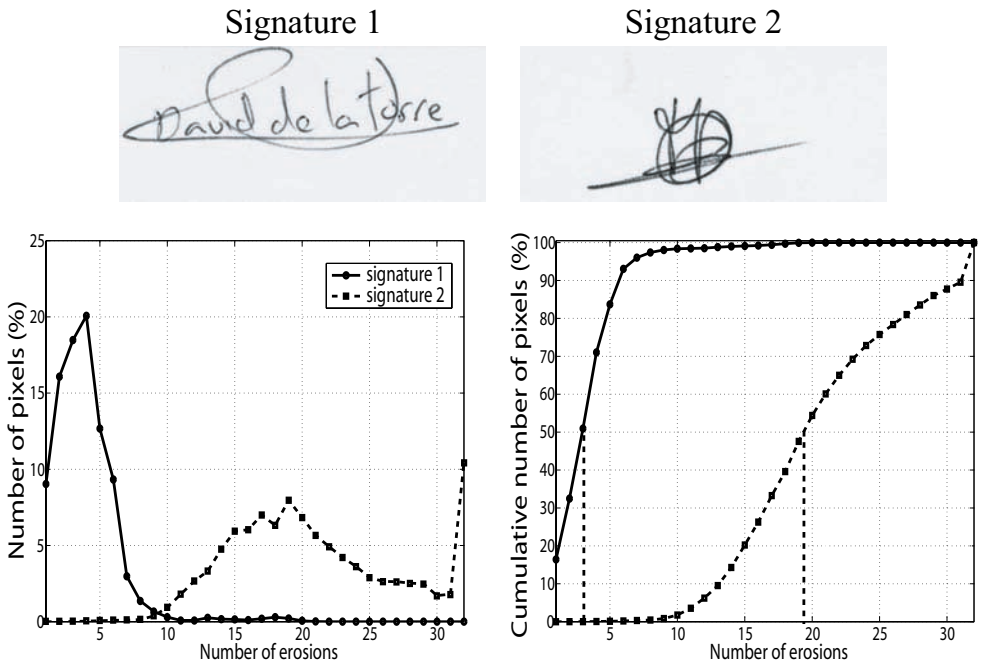


Figure 4.10: ***Slant measure.*** **Histogram (left bottom) and cumulative histogram (right bottom) of the number of eroded images in which a pixel is marked for the two example signatures shown.**

images as possible). However, there may be regions of the signature having various strokes crossing with several directions. In these regions, no predominant slant direction exists or, in other words, any estimation of a dominant slant direction will be unreliable. As a result, pixels of these regions will be marked in many of the eroded images, as can be seen in Figure 4.9. For each pixel of the signature, we count the number of eroded images in which it is marked and then, we plot the histogram and the cumulative histogram for all the pixels of the image (Figure 4.10). We can see from Figure 4.10 that the histogram of *signature 1* is concentrated in low values, whereas it is displaced to higher values for *signature 2*. This is because *signature 2* exhibits many regions having various strokes crossing with several directions. We measure the size of these regions by computing the x-axis point in which the cumulative histogram reaches a certain value (in our experiments, this value is set to 50%, as seen in Figure 4.10). The higher the value this point has, the larger is the area of the signature with no predominant slant direction. For now on, this measure will be denoted as *Slant Measure*.

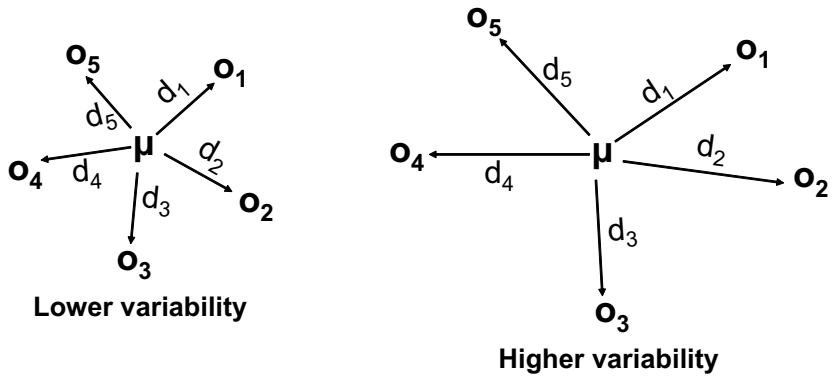


Figure 4.11: ***Variability measure.*** **Example of two signature sets of different variability. Vectors $\{\mathbf{o}_1, ..., \mathbf{o}_K\}$ denote the K different signatures (K=5 in this example). Parameter $\boldsymbol{\mu}$ denotes the mean vector of the K signatures $\{\mathbf{o}_1, ..., \mathbf{o}_K\}$. Parameters d_i are the Euclidean distances of each signature $\mathbf{o}_i$ to the mean vector $\boldsymbol{\mu}$ $(i = 1, ..., K)$.**

4.2.2.2 Variability Measure

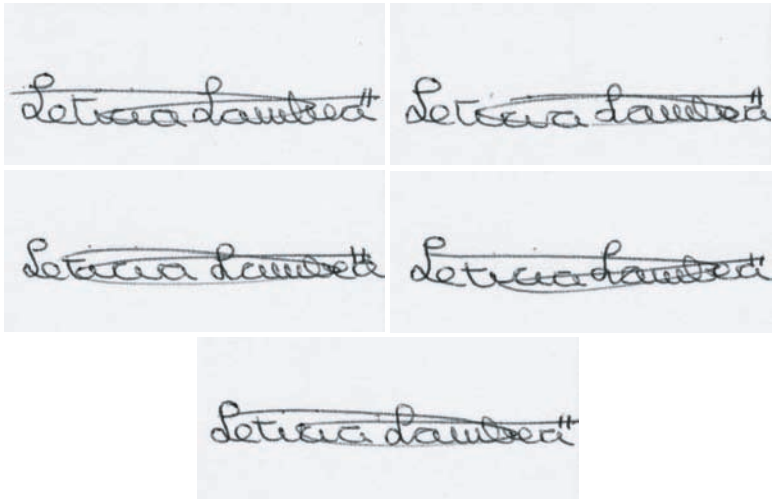
The intra-variability of a given set of K signatures of a client is computed as follows. We first extract an statistical model $\boldsymbol{\mu}$ of the client which is estimated by using the set of K signatures, parameterized as $\{\mathbf{o}_1, ..., \mathbf{o}_K\}$. The parameter $\boldsymbol{\mu}$ denotes the mean vector of the K signatures $\{\mathbf{o}_1, ..., \mathbf{o}_K\}$. We then compute the Euclidean distance (Theodoridis and Koutroumbas, 2003) of each signature $\mathbf{o}_i$ $(i = 1, ..., K)$ to the mean vector $\boldsymbol{\mu}$, resulting in K distances d_i $(i = 1, ..., K)$. The variability is finally computed as $E(d_1, ..., d_K)$, where the operator $E(.)$ is the statistical mean. The idea behind this measure is shown in Figure 4.11. In the rest of the chapter, this measure will be denoted as *Variability Measure*. An example of two signature sets of different variability based on this measure is shown in Figure 4.12.

Figure 4.13 depicts the cumulative distribution function of the *Slant* and *Variability* measures for all users of the database used in this chapter (Section 4.3).

4.2.3 Geometrical measures

We propose the evaluation of measures related with geometrical features of the signature image, that can be also extracted automatically:

- Gray level variance across the signature strokes (see Figure 4.14(a)), which can be considered as a measure of variance of the pen pressure during the process of signing.



(a) Low variability (measure value = 1,877.3)

(b) High variability (measure value = 12,241)

Figure 4.12: ***Variability measure.*** **Example of two signature sets of different variability from the MCYT database.**

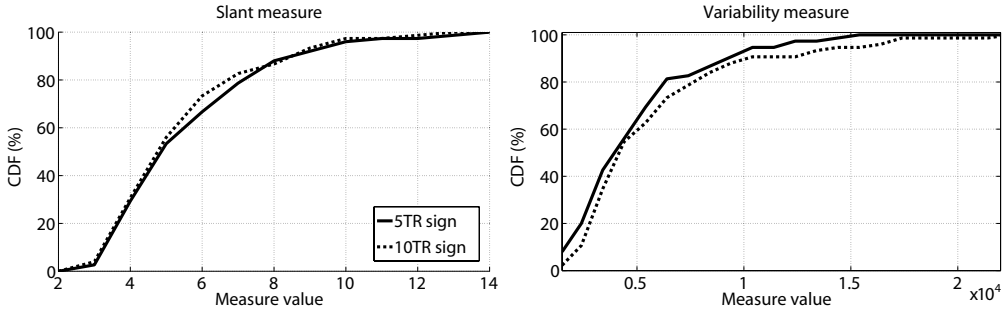


Figure 4.13: **Cumulative distribution function of the proposed Slant and Variability measures for all users of the database used in this Chapter.**

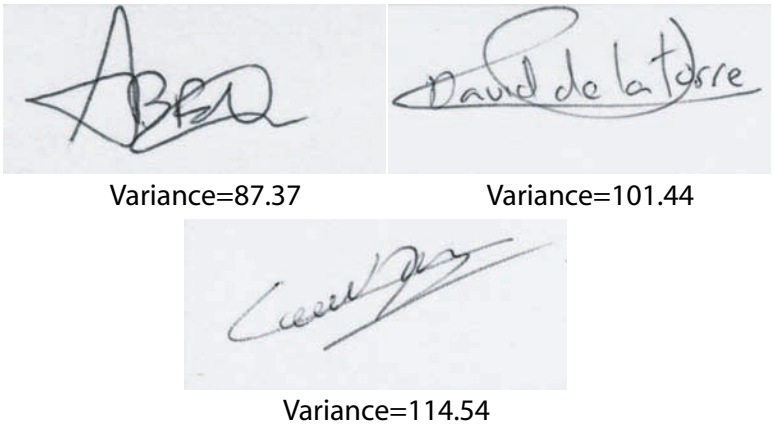
- Number of pixels of the signature (see Figure 4.14(b)), which can be considered as a measure of signature duration.
- Size of the bounding box that contains the signature (see Figure 4.14(c)), which is a measure of the signature area.

Strokes of the signature are extracted by binarizing the signature image by global thresholding of the histogram (Otsu, 1979), followed by a morphological closing operation on the binary image for noise removal. Figure 4.15 depicts the cumulative distribution function of the three geometrical measures for all users of the database used in this chapter (Section 4.3).

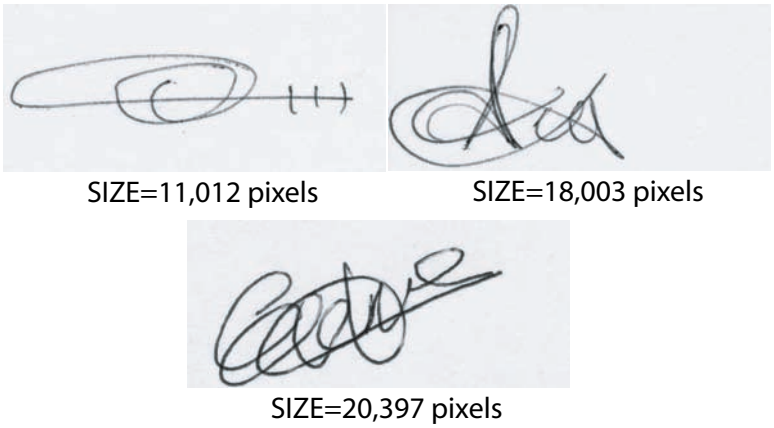
4.3 Experimental framework

4.3.1 Database and protocol

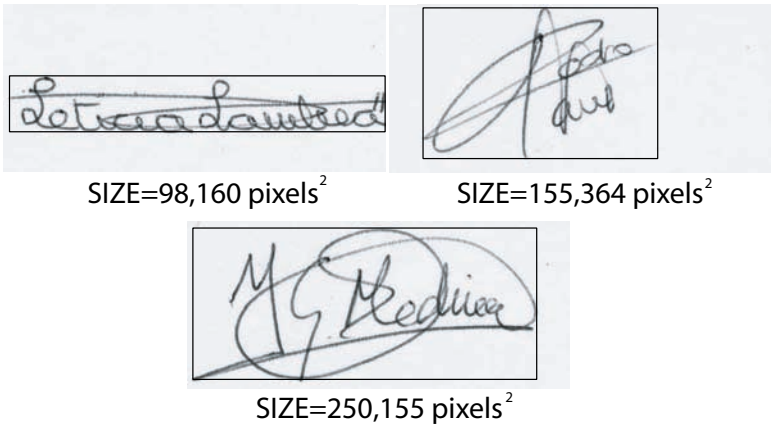
We have used for the verification experiments of this chapter a subcorpus of the MCYT bimodal database (Ortega-Garcia *et al.*, 2003b), which includes fingerprint and on-line signature data of 330 contributors. The MCYT database includes the largest existing western signature database publicly available (Garcia-Salicetti *et al.*, 2007). In the case of the signature data, skilled forgeries are also available. Imitators are provided the signature images of the client to be forged and, after an initial training period, they are asked to imitate the shape with natural dynamics. Signature data were acquired using an inking pen and paper templates over a pen tablet (each signature is written within a 1.75×3.75 cm^2 frame), so the signature images were available on paper. Paper templates of 75 signers (and their associated skilled forgeries) have been digitized with a scanner at 600 dpi (dots per inch). The resulting subcorpus comprises 2250 signature



(a) With increasing gray level variance across the signature strokes (from left to right).



(b) With increasing number of pixels (from left to right).



(c) With increasing size of the bounding box (from left to right).

Figure 4.14: ***Geometrical measures.*** **Example of signatures with different measure value.**

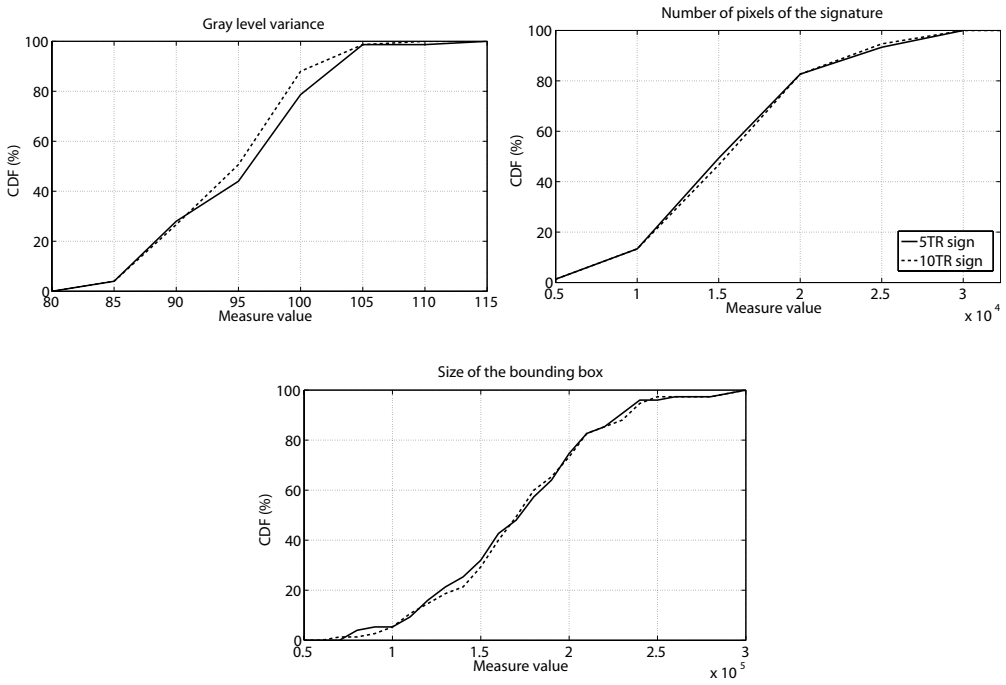


Figure 4.15: **Cumulative distribution function of the proposed geometrical measures for all users of the database used in this Chapter.**

images, with 15 genuine signatures and 15 forgeries per user (contributed by 3 different user-specific forgers). Examples can be seen in Figures 4.7 and 4.8.

The experimental protocol is as follows. The training set comprises either K =5 or K =10 genuine signatures (depending on the experiment under consideration). The remaining genuine signatures are used for testing. For a specific target user, casual impostor test scores are computed by using the genuine samples available from all the remaining targets. Real impostor test scores are computed by using the skilled forgeries of each target. As a result, we have $75 \times 10 = 750$ or $75 \times 5 = 375$ client similarity scores, $75 \times 15 = 1,125$ impostor scores from skilled forgeries, and $75 \times 74 \times 10 = 55,500$ or $75 \times 74 \times 5 = 27,750$ impostor scores from random forgeries.

In order to have an indication of the level of performance with an ideal score alignment between users, results here are based on using *a posteriori* user-dependent score normalization (Fierrez-Aguilar *et al.*, 2005d). The score normalization function is as follows $s' = s - s_\lambda(client, impostor)$, where s is the raw score computed by the signature matcher, s' is the normalized matching score and $s_\lambda(client, impostor)$ is the user-dependent decision threshold at a selected point obtained from the genuine and

impostor histograms of user λ. In the work reported here, we report verification results at three points: EER, FAR=10% and FRR=10%.

4.4 Signature matcher based on global information

This matcher is based on global image analysis and a minimum distance classifier as proposed by Lee and Lizarraga (1996), and further developed by Fierrez-Aguilar *et al.* (2004).

4.4.1 Signature preprocessing

Input signature images are first *preprocessed* according to the following consecutive steps: binarization by global thresholding of the histogram (Otsu, 1979), morphological opening plus closing operations on the binary image (Gonzalez and Woods, 2002), segmentation of the signature outer traces, and normalization of the image size to a fixed width of 512 pixels while maintaining the aspect ratio (see Figure 4.16 for an example). Normalization of the image size is used to make the proportions of different realizations of an individual to be the same, whereas segmentation of the outer traces is carried out because a signature boundary typically corresponds to a flourish, which has high intra-user variability. For this purpose, left and right height-wide blocks having all columns with signature pixel count lower than threshold T_p and top and bottom width-wide blocks having all rows with signature pixel count lower than T_p are discarded.

4.4.2 Feature extraction and matching

A *feature extraction stage* is then performed, in which slant directions of the signature strokes and those of the envelopes of the dilated signature images are extracted using mathematical morphology operators (Gonzalez and Woods, 2002), see Figure 4.17. These descriptors are used as features for recognition as proposed by Lee and Lizarraga (1996). For slant direction extraction, the preprocessed signature image is eroded with 32 structuring elements, thus generating 32 eroded images. A slant direction feature sub-vector of 32 components is then generated, where each component is computed as the signature pixel count in each eroded image. For envelope direction extraction, the preprocessed signature image is successively dilated 5 times with each one of 6 linear structuring elements, thus generating 5×6 dilated images. An envelope direction feature sub-vector of 5×6 components is then generated, where each component is computed as the signature pixel count in the difference image between successive dilations. The

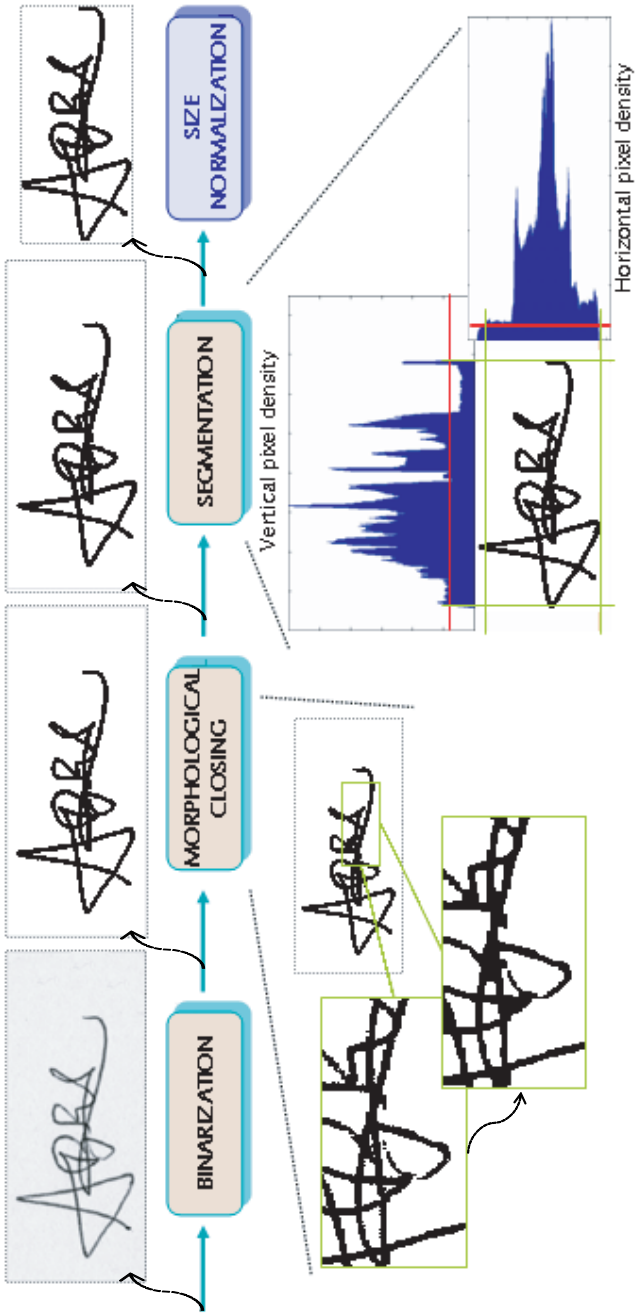


Figure 4.16: **Preprocessing stage performed in the signature matcher based on global analysis. Figure extracted from Alonso-Hermira (2003); Moreno-Marquez (2003).**

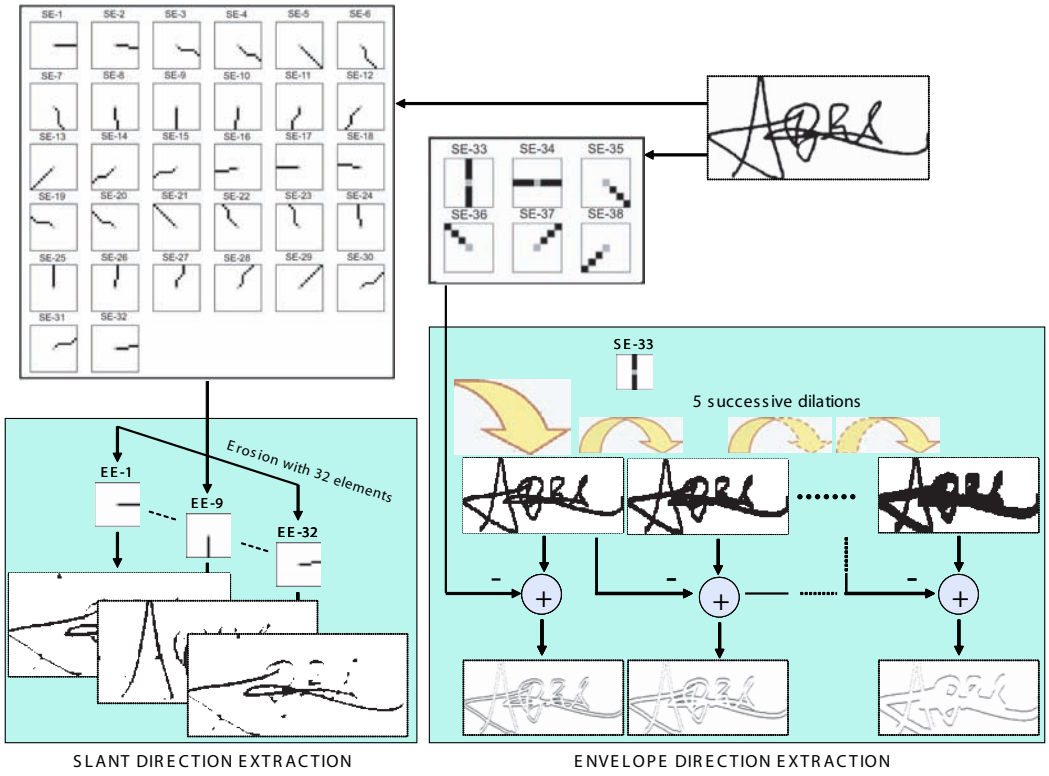


Figure 4.17: **Feature extraction stage performed in the signature matcher based on global analysis. Structuring elements used for slant direction extraction (SE-1 to SE-32) and envelope direction extraction (SE-33 to SE-38) are also shown. Origin of the element is indicated in gray. The area of SE-1 to SE-32 is 10 pixels and the angle between successive elements is approximately 11 degrees. The areas of SE-33/34 and SE-35/36/37/38 are 7 and 4 pixels respectively. Figure based on plots appearing in Alonso-Hermira (2003); Moreno-Marquez (2003).**

preprocessed signature is finally parameterized as a vector $\mathbf{o}$ with 62 components by concatenating the slant and envelope feature sub-vectors. Each client (enrolee) of the system is represented by a statistical model $\lambda = (\boldsymbol{\mu}, \boldsymbol{\sigma})$ which is estimated by using an enrolment set of K parameterized signatures $\{\mathbf{o}_1, ..., \mathbf{o}_K\}$. The parameters $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ denote mean and standard deviation vectors of the K vectors $\{\mathbf{o}_1, ..., \mathbf{o}_K\}$.

In the *similarity computation stage*, the similarity score between a claimed model $\lambda = (\boldsymbol{\mu}, \boldsymbol{\sigma})$ and a parameterized test signature $\mathbf{o}$ is computed as the inverse of the Mahalanobis distance (Theodoridis and Koutroumbas, 2003).

Figure 4.18: **Example of division of a signature image into overlapped column blocks. Figure extracted from Alonso-Hermira (2003); Moreno-Marquez (2003).**

4.5 Signature matcher based on local HMM analysis

The local HMM matcher is based on local image analysis and left-to-right Hidden Markov Models as used by Justino *et al.* (2001) but with a local parameterization derived from Lee and Lizarraga (1996), and also detailed by Fierrez-Aguilar *et al.* (2004).

In the *preprocessing stage*, images are first binarized and segmented as described in Section 4.4. Next, a *feature extraction step* is performed, in which slant directions and envelopes are locally analyzed using the approach described in Section 4.4, but applied to blocks. Preprocessed images are divided into height-wide blocks of 64 pixels width with an overlapping between adjacent blocks of 75%. An example is shown in Figure 4.18. A signature is then parameterized as a matrix $\mathbf{O}$ whose columns are 62-tuples, each one corresponding to a block. Each client of the system is represented by a Hidden Markov Model λ (HMM) (Ortega-Garcia *et al.*, 2003a; Rabiner, 1989), which is estimated by using an enrolment set of K parameterized signatures $\{\mathbf{O}_1, ..., \mathbf{O}_K\}$. A left-to-right topology of four hidden states with no transition skips between states is used in this work. Estimation of the model is made by using the iterative Baum-Welch procedure (Rabiner, 1989).

The *similarity computation* between a claimed model λ and a parameterized test signature $\mathbf{O}$ is computed by using the Viterbi algorithm (Ortega-Garcia *et al.*, 2003a; Rabiner, 1989).

4.6 Contribution: Signature matcher based on local contour analysis

This matcher is based on features proposed for writer identification and verification using images of handwriting documents (Bulacu and Schomaker, 2007), and has been

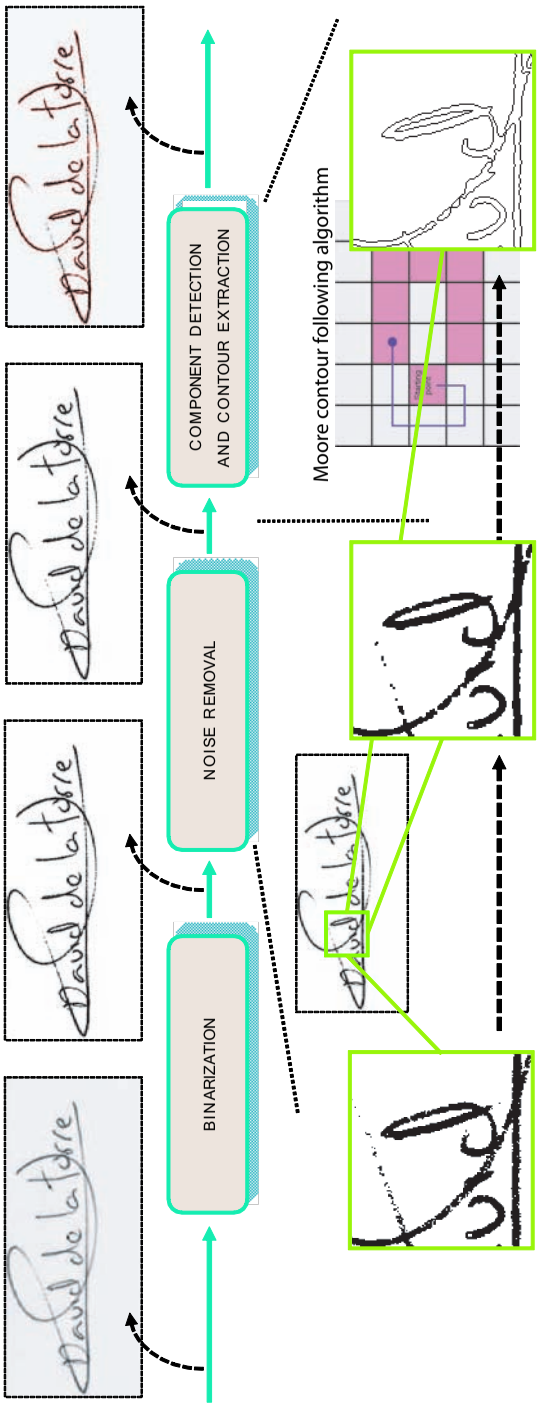


Figure 4.19: **Preprocessing stage performed in the signature matcher based on local contour analysis.**

developed jointly with Pecharroman-Balbas (2007). We have contributed by selecting and adapting a number of features to be used with handwritten signatures (Gilperez *et al.*, 2008). The features implemented work at the analysis of the contour level. The signature is seen as a texture described by some probability distributions computed from the image and capturing the distinctive visual appearance of the samples. User individuality is therefore encoded using probability distributions (PDF) extracted from signature images. The term "feature" is used to denote such a complete PDF, so we will obtain an entire vector of probabilities capturing the signature uniqueness.

4.6.1 Signature preprocessing

In the *preprocessing stage*, binarization and morphological closing operation on the binary image for noise removal are first carried out as described in Section 4.4. Then a connected component detection, using 8-connectivity, is carried out. In the last step, internal and external contours of the connected components are extracted using the Moore's algorithm (Gonzalez and Woods, 2002). Beginning from a contour pixel of a connected component, which is set as the starting pixel, this algorithm seeks a pixel boundary around it following the meaning clockwise, and repeats this process until the starting pixel is reached for the same position from which it was agreed to begin the algorithm. The result is a sequence with the pixels coordinates of the boundary of the component. This vectorial representation is very effective because it allows a rapid extraction of many of the features used later. The whole preprocessing stage is shown in Figure 4.19.

4.6.2 Feature extraction

Features are calculated from two representations of the signature extracted during the preprocessing stage: the binary image without noise and the contours of the connected components. The features used in this work are summarized in Table 4.2, including the signature representation used by each one. The signature is shaped like a texture that is described with probability distribution functions (PDFs). Probability distribution functions used here are grouped in two different categories: direction PDFs (features f1, f2, f3h, f3v) and length PDFs (features f5h, f5v). A graphical description of the extraction of direction PDFs is depicted in Figure 4.20. To be consistent with the work in which these features where proposed (Bulacu and Schomaker, 2007), we follow the same nomenclature used in it.

	Feature	Explanation	Dimensions	Source
f1	$p(\phi)$	Contour-direction PDF	12	contours
f2	$p(\phi_1, \phi_2)$	Contour-hinge PDF	300	contours
f3h	$p(\phi_1, \phi_3)_h$	Direction co-occurrence PDF, horizontal run	144	contours
f3v	$p(\phi_1, \phi_3)_v$	Direction co-occurrence PDF, vertical run	144	contours
f5h	$p(rl)_h$	Run-length on background PDF, horizontal run	60	binary image
f5v	$p(rl)_v$	Run-length on background PDF, vertical run	60	binary image

Table 4.2: **Features used in the signature matcher based on local contour analysis.**

Contour-Direction PDF (f1)

This directional distribution is computed directly using the contour representation, with the additional advantage that the influence of the ink-trace width is eliminated. The contour-direction distribution f1 is extracted by considering the orientation of local contour fragments. A fragment is determined by two contour pixels (x_k,y_k) and ($x_{k+\epsilon}$,$y_{k+\epsilon}$) taken a certain distance ϵ apart. The angle that the fragment makes with the horizontal is computed using

$$\phi = \arctan\left(\frac{y_{k+\epsilon} - y_k}{x_{k+\epsilon} - x_k}\right) \tag{4.1}$$

As the algorithm runs over the contour, the histogram of angles is built. This angle histogram is then normalized to a probability distribution f1 which gives the probability of finding in the signature image a contour fragment oriented with each ϕ. The angle ϕ resides in the first two quadrants because, without online information, we do not know which inclination the writer signed with. The histogram is spanned in the interval 0°-180°, and is divided in $n = 12$ sections (bins). Therefore, each section spans 15°, which is a sufficiently detailed and robust description (Bulacu and Schomaker, 2007). We also set $\epsilon = 5$. These settings will be used for all of the directional features presented in this chapter.

Contour-Hinge PDF (f2)

In order to capture the curvature of the contour, as well as its orientation, the "hinge" feature f2 is used. The main idea is to consider two contour fragments attached at a common end pixel and compute the joint probability distribution of the orientations ϕ_1 and ϕ_2 of the two sides. A joint density function is obtained, which

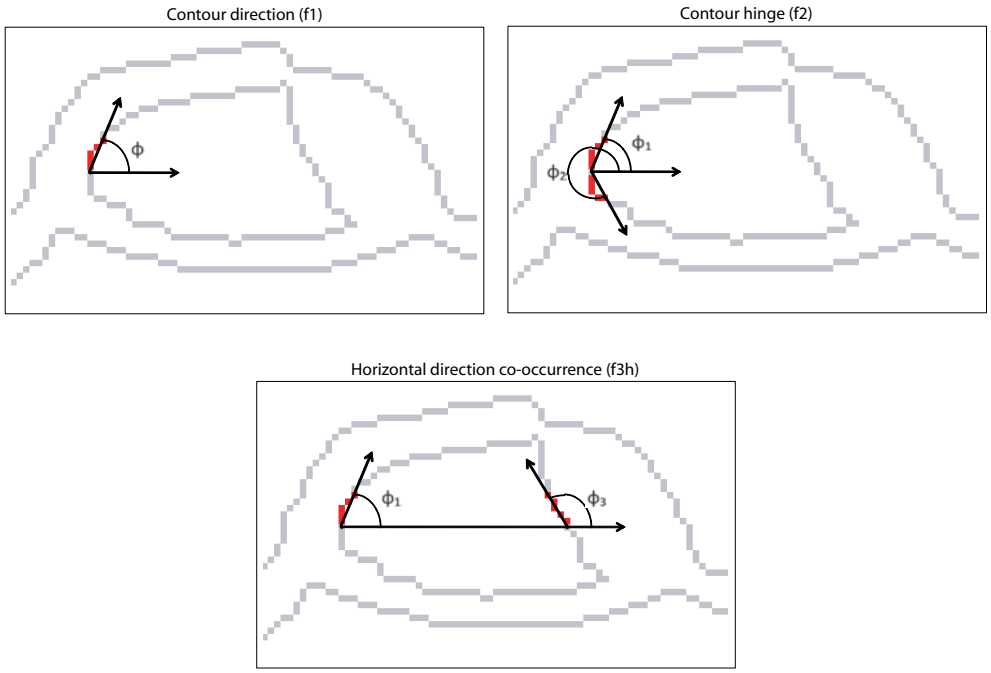


Figure 4.20: **Graphical description of the feature extraction. From left to right: contour direction (f1), contour hinge (f2) and horizontal direction co-occurrence (f3h).**

quantifies the chance of finding two "hinged" contour fragments with angles ϕ_1 and ϕ_2, respectively. It is spanned in the four quadrants (360°) and there are $2n$ sections for every side of the "contour-hinge", but only non-redundant combinations are considered (i.e. $\phi_2 \geq \phi_1$). For $n = 12$, the resulting contour-hinge feature vector has 300 dimensions (Bulacu and Schomaker, 2007).

Direction Co-Occurrence PDFs (f3h, f3v)

Based on the same idea of combining oriented contour fragments, the directional co-occurrence is used. For this feature, the combination of contour-angles occurring at the ends of run-lengths on the background are used, see Figure 4.20. Horizontal runs along the rows of the image generate f3h and vertical runs along the columns generate f3v. They are also joint density functions, spanned in the two first quadrants, and divided into n^2 sections. These features give a measure of a roundness of the written characters and/or strokes.

Run-Length PDFs (f5h, f5v)

These features are computed from the binary image of the signature taking into consideration the pixels corresponding to the background. They capture the regions enclosed inside the letters and strokes and also the empty spaces between them. The probability distributions of horizontal and vertical lengths are used.

4.6.3 Feature matching

Each client of the system (enrolee) is represented by a PDF that is computed using an enrolment set of K signatures. For each feature, the histogram of the K signatures together is computed and then normalized to a probability distribution.

To compute the similarity between a claimed identity q and a given signature i, the χ^2 distance is used (Bulacu and Schomaker, 2007):

$$\chi^2_{qi} = \sum_{n=1}^{N} \frac{(p_q[n] - p_i[n])^2}{p_q[n] + p_i[n]} \tag{4.2}$$

where p are entries in the PDF, n is the bin index, and N is the number of bins in the PDF (the dimensionality).

We also perform experiments combining the different features. The final distance in this case is computed as the mean value of the χ^2 distances due to the individual features, which are first normalized to be similarity scores in the $[0, 1]$ range using the tanh-estimators described by Jain *et al.* (2005):

$$s' = \frac{1}{2}\left\{\tanh\left(0.01\left(\frac{s - \mu_s}{\sigma_s}\right)\right) + 1\right\} \tag{4.3}$$

where s is the raw similarity score, s' denotes the normalized similarity score, and μ_s and σ_s are respectively the estimated mean and standard deviation of the genuine score distribution.

4.6.4 System development

The system performance for *a posteriori* user-dependent score normalization following the experimental procedure of Section 4.3 is given in Table 4.3 (individual features) and Table 4.4 (combination of features). DET curves for the individual features without score normalization are plotted in Figure 4.21.

SKILLED FORGERIES

	Direction PDFs				Length PDFs	
	f1	**f2**	**f3h**	**f3v**	**f5h**	**f5v**
5 TR	12.71	10.18	11.40	12.31	30.33	31.78
10 TR	10.00	6.44	7.78	9.16	28.89	33.78

RANDOM FORGERIES

Direction PDFs				Length PDFs	
f1	**f2**	**f3h**	**f3v**	**f5h**	**f5v**
3.31	2.18	3.09	3.21	22.18	28.03
1.96	1.18	1.40	1.49	20.46	28.58

Table 4.3: **System Performance in terms of EER (in %) of the *individual features* with *a posteriori* user-dependent score normalization when using $K = 5$ or 10 training signatures.**

SKILLED FORGERIES

	f3=f3h+f3v	**f5=f5h+f5v**	**f1 & f5**	**f2 & f5**	**f3 & f5**	**f1 & f2**	**f1 & f3**	**f2 & f3**
5 TR	**10.82**	**26.91**	14.78	13.91	12.36	10.49	**10.44**	**9.96**
10 TR	**7.47**	**25.07**	12.00	9.78	8.53	7.64	**7.38**	**6.36**

RANDOM FORGERIES

	f3=f3h+f3v	**f5=f5h+f5v**	**f1 & f5**	**f2 & f5**	**f3 & f5**	**f1 & f2**	**f1 & f3**	**f2 & f3**
5 TR	**2.64**	**21.33**	4.69	4.95	3.81	2.49	**2.47**	**2.16**
10 TR	**1.36**	**18.30**	2.77	3.00	2.12	1.41	**1.14**	**0.93**

Table 4.4: **System Performance in terms of EER (in %) of the *combination of features* with *a posteriori* user-dependent score normalization when using $K = 5$ or 10 training signatures. They are marked in bold the cases in which there is a performance improvement with respect to the best individual feature involved.**

It is observed that the best individual feature is always the Contour-Hinge PDF f2, independently of the number of signatures used for training and both for random and skilled forgeries. This feature encodes simultaneously curvature and orientation of the signature contours. It is remarkable that the other features using two angles (f3h, f3v) perform worse than f2. Also worth noting, the feature using only one angle (f1) exhibits comparable performance to f3h and f3v, even outperforming them in some regions of the DET. It is interesting to point out the bad result obtained by the length PDFs (f5h and f5v). This suggests that the length of the regions enclosed inside the letters and strokes is not a good distinctive feature in offline signature verification (given a preprocessing stage similar to ours).

We observe that there are several combination of features that result in performance improvement with respect to the best individual feature involved (marked in bold in Table 4.4). However, the best error rate attained by combining features (achieved with the combination of f2 and f3) is similar to that obtained with the best individual feature.

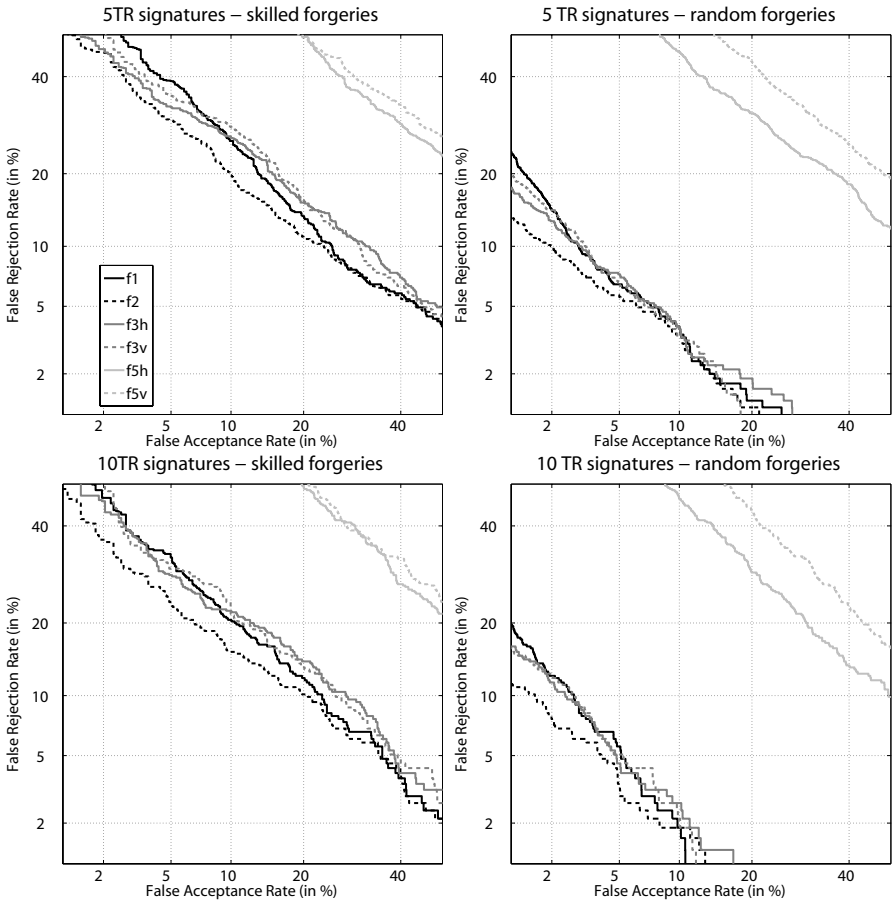


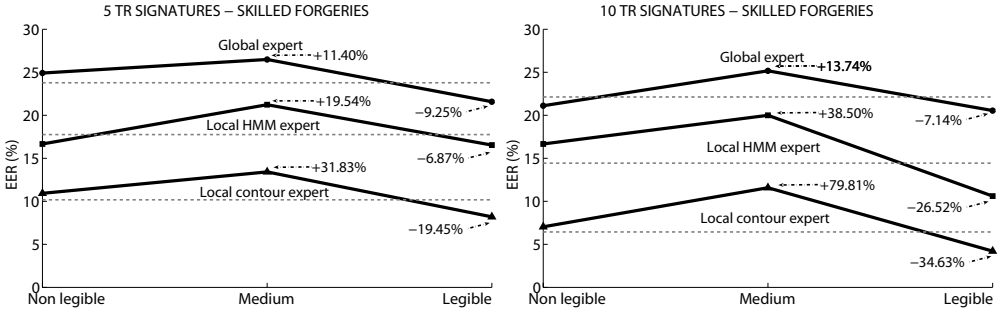
Figure 4.21: **Verification performance without score normalization (user-independent decision thresholds).**

4.7 Results and discussion

4.7.1 Legibility and type of signature

Table 4.5 shows the system performance based on name legibility for the three machine experts. Regarding skilled forgeries, when comparing among legibility groups, we find that the best results are always obtained for the legible case. The non legible case results in no significant improvement or even worse performance. It could be expected that legible signatures result in worse performance, since they are easier to imitate, because imitators have some background knowledge of what they have to imitate. However, it is observed that legible signatures provide better performance than non legible ones. This may be due to the simplicity of most non-legible signatures. Also worth noting, the group of medium legibility is always the worst performing one.

Skilled forgeries					
TR sign	expert	**Non legible**	**Medium**	**Legible**	**Overall**
5	global	24.91	26.49	**21.58**	23.78
	local HMM	16.67	21.23	**16.54**	17.76
	local contour	10.93	13.42	**8.20**	10.18
10	global	21.11	25.17	**20.55**	22.13
	local HMM	16.67	20.00	**10.61**	14.44
	local contour	7.04	11.58	**4.21**	6.44



Random forgeries					
TR sign	expert	**Non legible**	**Medium**	**Legible**	**Overall**
5	global	**8.41**	10.58	9.94	9.79
	local HMM	**4.45**	5.26	5.59	5.21
	local contour	2.96	**1.70**	1.93	2.18
10	global	6.57	9.47	**5.97**	7.26
	local HMM	**1.51**	2.28	3.27	2.74
	local contour	2.34	**0.49**	1.05	1.18

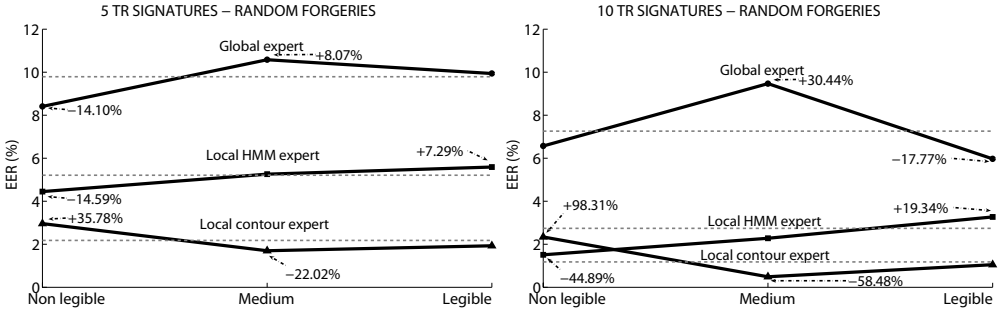
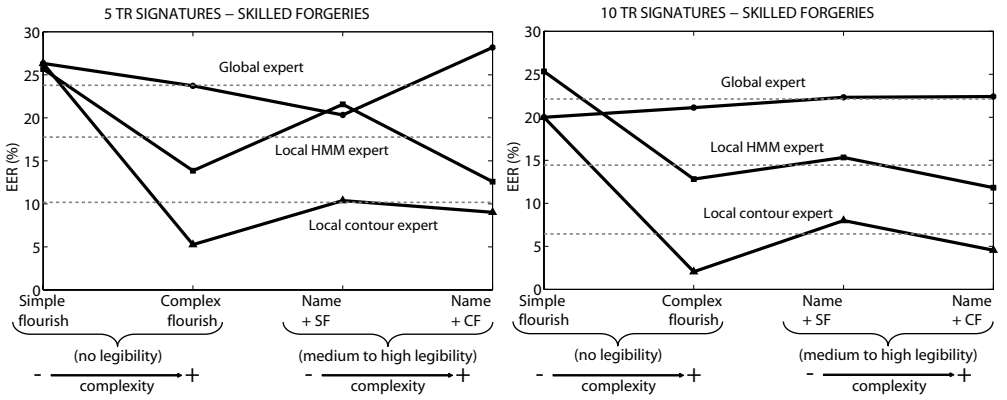


Table 4.5: **System performance based on *name legibility* in terms of EER. Results are given in %. Grey dashed lines denote the overall performance of each matcher in the whole dataset. For each matcher, it is also given the relative gain/loss of performance with respect to the overall results.**

Skilled forgeries						
TR sign	expert	**Simple flourish**	**Complex flourish**	**Name + simple flourish**	**Name + complex flourish**	**Overall**
5	global	26.33	23.72	**20.33**	28.18	23.78
	local HMM	25.67	13.85	21.57	**12.58**	17.76
	local contour	26.33	**5.26**	10.38	9.02	10.18
10	global	**20.00**	21.12	22.32	22.41	22.13
	local HMM	25.33	12.82	15.33	**11.82**	14.44
	local contour	20.00	**2.05**	8.00	4.55	6.44



Random forgeries						
TR sign	expert	**Simple flourish**	**Complex flourish**	**Name + simple flourish**	**Name + complex flourish**	**Overall**
5	global	**4.14**	10.06	**7.24**	14.74	9.79
	local HMM	**4.00**	**4.67**	**4.86**	6.41	5.21
	local contour	4.62	2.32	**2.02**	**1.81**	2.18
10	global	7.97	**6.94**	**5.70**	9.53	7.26
	local HMM	**0.03**	**2.08**	**1.71**	4.84	2.74
	local contour	5.51	**0.37**	**0.83**	**0.90**	1.18

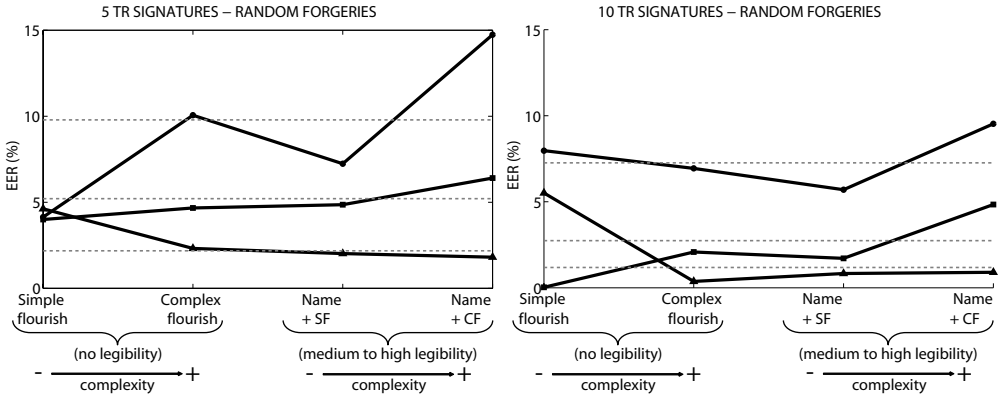


Table 4.6: **System performance based on *signature type* in terms of EER. Results are given in %. Grey dashed lines denote the overall performance of each matcher in the whole dataset.**

Regarding random forgeries, we observe that each matcher exhibits a different behavior:

- For the expert based on global information, the legible and non-legible cases result in performance improvement over the medium legibility case, and the opposite happens with the group of medium legibility.
- For the local HMM expert, performance is improved as signature legibility is decreased.
- The opposite happens for the local expert based on contour features, resulting in better performance as signature legibility increases.

System performance in relation to signature type is shown in Table 4.6. Regarding skilled forgeries, we observed in Table 4.5 that non legible signatures result in no significant improvement with either matcher compared to legible ones, or even in a performance worsening. If we divide non legible signatures into "simple flourish" and "complex flourish", we observe that complex flourish signatures result in improved performance. This could be because simple flourish signatures are easier to imitate than complex flourish ones. It is also worth noting that signatures classified as "name + simple flourish" result in improved performance with the global expert and few signatures for enrolment, but worse performance is obtained with the local experts. The opposite happens with the "name + complex flourish" ones. This could be because local machine experts processes signature images locally, so they better deal with most complex signatures such as the "name + complex flourish" case. In complex signatures, there are regions of the signature image having various strokes crossing in several directions. The global machine expert is not able to deal satisfactorily with this case, since it processes the signature image as a whole.

Regarding random forgeries, we observe from Table 4.6 that signatures classified as "name + complex flourish" always result in worse performance, except with the local expert based on contour features. On the other hand, signatures classified as "name + simple flourish" result in improved performance with the three matchers. Also here, similarly to what it is observed in the results based on name legibility, the two local experts exhibit an opposite behavior.

4.7.2 Slant and variability measures

In order to evaluate the performance based on these two quality measures, a ranking of signers is carried out. For the measure that computes the area where slants with

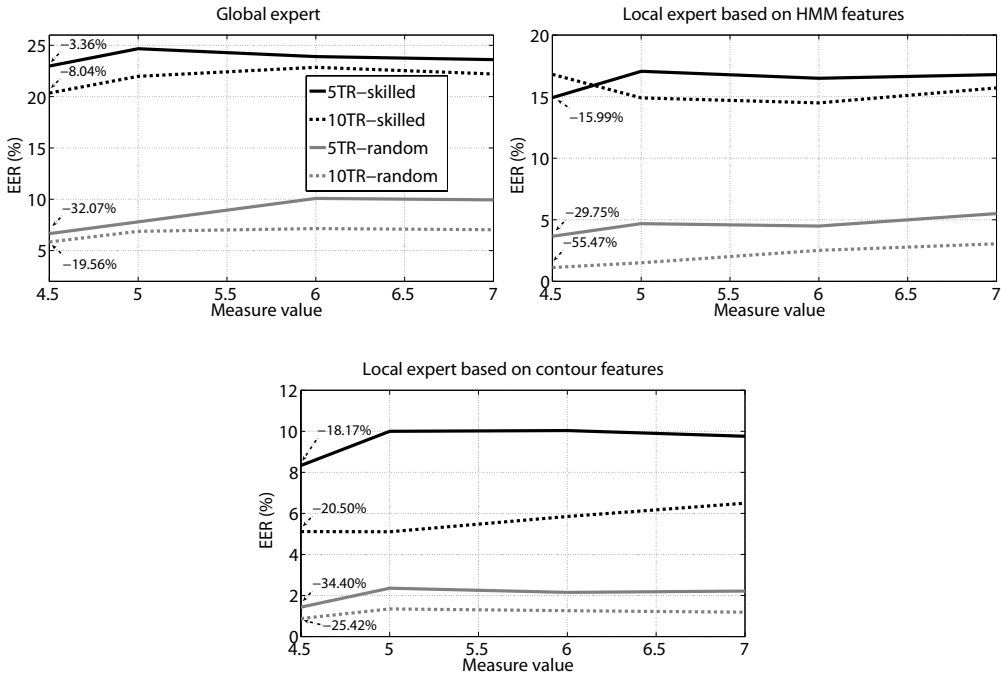


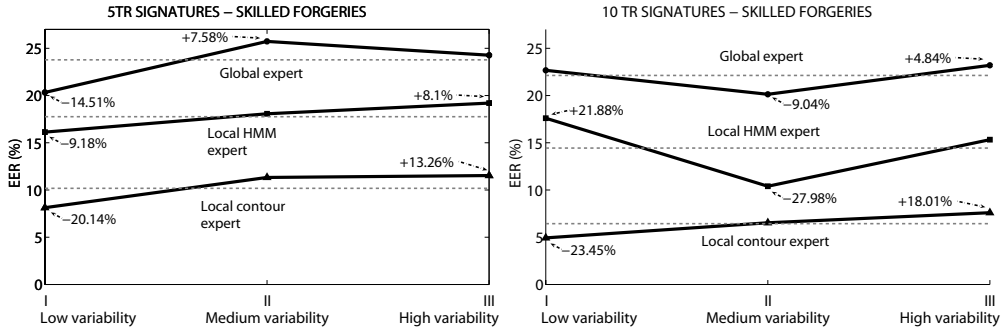
Figure 4.22: **System performance based on the Slant Measure. For each matcher, it is also given the relative gain of performance with respect to the overall results for the point x=4.5.**

different directions intersects, the ranking is based on the average measure of the set of enrolment signatures. For the measure that computes the intra-variability of a set of signatures, the ranking is based on the intra-variability of the signatures of the enrolment set. We depicted in Figure 4.13 the cumulative distribution function of these two measures for all users of the database.

In Figure 4.22, we can see the verification performance in terms of EER as we reject users with the largest area with no predominant slant direction (from right to left in the $x-$axis). Results are provided for the three off-line signature matchers studied in this Chapter. It is observed that, in general, the performance improves as we consider signers with lowest Slant Measure (i.e. smaller area with no predominant slant direction). This is particularly evident for the case of random forgeries. It is also remarkable that higher relative improvements are obtained with the two matchers based on local information. This may be because the Slant measure also works at local level (i.e. it is based on analysis of individual pixels of the image).

Regarding the Variability measure, Table 4.7 shows the verification performance results in relation to the intra-variability of the signatures of the enrolment set. Users

Skilled forgeries					
TR sign	expert	I (low var)	II (med)	III (high)	Overall
5	global	**20.33**	25.73	24.27	23.78
	local HMM	**16.13**	18.07	19.2	17.76
	local contour	**8.13**	11.33	11.53	10.18
10	global	22.67	**20.13**	23.20	22.13
	local HMM	17.6	**10.4**	15.33	14.44
	local contour	**4.93**	6.53	7.6	6.44



Random forgeries					
TR sign	expert	I (low var)	II (med)	III (high)	Overall
5	global	**8.05**	9.85	11.46	9.79
	local HMM	**2.87**	5.62	6.99	5.21
	local contour	**1.36**	2.44	2.55	2.18
10	global	6.62	**5.90**	8.91	7.26
	local HMM	**1.82**	2.58	3.36	2.74
	local contour	1.64	**0.82**	1.17	1.18

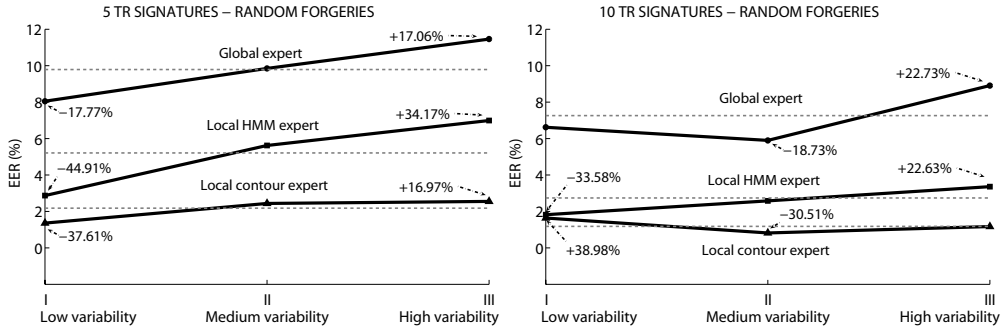
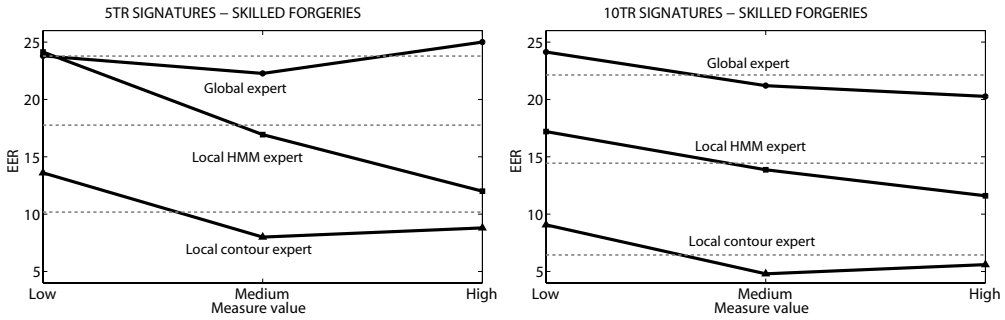
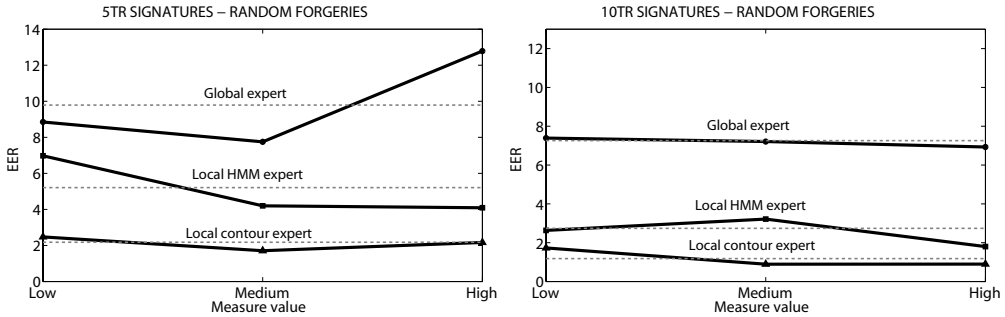


Table 4.7: **System performance based on the *Variability Measure* in terms of EER (results are given in %). Grey dashed lines denote the overall performance of each matcher in the whole dataset. For each matcher, it is also given the relative gain/loss of performance with respect to the overall results.**



(a) Skilled forgeries



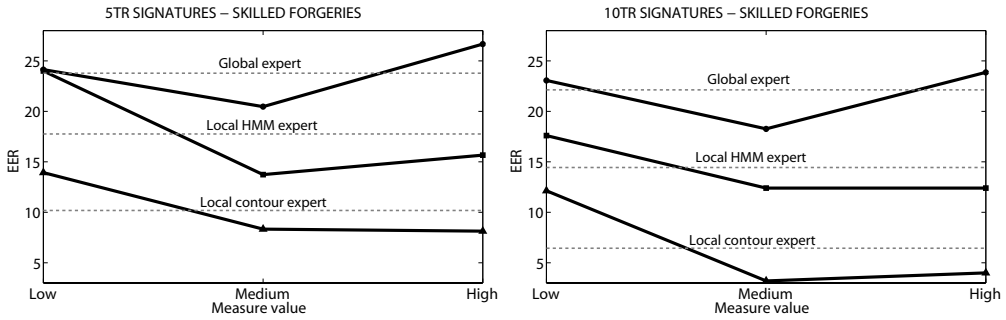
(b) Random forgeries

Figure 4.23: **System performance based on the *gray level variance* across signature strokes. Grey dashed lines denote the overall performance of each matcher in the whole dataset.**

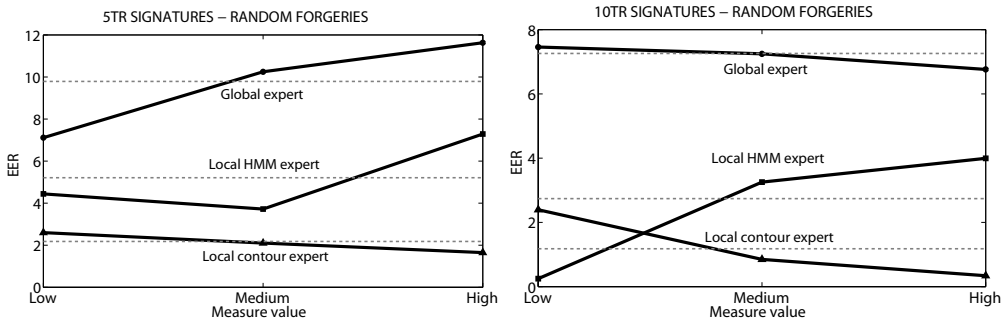
are classified into three equal-sized disjoint groups, from I (low variability) to III (high variability), resulting in 25 users per group. It is observed that:

- Performance is always worsened with a highly variable set of signatures (group III), specially with few enrolment data.
- With few signatures for enrolment, the best performance is obtained with the least variable set (group I), but allowing more signatures for enrolment, the best performance is obtained in most cases for the group II.

An explanation of these results is as follows. Supposing high variability and few enrolment data, we are not able to build a reliable identity model, suffering lack of data with which to characterize the signature style. As we increase the size of the enrolment set, we are able to account for more variability. Nevertheless, very high variability is a source of uncertainty and it is not desirable, as shown by the fact that signatures of the group III always result in a worsened performance.



(a) Skilled forgeries



(b) Random forgeries

Figure 4.24: **System performance based on the *number of pixels* of the signature. Grey dashed lines denote the overall performance of each matcher in the whole dataset.**

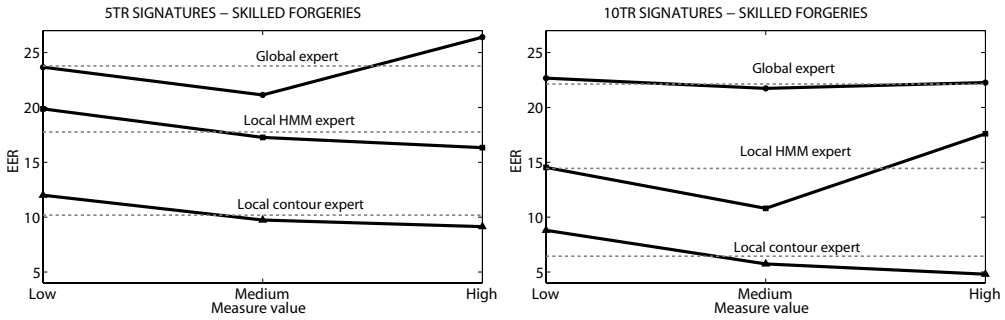
4.7.3 Geometrical measures

Similarly as Section 4.7.2, we carry out a ranking of signers based on the three geometrical measures studied. For each signer, we compute the average measures of the set of enrolment signatures. We depicted in Figure 4.15 the cumulative distribution functions of these three measures for all users of the database.

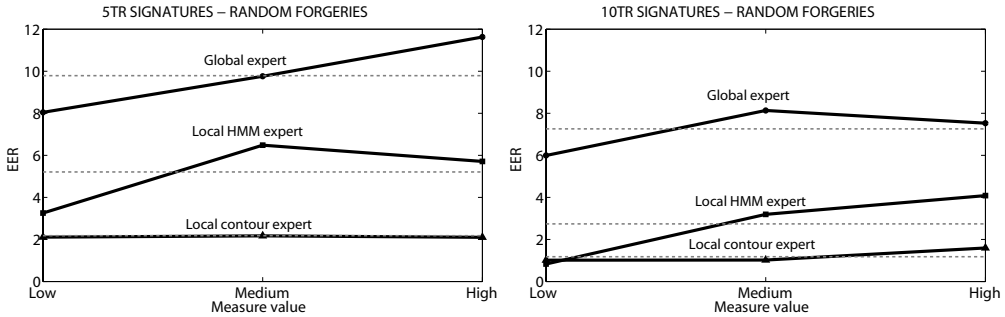
Figures 4.23 to 4.25 show the verification performance results in relation to the geometrical measures. Users are classified into three equal-sized disjoint groups, from I (low value) to III (high value), resulting in 25 users per group.

As a general rule, high gray level variance is desirable, as can be observed in Figure 4.23. The only exception is the global expert with 5 signatures for enrolment, which shows the opposite trend (specially for random forgeries). Also for random forgeries, as we increase the size of the enrolment set, the three matchers become more robust to variations of this measure.

In Figure 4.24, we plot the results in relation to the number of pixels of the signature. We observe that for the case of skilled forgeries, a higher number of pixels is desirable,



(a) Skilled forgeries



(b) Random forgeries

Figure 4.25: **System performance based on the *size of the bounding box* of the signature. Grey dashed lines denote the overall performance of each matcher in the whole dataset.**

except for the global expert. If we consider this measure as an estimation of the signature duration, we can conclude that longer signatures are in general more robust to imitations. On ther other hand, for the case of random forgeries we observe that each matcher exhibits a different behavior:

- For the expert based on global information, the behavior depends of the size of the enrolment set.
- For the local HMM expert, performance is improved as signature duration is decreased.
- The opposite happens for the local expert based on contour features, resulting in better performance as signature duration is increased.

Finally, we plot in Figure 4.25 results in relation to the size of the bounding box that contains the signature. For this measure, no consensus between the matchers is found:

- The global expert performs better in general as the size of the box is decreased. The same behavior is observed for the local HMM expert, except with skilled forgeries and few training signatures.
- Contrarily, the local expert based on contour features works better as the size of the box is increased. Also, for random forgeries, this matcher shows high robustness to variations of this measure.

4.8 Chapter summary and conclusions

The performance of three approaches for off-line signature recognition has been evaluated in terms of several measures that are extracted from signature images. The three matchers make use of different approaches that are based on global and local image analysis. The following five measures have been studied in this chapter to predict the performance of the system:

- Two manually assessed measures, signature legibility and signature type, aimed at evaluating how the knowledge about letters, syllables or name instances may help in the process of imitating a signature.
- One measure that computes the area of a signature where slants with different directions intersect, which could be considered as a measure of complexity.
- One measure that computes the intra-variability of a given set of signatures with the aim of estimating its stability.
- Three geometrical measures aimed at evaluating the variance of the pen pressure during the process of signing, the signature duration and the signature area.

A number of experimental findings are obtained in this chapter. First, for skilled forgeries, we find that the best performance is obtained with legible signatures. Also, performance is always worsened with highly variable signatures, specially with few enrolment data, or with low variance of the pen pressure. For the other measures, different behavior is observed between the matchers.

This chapter presents novel contributions in the verification system based on contour analysis, in the proposed measures intended to predict the performance of signature systems, and in the study of their utility for three different matchers.

Chapter 5

Quality-Based Processing and Fusion in Multibiometrics

This chapter describes a quality-based fusion strategy developed in the framework of this Thesis that has been submitted to the recent *quality-based Evaluation* of the BioSecure Multimodal Evaluation Campaign (BMEC, 2007; Poh and Bourlai, 2007), with very good results (2nd position in terms of Half Total Error Rate out of 13 systems participating) (BMEC, 2007). It makes use of linear logistic regression fusion (Brummer *et al.*, 2007; Pigeon *et al.*, 2000), a trained classification fusion approach, in such a way that good calibration of the output score is encouraged. Calibration means that output scores are mapped to *log-likelihood-ratios* (LLR). This allows to efficiently combine scores originated from different biometric devices, as is the case of the quality-based evaluation.

The aim of this evaluation was to compare several fusion algorithms when biometric signals were originated from several face and fingerprint biometric devices in mismatched conditions. Face still samples collected with two cameras of different resolution and fingerprint samples collected both with an optical and a thermal sensor were used in the evaluation. Quality information of the biometric samples was also provided with the aim of adapting the fusion algorithms to the different devices. These samples were extracted from the recently acquired Biosecure Multimodal Database (Alonso-Fernandez *et al.*, 2008b), acquired in the framework of this Thesis.

In this chapter, we contribute with a quality-based multibiometric architecture that is generalizable to biometric systems working with multiple sources of information (different modalities, matchers, acquisition devices, etc.). So far, incorporation of qual-

ity measures has been done mostly by heuristically adapting the biometric system (Kryszczuk, 2007). With the proposed architecture, newer developments and additional modalities can be easily incorporated, while efficiently handling information from the different sources. In our approach, quality is used to switch between different system modules depending on the data source, and to consider only data of enough quality. The proposed fusion scheme is compared in this chapter with a set of simple fusion rules. The use of simple fusion rules is motivated by the fact that complex trained fusion approaches do not clearly outperform simple fusion approaches, e.g. see Fierrez-Aguilar *et al.* (2005c). We demonstrate in our experiments that the proposed system outperforms the rest when coping with signals originated from heterogeneous biometric sources, pointing out the effectiveness of the proposed approach. An additional overall improvement of 25% is observed in the EER by incorporating a quality-based score rejection scheme, showing the benefits of incorporating quality information in biometric systems.

This chapter is structured as follows. We first survey the related works on multibiometric systems and the use of quality information in biometric systems. Also, the concepts of calibration and linear logistic regression fusion are introduced. We then describe the evaluation framework and the dataset used in our experiments. The proposed fusion architecture is then presented, and comprehensive experimental results are finally given.

Original contributions in this chapter include the definition of a quality-based multibiometric architecture that is generalizable to biometric systems working with multiple sources of information; the use of quality information to estimate the input device used in the acquisition of biometric data in order to switch between different processing modules; and the use of a score-rejection scheme that only considers sources of enough quality in the fusion with the objective of improving the overall performance.

This chapter is based on the publication Alonso-Fernandez *et al.* (2008b).

5.1 Calibration and fusion of biometric systems

5.1.1 Calibration of scores from a biometric system

A biometric verification system can be defined as a pattern recognition machine that, by comparing two (or more) samples of input signals such as speech, face images, etc., is designed to recognize two different classes. These two classes are known as *target* or *client* class, if both samples were originated by the same subject, and *non-target* or *impostor* class, if both samples were not originated by the same subject. As a result

of the comparison, the biometric system outputs a real number known as *score*. The sense of this score is that the higher scores, the more support to the target hypothesis, and vice-versa. However, if we consider a single isolated score from a biometric system, it is in general not possible to determine which is the hypothesis the score supports the most. For instance, if we get a single score of 5 from a biometric system, and if we do not know the distributions of target or non-target scores from such system or any threshold, we will not be able to classify the associated biometric sample in general.

Moreover, each biometric system usually outputs scores which are in a range that is specific of the system. For instance, a particular system can output scores in the $[0, 1]$ range, whereas another system can output scores in the $[-1, 1]$ range. Therefore, an score value of 0 has different meaning depending on the system. Even if two systems output scores in the same range by means e.g. of score normalization (Jain *et al.*, 2005), the same output value might does not favor the target or non-target hypotheses with the same strength. In this context, outputs are dependent of the system and thus, the acceptance/rejection decision also depends on the system.

These problems are addressed with the concept of *calibrated* score. A calibration transformation may be trained from a set of target and non-target scores from a given biometric system, obtained from a database of known individuals. Such calibration algorithms have been recently explored in the field of speaker recogniton. As it can be seen in works by Brummer *et al.* (2007); Brummer and du Preez (2006); Ramos (2007), a calibration transformation reduces the classification cost if the score is used as the logarithm of a likelihood ratio (log-likelihood-ratio, LLR):

$$s_{cal} \simeq \log\left(\frac{p\left(\mathbf{s}|\omega_i\right)}{p\left(\mathbf{s}|\omega_j\right)}\right) \tag{5.1}$$

where s represents the score of a biometric system and s_{cal} the calibrated score. Then, a decision can be taken using the Bayes decision rule (Duda *et al.*, 2004):

$$\begin{gathered}\text{Assign} \quad \mathbf{s} \rightarrow \omega_i \quad \text{if} \\ \frac{p(\mathbf{s}|\omega_i)}{p(\mathbf{s}|\omega_j)} > \tau, i \neq j \quad \text{and} \quad i, j = \{0, 1\}\end{gathered} \tag{5.2}$$

where $p\left(\mathbf{s}|\omega_i\right)/p\left(\mathbf{s}|\omega_j\right)$ is a *likelihood ratio* and $\tau = P(\omega_j)/P(\omega_i)$ is a pre-determined threshold that depends on the *a priori* probability of observing classes ω_j and ω_i[1]. The more accurate the calibration of s_{cal}, the lower the misclassification cost of the biometric system following Equation 5.2. Moreover, for a given set of scores, it can

[1]Bayes' rule as expressed here assumes that the cost of each type of misclassification error is the same for all possible classes (Duda *et al.*, 2004). Since this particularization has not been considered in this Thesis, we will not introduce misclassification costs for clarity.

be demonstrated that optimal calibration means that the Bayes classification cost is achieved (Brummer and du Preez, 2006), which is known to be minimum for the given score dataset from a biometric system (Duda *et al.*, 2004).

Some advantages of calibrated scores are highlighted here:

- As calibrated scores can be used as LLR in a Bayesian framework, we can therefore state that a calibrated score is meaningful by itself. This is because, in a Bayesian context, a LLR of a biometric score means a *degree* of support of such score for a given hypothesis. For instance, LLR= 5 means that the score supports the target hypothesis with a strength of e^5 vs. 1 with respect to the non-target hypothesis.
- The meaning of a LLR value is the same across different biometric systems. This advantage allows to compare systems in the same probabilistic range.
- Under independence assumptions, different calibrated scores from different biometric systems can be easily combined, since the joint LLR of independent scores is the sum of their individual LLR (Duda *et al.*, 2004). Thus, by summing calibrated scores coming from independent sources, we also obtain a fused calibrated LLR.

This calibration transformation then solves the two previously commented problems. First, it map scores from a biometric system to a common domain. Second, it allows the interpretation of scores of a biometric system as a degree of support. Note that the decision minimum-cost threshold for a calibrated score only depends on the prior probabilities (Equation 5.2), and therefore it may be changed if such probabilities change and are known. In this sense, calibration can be viewed as a score normalization process, where the scores are mapped to a probabilistic domain.

The act of designing and optimizing a calibration transformation is also known as *calibration* (Brummer and du Preez, 2006), and several strategies can be used to train such mapping (Brummer and du Preez, 2006; Ramos, 2007). Among them, logistic regression have been successfully and recently used for voice biometrics (Brummer *et al.*, 2007; Brummer and du Preez, 2006; Gonzalez-Rodriguez and Ramos, 2007; Gonzalez-Rodriguez *et al.*, 2007; Pigeon *et al.*, 2000) and for score fusion using side information (Ferrer *et al.*, 2008).

5.1.2 Linear logistic regression fusion

We present here a linear logistic regression training method in which the scores of multiple sub-systems are fused together, primarily to improve the discriminating ability

(measured by ROC or DET curves (Martin *et al.*, 1997)), in such a way as to encourage good calibration of the output scores. Given N matchers which output the scores $(s_{1j}, s_{2j}, ...s_{Nj})$ for an input trial j, a linear fusion of these scores is:

$$f_j = a_0 + a_1 \cdot s_{1j} + a_2 \cdot s_{2j} + ... + a_N \cdot s_{Nj} \tag{5.3}$$

The constant a_0 does not contribute to the discriminating ability of the fusion, but it can improve the calibration of the fused score. When these weights $\{a_0, ..., a_N\}$ are trained via logistic regression, the fused score f_j tends to be a well-calibrated log-likelihood-ratio (Brummer *et al.*, 2007; Brummer and du Preez, 2006).

Let $[s_{ij}]$ be an $N \times N_T$ matrix of scores built from N component systems and N_T target trials, and let $[r_{ij}]$ be an $N \times N_{NT}$ matrix of scores built from the same N component systems with N_{NT} non-target trials. We use a logistic regression objective (Brummer *et al.*, 2007; Pigeon *et al.*, 2000) that is normalized with respect to the proportion of target and non-target trials (N_T and N_{NT}, respectively), and weighted with respect to a given prior probability $P = P(\text{target})$. The objective is stated in terms of a *cost* C, which must be *minimized*:

$$C = \frac{P}{N_T} \sum_{j=1}^{N_T} \log\left(1 + e^{-f_j - \text{logit}P}\right) + \frac{1-P}{N_{NT}} \sum_{j=1}^{N_{NT}} \log\left(1 + e^{-g_j - \text{logit}P}\right) \tag{5.4}$$

where the fused target and non-target scores are respectively:

$$\begin{aligned} f_j &= a_0 + \sum_{i=1}^{N} a_i s_{ij} \\ g_j &= a_0 + \sum_{i=1}^{N} a_i r_{ij} \end{aligned} \tag{5.5}$$

and where:

$$\text{logit}P = \log\left(\frac{P}{1-P}\right) \tag{5.6}$$

It can be demonstrated that minimizing the objective C with respect to $\{a_0, ..., a_N\}$ tends to give good calibration of the fused scores (Brummer *et al.*, 2007; Brummer and du Preez, 2006). In practice, it is observed that changing the value of P has a small effect. The default of 0.5 is a good choice for a general application and it will be used in this work. The optimization objective C is convex and therefore has a unique global minimum. To find this minimum, a conjugate gradient algorithm can be used (Brummer).

DATASETS		Num. of match scores per subject	
		Training set (51 subjects)	Evaluation set (156 subjects)
Session 1	Genuine	1	1
	Impostor	103×4	126×4
	Purpose	Algorithm development	User specific adaptation
Session 2	Genuine	2	2
	Impostor	103×4	126×4
	Purpose	Algorithm development	Test

Table 5.1: **Experimental protocol.**

5.2 Dataset and experimental protocol

As dataset for our experiments, we use the set of scores of the *Access Control Scenario Evaluation* of the BioSecure Multimodal Evaluation Campaign (BioSecure, 2004; BMEC, 2007). This evaluation campaign has been conducted during 2007 by the BioSecure Network of Excellence (BioSecure, 2004), as a continuation of the acquisition campaign of the Biosecure Multimodal Database (Alonso-Fernandez *et al.*, 2008b). The aim of this evaluation was to compare the performance of multi-modal fusion algorithms, assuming that the environment is relatively well controlled and the users are supervised. We focus on the *quality-based evaluation* (Poh and Bourlai, 2007), whose objective was to test the capability of a fusion algorithm to cope with query biometric signals originated from heterogeneous biometric devices.

The Biosecure Multimodal Database has been collected by 11 European institutions and it contains six biometric modalities (Alonso-Fernandez *et al.*, 2008b): face, speech, signature, fingerprint, hand and iris. Several devices under different conditions and levels of supervision were used for the acquisition. In this work, we use a subset of 333 persons designed for the purpose of the *Access Control Evaluation* (Poh *et al.*, 2007). This subset was collected over two sessions, separated by about one month interval, with two biometric samples per device and session. The first sample of session one was considered as the template, whereas the remaining three samples were considered as query data.

Among the 333 subjects of the database, 207 were considered "clients" for whom a template was created: 51 "clients" for *training* (whose scores and identity labels were provided to the participants to tune their algorithms) and 156 for *evaluation*) (whose scores -mixed genuine and impostor claims- were provided to the participants to be fused without identity labels, which were sequestered by the evaluation organizers to

MODE	DATA TYPE	SENSOR	CONTENTS
fnf1	Face still	Digital camera (high res.)	Frontal face images
fa1		Webcam (low resolution)	
fo1, *fo2*, *fo3*	Fingerprint	Optical (flat)	1 right thumb, 2 right index
ft1, *ft2*, *ft3*		Thermal (sweeping)	3 right middle finger

Table 5.2: **Biometric traits and biometric devices considered for the experiments.**

MODALITY	REF. SYSTEM	QUALITY MEASURES
Face still	Omniperception SDK[1] LDA-based face verifier (Martinez and Kak, 2001)	Face detection reliability, Brightness, Contrast, Focus, Bits per pixel, Spatial resolution, Illumination, Uniform Background, Background Brightness, Reflection, Glasses, Rotation in plane, Rotation in Depth, Frontalness
Fingerprint	NIST fingerpr3int system (Watson *et al.*, 2004)	Texture richness based on local gradient (Chen *et al.*, 2005)

Table 5.3: **Reference systems and quality measures used in the experiments.**

evaluate the competing algorithms). The remaining 126 subjects were considered an external population of users who serve as "zero-effort impostors", i.e. no template is created for these users. The experimental protocol is summarized in Table 5.1. The *training* impostor set of scores of Session 1 contains 103×4 samples per subject, meaning that when the reference subject is considered a template, all the 4 samples of the half of the remaining 206 subjects are considered impostors. The other half are used as impostors in Session 2. This ensures that the impostors used in Sessions 1 and 2 are not the same. Note that the *evaluation* impostor score sets contain the 126 subjects set apart as zero-effort impostors. In this way, a fusion algorithm will not have already "seen" the impostors during its training stage, avoiding systematic and optimistic bias of performance. Prior to the Evaluation, the *training* set of scores (with both Sessions 1 and 2) was released to the participants to tune their algorithms. It was recommended to use only Session 2 as training data, since Session 1 may be optimistically biased due to the use of template and query data acquired on the same session. In this work, we follow this recommendation, using only Session 2 of the training set for training our algorithms. Session 1 of the evaluation set is intended for user-adapted fusion (Fierrez-Aguilar *et al.*, 2005e), whereas Session 2 is for testing purposes. The work reported here is not user-adaptive and therefore, it will only be run on Session 2 of the evaluation set.

The *Access Control Evaluation* only considered face and fingerprint modalities (Poh *et al.*, 2007), see Table 5.2. Several reference systems and quality measures were used

DATA FORMAT - TRAINING SET
<claimed ID> <true ID>
<*fnf1* score> <quality measures of template of *fnf1*> <quality measures of query of *fnf1*>
<*fo1* score> <quality measures of template of *fo1*> <quality measures of query of *fo1*>
<*fo2* score> <quality measures of template of *fo2*> <quality measures of query of *fo2*>
<*fo3* score> <quality measures of template of *fo3*> <quality measures of query of *fo3*>
<*xfa1* score> <quality measures of template of *xfa1*> <quality measures of query of *xfa1*>
<*xft1* score> <quality measures of template of *xft1*> <quality measures of query of *xft1*>
<*xft2* score> <quality measures of template of *xft2*> <quality measures of query of *xft2*>
<*xft3* score> <quality measures of template of *xft3*> <quality measures of query of *xft3*>

DATA FORMAT - EVALUATION SET
<claimed ID>
<*fnf1*|*xfa1* score>
<quality measures of template of *fnf1*|*xfa1*> <quality measures of query of *fnf1*|*xfa1*>
<*fo1*|*xft1* score>
<quality measures of template of *fo1*|*xft1*> <quality measures of query of *fo1*|*xft1*>
<*fo2*|*xft2* score>
<quality measures of template of *fo2*|*xft2*> <quality measures of query of *fo2*|*xft2*>
<*fo3*|*xft3* score>
<quality measures of template of *fo3*|*xft3*> <quality measures of query of *fo3*|*xft3*>

MIXTURE	MODALITIES	FACE SENSOR	FINGERPRINT SENSOR
1	(*fnf1*/*fo1*/*fo2*/*fo3*)	High resolution	Flat acquisition
2	(*fnf1*/*xft1*/*xft2*/*xft3*)	High resolution	Sweep acquisition
3	(*xfa1*/*fo1*/*fo2*/*fo3*)	Low resolution	Flat acquisition
4	(*xfa1*/*xft1*/*xft2*/*xft3*)	Low resolution	Sweep acquisition

Table 5.4: **Data format and possible mixtures for each access (the query sensors are specified, all templates acquired with the high resolution face camera and the flat fingerprint sensor).**

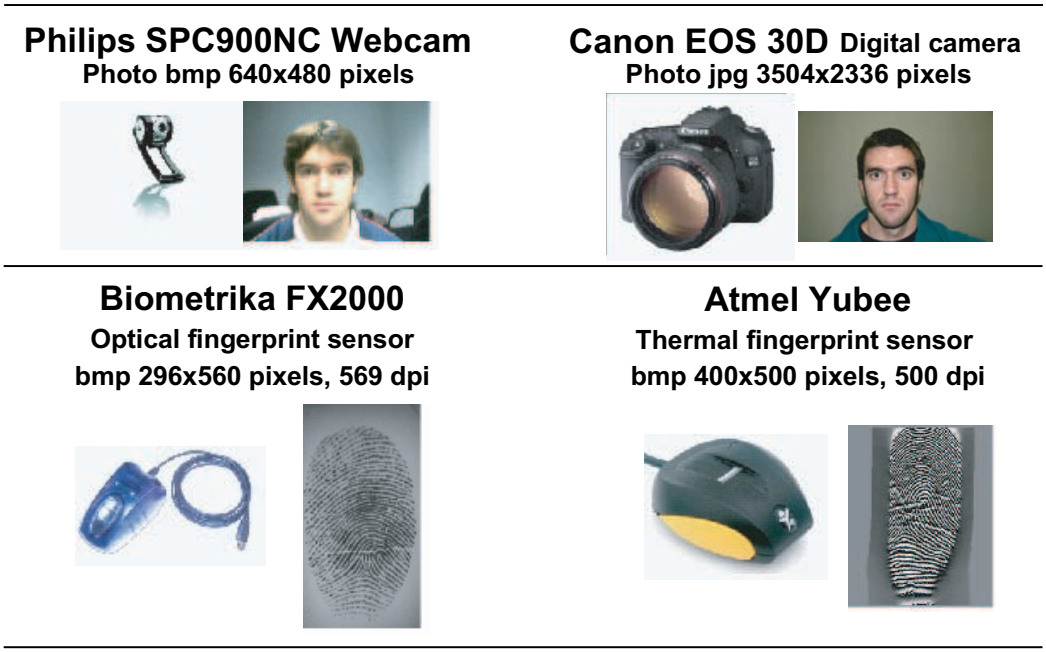


Figure 5.1: **Modalities considered in the *Access Control Evaluation*. Top row: hardware devices and acquisition samples for the face modality (left: low resolution webcam, right: high resolution digital camera). Bottom row: hardware devices and acquisition samples for the fingerprint modality (left: optical sensor with flat positioning of the finger, right: thermal sensor with finger sweeping).**

with the biometric modalities in order to compute the scores for the evaluation, which are summarized in Table 5.3. Low and high quality still frontal face images were collected with two different cameras (denoted as *fa1* and *fnf1*, respectively). The face reference system used is an LDA-based face verifier (Martinez and Kak, 2001), and the 14 face quality measures indicated in Table 5.3 were computed using the Omniperception SDK. The fingerprint data was collected with an optical and a thermal sensor, denoted as $fo\{n\}$ and $ft\{n\}$ respectively, with $n = \{1{=}\text{thumb}, 2{=}\text{index}, 3{=}\text{middle}\}$ fingers of the right hand. The reference system used is the NIST fingerprint system (Watson *et al.*, 2004), whereas the quality measure is based on averaging local gradients (Chen *et al.*, 2005). In Figure 5.1, the biometric sensors as well as acquisition samples of the modalities used in the evaluation are shown.

The set of scores provided is a text file, with each line representing an access request. For the *quality-based evaluation*, each line had the structure shown in Table 5.4. Mode *xfa1* is the mismatched counterpart of *fnf1*, i.e. the template is captured using

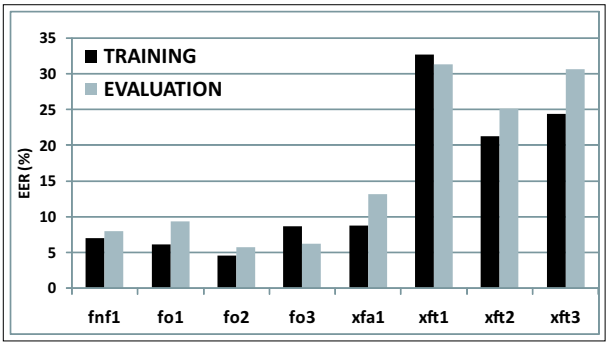


Figure 5.2: **Performance in terms or EER of the different modalities defined in Table 5.2 in the training and evaluation sets defined in Table 5.1.**

the high resolution camera and the query image is captured using a webcam (low resolution). Similarly, *xft1* (*xft2*, *xft3*) is the mismatched counterpart of *fo1* (*fo2*, *fo3*), i.e. the template is captured using the fingerprint optical sensor (flat positioning of the finger) and the query image is captured using the thermal sensor (sweeping the finger). Notation "|" means "either ... or", so the two streams were mixed during the evaluation and the fusion algorithm had to determine from which device the query was extracted. The mixture could be one of the combinations shown at the bottom of Table 5.4 (for a given access all fingerprints were acquired with the same device). The performance of the different modalities on the training and evaluation sets are shown in Figure 5.2.

It should be noted that there were missing data in the sets of scores and quality measures due to the fact that some matchings or quality estimates could not be computed by the algorithms used in the Evaluation. It is not the target of this chapter to study the effects of and how to deal with missing data in multi-biometrics. Therefore, prior to the experiments, we have corrected the missing values of the *training* set as follows. When a genuine (impostor) score of an specific sensor is missing, its value is set to the mean value of the remaining valid genuine (impostor) scores over the training set. Similarly, when a quality measure of an specific sensor is missing, its value is set to the mean value of the remaining valid measures. For the *evaluation* set, since it is not known in advance if we are dealing with a genuine or an impostor access, the missing score or quality measure will not be taken into account in the fusion process, as explained later.

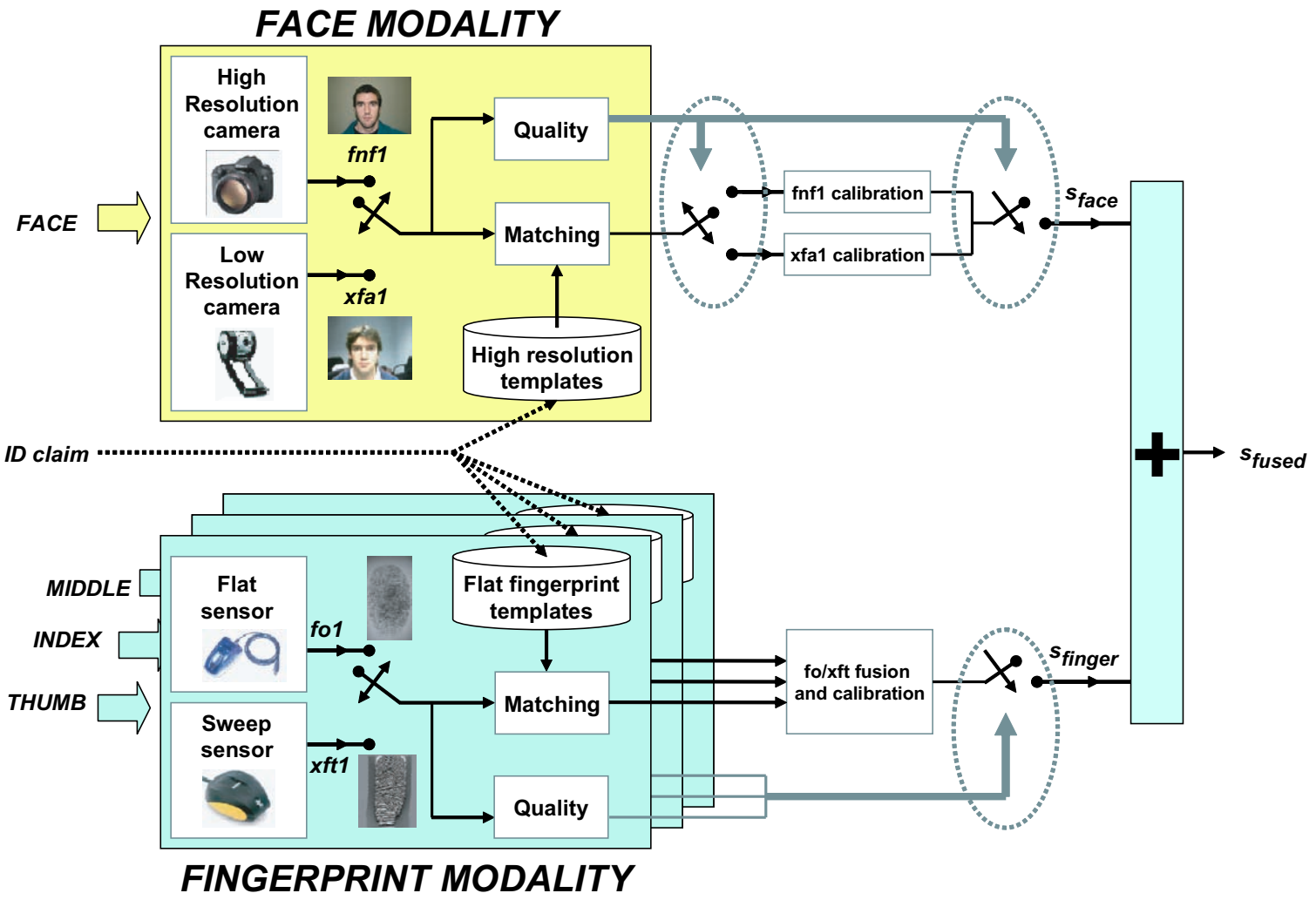


Figure 5.3: **Architecture of the proposed fusion strategy, including some quality-based conditional processing steps (highlighted with dashed ellipses).**

5.3 Contribution: System architecture with quality-based conditional processing

Following the nomenclature presented in Sections 1.2 and 1.3, the system proposed in this chapter uses a density-based fusion method in which output scores of the individual matchers are first mapped to log-likelihood-ratios by linear logistic regression classification, prior to the fusion stage. This approach allows to combine scores from different sources, such as multiple biometric modalities, multiple matchers or devices from the same modality, etc. Quality information is incorporated in two stages: in the score mapping stage, by estimating the device used in each access in order to switch between different linear logistic regression classifier, and in the fusion stage by rejecting scores from low quality biometric samples.

For our fusion experiments, we have used the tools for Linear Logistic Regression (LLR) included in the toolkit FoCal (Brummer). The architecture of the proposed fusion mechanism is shown in Figure 5.3. For each access, we compute one calibrated face score s_{face} and one calibrated fingerprint score s_{finger} which combines the three fingerprint scores provided (one from each finger: thumb, index, and middle of the right hand). Calibrated scores may be viewed as log-likelihood ratios. Therefore, assuming independence between them (since s_{face} and s_{finger} are computed from different biometric traits), their sum will tend to be a log-likelihood ratio (Brummer and du Preez, 2006; Duda *et al.*, 2004):

$$s_{fused} = s_{face} + s_{finger} \tag{5.7}$$

Quality information is used in two stages of the system proposed in Figure 5.3: *i*) classification stage, using different score normalization functions depending on the device used for query acquisition, which is estimated from quality signals; and *ii*) fusion stage, discarding scores which come from low quality sources. These two stages are further detailed and evaluated in the following sections, in which they are compared to a set of common fixed fusion rules: arithmetic mean, minimum and maximum (Kittler *et al.*, 1998). For these fusion experiments, matching scores are first normalized to be similarity scores in the $[0, 1]$ range using the tanh-estimators described by Jain *et al.* (2005):

$$s' = \frac{1}{2}\left\{\tanh\left(0.01\left(\frac{s-\mu_s}{\sigma_s}\right)\right)+1\right\} \tag{5.8}$$

where s is the raw similarity score, s' denotes the normalized similarity score, and μ_s

and σ_s are respectively the estimated mean and standard deviation of the genuine score distribution. Similarly to the architecture proposed in Figure 5.3, face and fingerprint scores are normalized separately and subsequently fused.

In the experiments reported in this chapter, we follow the same benchmarking procedure of the BioSecure Multimodal Evaluation Campaign (see Section 5.2): training of the fusion scheme (*fnf1* and *xfa1* calibration functions, and $fo\{n\}/xft\{n\}$ fusion and calibration functions in Figure 5.3, with $n = \{1, 2, 3\}$) is carried out only on the Session 2 training set of scores, whereas testing and performance comparison is then done on the Session 2 evaluation set of scores. We cope with missing values of the *evaluation* set as follows. When a fingerprint score of an access is missing, its value is set to the mean value of the remaining valid scores prior to the fusion (the same applies to the quality values). If an entire modality is missing, it is not used in the fusion. If both modalities are missing, the fused score is set to the threshold value at the EER point on the *training* set. This was the procedure followed in our submission to the *quality-based evaluation* of Biosecure, where the rejection of an access was not allowed (Poh and Bourlai, 2007). To be consistent with the evaluation, this procedure is also used in the experiments reported in this chapter, unless indicated.

5.4 Results

5.4.1 Estimation of the input device from quality measures

According to the protocol of the *quality-based evaluation* (Poh and Bourlai, 2007), no information was given regarding the device used for query acquisition during the evaluation. In this scenario, we were interested in exploring the potential benefits of conditional processing based on a prediction of the input device. For this purpose, we used the quality measures provided together with the training scores, and assumed that:

- if the template and the query were from the same device (i.e. *fnf1*, *fo1*, *fo2*, *fo3*), both images would have similar quality values and they would be high,
- if the template and the query were from different devices (i.e. *xfa1*, *xft1*, *xft2*, *xft3*), the quality value of the template would be higher than the quality value of the query, and the quality value of the query would be low.

We estimated the device separately for face and fingerprint modalities. For that purpose, we used a quadratic discriminant function with multivariate normal densities

Face feature	TRAINING SET Error fnf1+xfa1	Error fnf1	Error xfa1	EVALUATION SET Error fnf1+xfa1	Error fnf1	Error xfa1
8	0.20%	0.04%	0.37%	12.15%	4.43%	17.59%
6-8	0.20%	0.04%	0.37%	12.15%	4.14%	17.79%
8-9	0.20%	0.04%	0.37%	13.12%	4.14%	19.44%
6-8-9	0.08%	0.04%	0.12%	12.76%	4.14%	18.82%

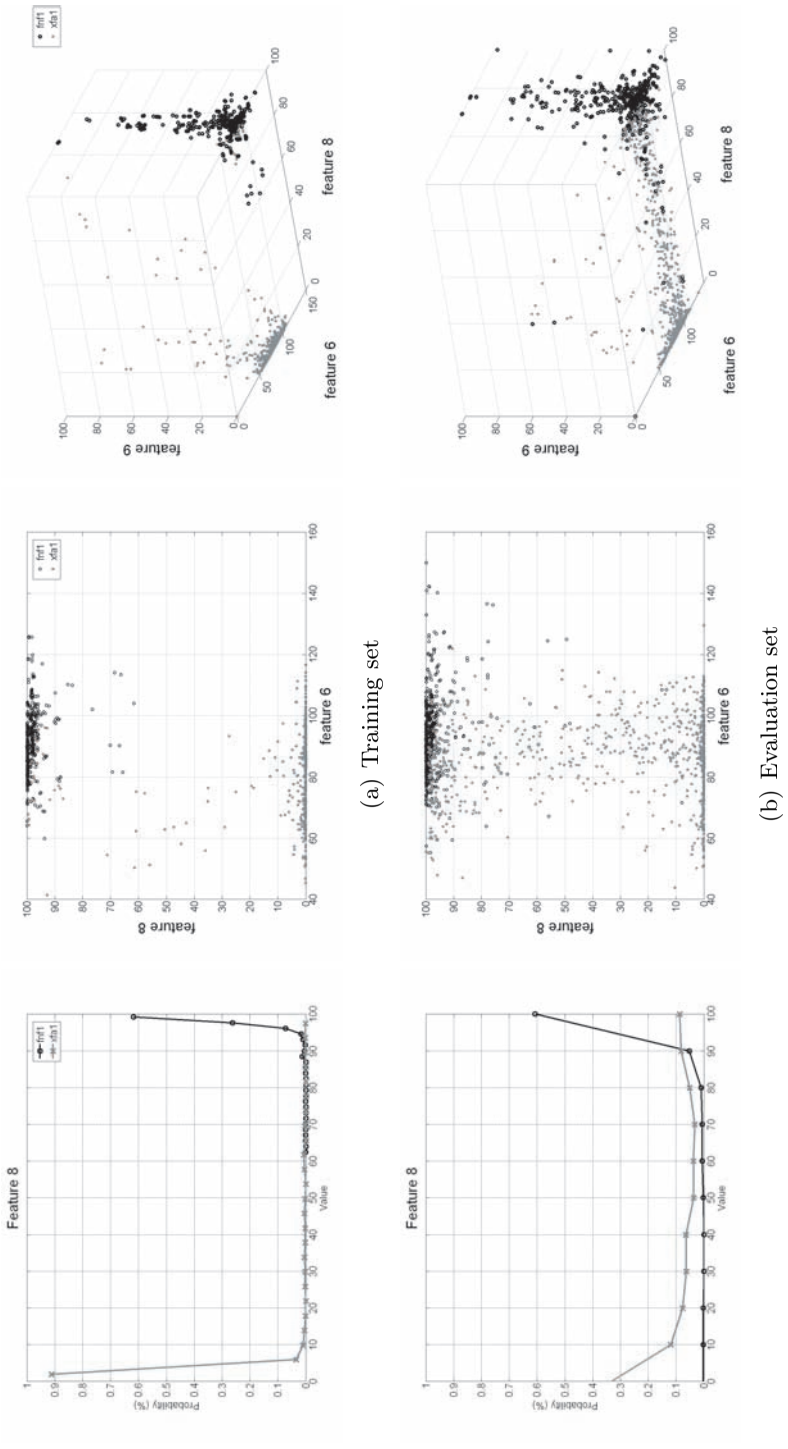
Fingerprint feature	TRAINING SET Error fo+xft	Error fo	Error xft	EVALUATION SET Error fo+xft	Error fo	Error xft
2	14.92%	21.81%	8.03%	20.00%	29.26%	10.73%
1-2	16.68%	22.89%	10.47%	21.69%	28.86%	14.53%
2-3-6	15.75%	22.08%	9.41%	20.76%	21.69%	12.82%

Table 5.5: **Quality feature combination for the estimation of the device used for the query acquisition.**

for each class (Duda *et al.*, 2004). For the face modality, we used the 14 quality measures of the query image (see Table 5.3). For the fingerprint modality, we derived the following 8 parameters from the quality of the templates (Q_{ti}) and queries (Q_{qi}) of the three scores corresponding to each access ($i = 1, 2, 3$): 1) Number of fingerprint scores such as $Q_{ti} > Q_{qi}$, 2) $\max(Q_{qi})$, 3) $\max(|Q_{ti} - Q_{qi}|)$, 4) $\min(Q_{qi})$, 5) $\min(|Q_{ti} - Q_{qi}|)$, 6) $\text{mean}(Q_{qi})$, 7) $\text{mean}(|Q_{ti} - Q_{qi}|)$, and 8) $\max(Q_{ti} - Q_{qi})$.

We tested all the combinations of one, two and three quality features in order to determine the device used for the query acquisition. Results of the best cases are shown in Table 5.5. For the face modality, a remarkably low error rate is obtained using the training set, even with only one parameter. However, this is not true for the evaluation set. This can be observed in Figure 5.4, where the distribution of several face quality features are depicted for both data sets. This could be due to the small size of the data set provided for training ($51 \times 103 \times 4 = 21012$ impostor scores but only $51 \times 2 = 102$ genuine scores, according to the figures of Table 5.1). On the other hand, we observe high error rates in the estimation for the fingerprint modality in both data sets. Interestingly enough, the estimation fails mostly with the optical sensor.

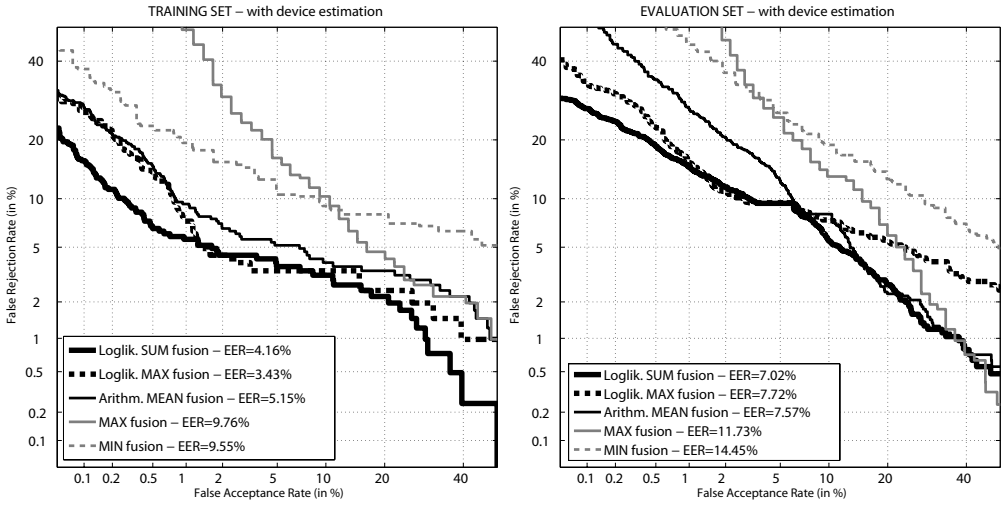
Based on the results of the estimation on the training set, we proposed to train a score normalization function independently for each face modality (*fnf1* and *xfa1*), and a unique fusion function for both fingerprint modalities (*fo* and *xft*), as shown in Figure 5.3 (Alonso-Fernandez *et al.*, 2008b). This was the approach submitted by our institution to the *quality-based evaluation* of the Biosecure Multimodal Evaluation Campaign, but using the MAX rule of the two calibrated scores instead of the SUM



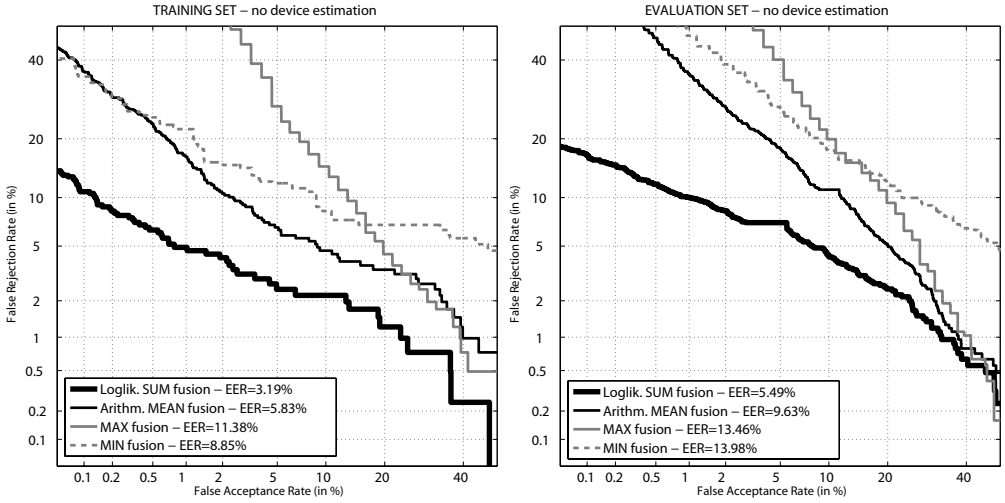
(a) Training set

(b) Evaluation set

Figure 5.4: **Face quality features for query device estimation.**



(a) With device estimation using quality measures.



(b) Without device estimation (knowing the actual device used in each access).

Figure 5.5: **Verification results of the proposed log-likelihood fusion (Loglik.) together with simple fusion rules used for comparison (Loglik. SUM is further studied in the present chapter, Loglik. MAX was the approach submitted by the authors to the quality-based Biosecure evaluation).**

rule used in this chapter. The submitted approach was ranked 2nd in terms of Half Total Error Rate (HTER) out of 13 participants (BMEC, 2007). Results of both approaches are shown in Figure 5.5a, together with the simple fusion rules used for comparison. As it can be observed in Table 5.5, the device estimation did not perform well on the evaluation set, so with the aim of evaluating the effects of such a bad device estimation, we also depict in Figure 5.5b results considering the actual device used in each access, training in this case a modality-specific score normalization function based on linear logistic regression. Although that was not the protocol in the Biosecure evaluation, it is reasonable to assume that the specific sensor used in an operational environment is known.

As can be observed in Figure 5.5a, although the proposed approach based on log-likelihood fusion results in worse EER value, it outperforms our submission to the evaluation (which was also based on log-likelihood but using MAX instead of SUM fusion) in most regions of the DET curve. We also observe that the performance of the proposed fusion scheme is better than the performance of all simple fusion rules. Only the arithmetic mean rule result in similar performance on the evaluation set for low FRR values, being this difference higher when knowing the actual device used in each access (Figure 5.5b).

Comparing Figure 5.5b to Figure 5.5a, we can also observe the decrease in performance when using device estimation in comparison to knowing the actual device used in each access.

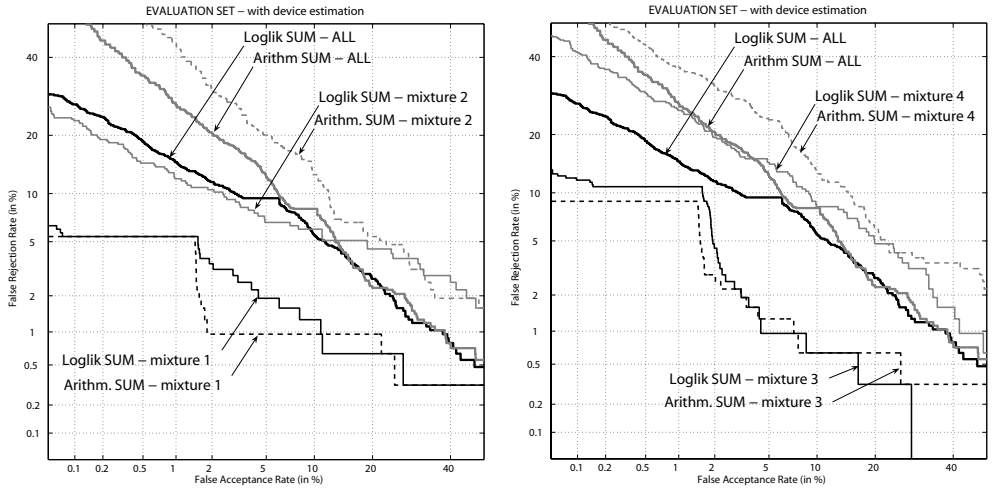
5.4.2 Sensor interoperability

We now evaluate the capability of the proposed log-likelihood fusion algorithm to cope with query biometric signals originated from heterogeneous biometric devices by reporting the performance on the different mixtures of Table 5.4. We report in Table 5.6 the performance of the four possible combinations for an access using the proposed log-likelihood sum fusion rule s_{fused} and the best simple fusion rule (the arithmetic mean). DET curves are also plotted in Figure 5.6. It can be observed that for the mixtures involving only the optical sensor (mixtures 1 and 3), there are not big differences in performance between the two fusion schemes. On the other hand, for the mixtures involving mismatched fingerprint devices (mixtures 2 and 4), the proposed fusion scheme outperforms the simple fusion rule. This is specially evident for the mixture 2, which does not involve mismatched face devices (only the high resolution camera). We can also see that the proposed scheme performs best in overall terms, i.e. when pooling all the mixtures.

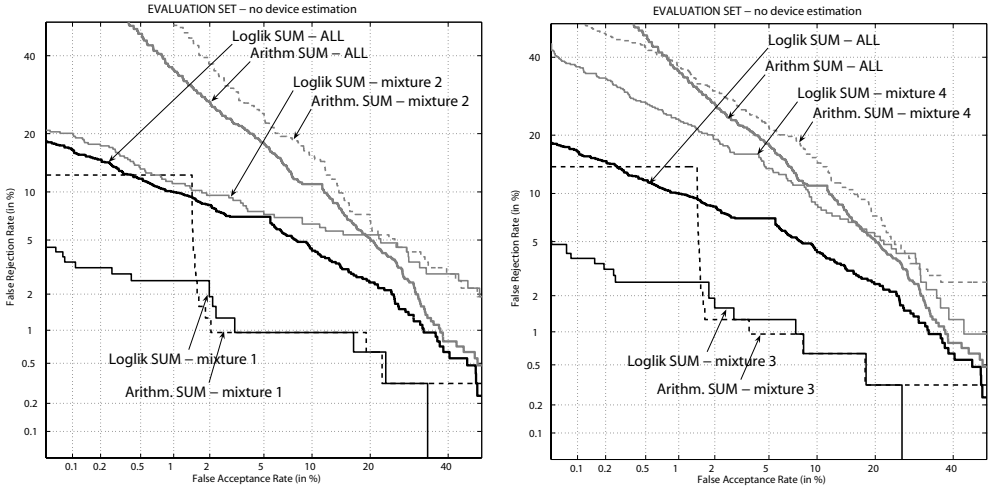
		With device estimation		With correct device model	
M.	**Modalities**	**loglik SUM**	**Arithm. mean**	**loglik SUM**	**Arithm. mean**
1	fnf1/fo1/fo2/fo3	2.88% (-50.30%)	1.64% (-71.70%)	1.55% (-73.25%)	1.61% (-72.22%)
2	fnf1/xft1/xft2/xft3	6.69% (-16.49%)	11.18% (+39.56%)	6.97% (-12.99%)	12.38% (+54.54%)
3	xfa1/fo1/fo2/fo3	2.55% (-56.00%)	2.26% (-61.00%)	1.91% (-67.04%)	1.62% (-72.05%)
4	xfa1/xft1/xft2/xft3	9.24% (-29.81%)	11.35% (-13.79%)	9.26% (-29.66%)	12.05% (-8.47%)
	ALL	**7.02%**	**7.57%**	**5.49%**	**9.63%**

Table 5.6: **Verification results of the fusion in terms of EER (%) for the four different mixtures defined in Table 5.4 on the evaluation set. The relative EER increase with respect to the best modality involved (see Figure 5.2) is also given in brackets.**

It is also worth noting that the best mixtures (mixtures 1 and 3) are the ones that do not use mismatched fingerprint devices and they also result in the highest relative improvement with respect to the best individual modality involved, as observed in Table 5.6. The mixture involving both mismatched fingerprint and face devices (mixture 4) performs always the worst. However, it should be noted that about a 30% of improvement is obtained in terms of EER for this mixture when fusing, as compared to the best single modality.

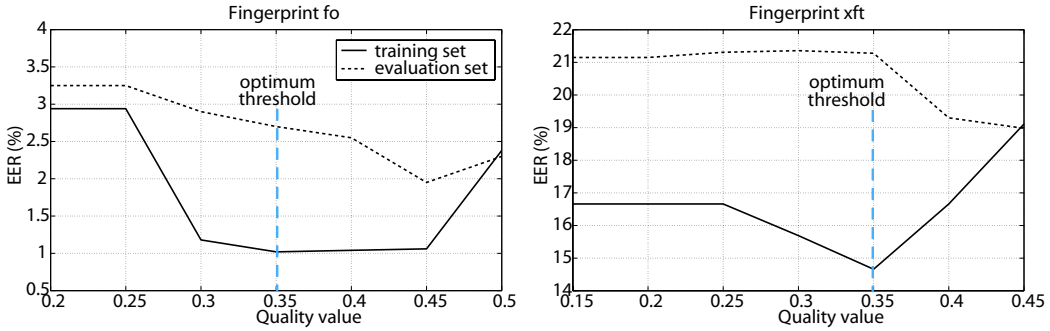


(a) With device estimation using quality measures.



(b) Without device estimation (knowing the actual device used in each access).

Figure 5.6: **Verification results of the fusion for the different mixtures defined in Table 5.4.**



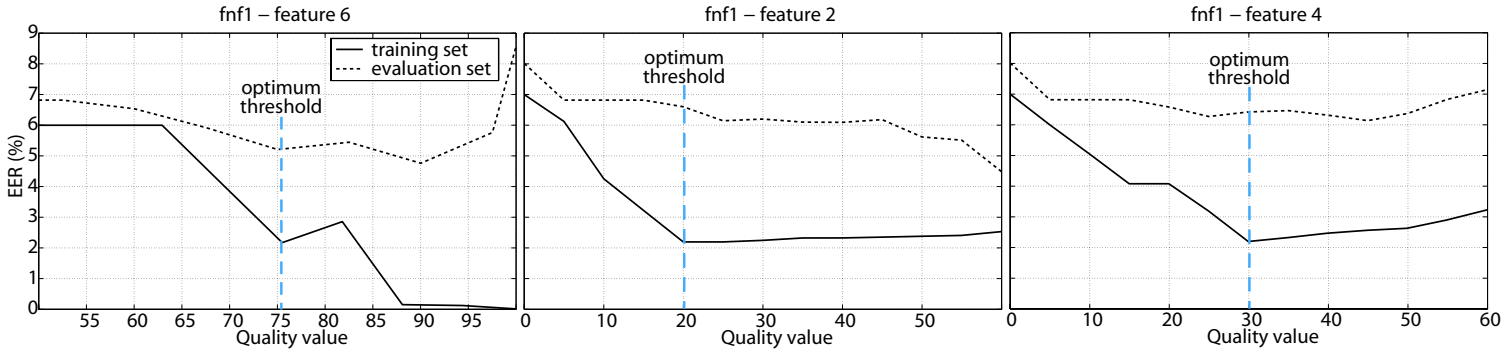
(a) Fingerprint. Left: template and query with flat acquisition. Right: template and query with flat and sweep acquisition, respectively.

Figure 5.7: **Verification performance in terms of EER for the fingerprint modality as scores with the lowest quality value are discarded.**

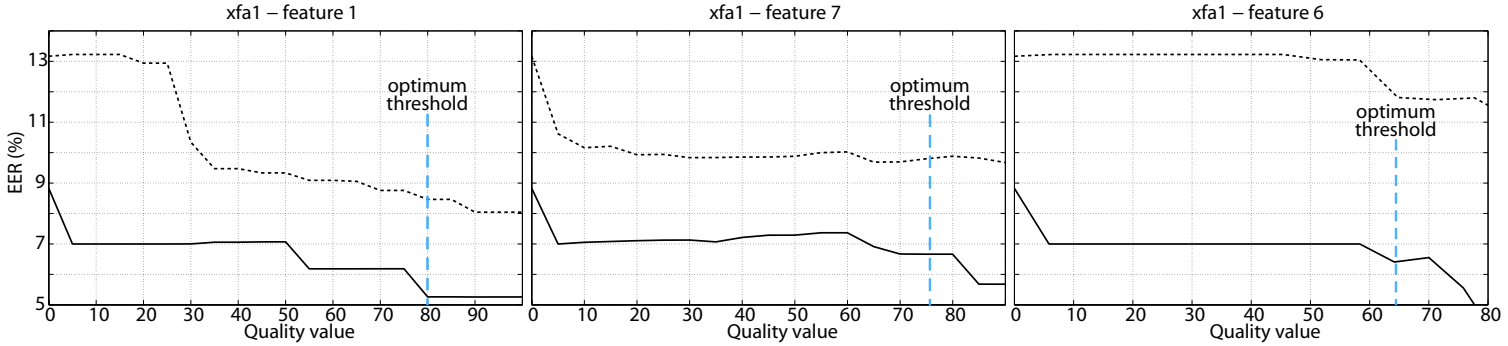
5.4.3 Quality-dependent multimodal fusion

There is now international consensus in industry (Benini and et al, 2006), academia (Chen *et al.*, 2005) and government (Tabassi *et al.*, 2004) that a measure of a biometric sample's quality should be related to its recognition performance. Broadly, a sample should be of good quality if it is suitable for automated matching. Based on this concept, sample quality can be formalized as a scalar quantity that is related monotonically to the performance of biometric matchers (Grother and Tabassi, 2007). Based on this, an operational approach to incorporate quality information in biometric systems is to reject low quality samples, as done in several studies (Alonso-Fernandez *et al.*, 2007c, 2008). This policy implies to increase the inconvenience to users whose samples are rejected by the system who are requested to be recaptured, or even to make a biometric system unsuitable to certain individuals whose data is not consistently of enough quality. To cope with this, multibiometric systems use multiple sources of information (Ross *et al.*, 2006), thus alleviating the problem of asking an individual to be recaptured when particular samples are of low quality (Fierrez-Aguilar *et al.*, 2005e). Similarly, users having a trait not suitable to be used (e.g. damaged fingers) still can use the other available information for recognition.

In this work, we have tested this quality-based modality rejection by not considering in the fusion the scores having a quality value lower than a predefined threshold. The quality value of a matching score is defined as $\min(Q_e, Q_t)$, where Q_e and Q_t are the qualities of the enrolled and input biometric samples respectively corresponding to the



(a) Face: template and query with high resolution camera.



(b) Face: template and query with high and low resolution cameras, respectively.

Figure 5.8: **Verification performance in terms of EER for the face modality as scores with the lowest quality value are discarded. Results are shown using the quality features that result in the highest improvement of the EER.**

EVALUATION SET

Modality discarded	feature	thres.	mixture 1	mixture 2	mixture 3	mixture 4	ALL
	6	75	1.59% (+2.58%)	5.73% (-17.79%)	-	-	5.41% (-1.45%)
Face							
fnf1	2	20	1.56% (+0.65%)	6.11% (-12.34%)	-	-	5.37% (-2.19%)
	4	30	1.57% (+1.29%)	6.39% (-8.32%)	-	-	5.44% (-0.91%)
	1	80	-	-	1.33% (-30.37%)	8.29% (-10.48%)	5.12% (-6.74%)
Face							
xfa1	7	75	-	-	1.37% (-28.27%)	9.90% (+6.91%)	5.52% (+0.55%)
	6	65	-	-	1.49% (-21.99%)	9.24% (-0.22%)	5.26% (-4.19%)
Fing. *fo*	-	0.35	1.51% (-2.58%)	-	1.40% (-26.70%)	-	5.57% (+1.46%)
Fing. *xft*	-	0.35	-	6.77% (-2.87%)	-	11.15% (+20.41%)	5.91% (+7.65%)

Table 5.7: **Effects on the performance of the proposed log-likelihood sum fusion on the different mixtures defined in Table 5.4 in terms of EER as scores with quality value lower than the predefined thresholds are not considered in the fusion. Results are shown by either discarding face or fingerprint scores, together with the resulting relative EER increase in brackets (reference results without quality-based score rejection are shown in Table 5.6, fifth column). Threshold values are selected on the basis of Figures 5.7 and 5.8.**

matching, so the worse of the two biometric samples drives the score (Grother and Tabassi, 2007). For a given access (consisting of a face sample and 3 fingerprints, see Figure 5.3), fingerprint scores whose quality is lower than the threshold are replaced with the fingerprint score having the maximum quality value. If the three fingerprint scores of an access have their quality lower than the threshold, then the fingerprint modality is entirely discarded. In order to set the "optimum" quality threshold, we used the verification performance of the fingerprint and face modalities as scores with the lowest quality value are discarded, as shown in Figures 5.7 and 5.8, respectively. Thresholds are set for each modality by choosing the value that minimizes the EER on the training set (indicated in Figures 5.7 and 5.8 as vertical lines). Except for the *xft* fingerprint modality (template and query with flat and sweep acquisition, respectively), an EER reduction is also observed on the evaluation set for the selected thresholds.

Once the optimum thresholds are selected, we evaluate the effects on the performance of the proposed log-likelihood sum fusion on the mixtures defined in Table 5.1 by separately discarding face or fingerprint scores. The results are shown in Table 5.7. It is observed in all cases an EER decrease (or at least, no significant EER increase) except when discarding scores of the *xft* modality. This is consistent with the results reported on Figure 5.7, where no reduction on the EER was observed on the evaluation set for the selected quality threshold. Based on these results, no threshold will be subsequently applied to the *xft* modality.

Finally, we jointly apply the score quality-based rejection in all the modalities using the optimum thresholds selected. To be consistent with the constraints of the BioSecure Multimodal Evaluation Campaign (Poh and Bourlai, 2007), where no access can be rejected, if all the quality measures of an access are lower than the thresholds, then the resulting fused score is set to 0. In the proposed log-likelihood fusion strategy, this means that there is the same likelihood if signals are assumed to be originated or not by the given subject. However, we also report results discarding these accesses of the computation of the error rates to show the benefits of this policy. In Figure 5.9, we show the number of accesses per modality that do not comply with the quality requirements, showing that the fusion allows to recover a significant number of them. Verification results of the fusion with the proposed quality-based rejection scheme are shown in Table 5.8 and Figures 5.10 and 5.11.

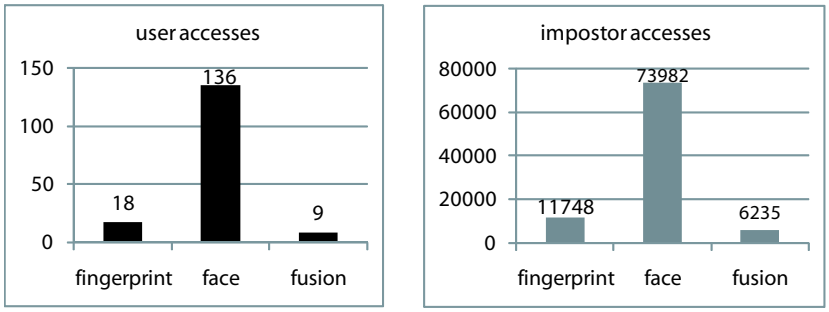


Figure 5.9: **Incorporation of quality information in the fusion stage. Results show the number of accesses per modality with quality value lower than the predefined thresholds. It can be observed that the fusion reduces significantly the number of rejected accesses.**

Mixture	Modalities	No quality	Quality	Quality+ rejection
1	(fnf1/fo1/fo2/fo3)	1.55%	1.56% (-0.65%)	1.28% (-17.42%)
2	(fnf1/xft1/xft2/xft3)	6.97%	5.73% (-17.79%)	5.45% (-21.81%)
3	(xfa1/fo1/fo2/fo3)	1.91%	1.30% (-31.94%)	0.96% (-49.74%)
4	(xfa1/xft1/xft2/xft3)	9.26%	8.29% (-10.48%)	7.48% (-19.22%)
	ALL	5.49%	4.45% (-18.94%)	4.17% (-24.04%)

Table 5.8: **Verification results of the fusion on the mixtures defined in Table 5.2 in terms of EER (%) for the evaluation set incorporating quality information in the fusion stage (without device estimation). The relative EER increase as a result of quality incorporation is also shown (in brackets).**

It is remarkable that even keeping invalid accesses in the fusion, a performance improvement is obtained (see Figure 5.10, curves named "quality"). Additional improvement results from discarding these accesses (curves named "quality and rejection"). It is also observed from Table 5.8 that the highest improvement is obtained for the mixture incorporating quality-based rejection both on the fingerprint and face modalities (the mixture 3). Worth noting, the mixture involved both mismatched face and fingerprint devices (the mixture 4) also results in a considerable improvement. The mixture having the smallest improvement is the one involving no mismatched devices (the mixture 1).

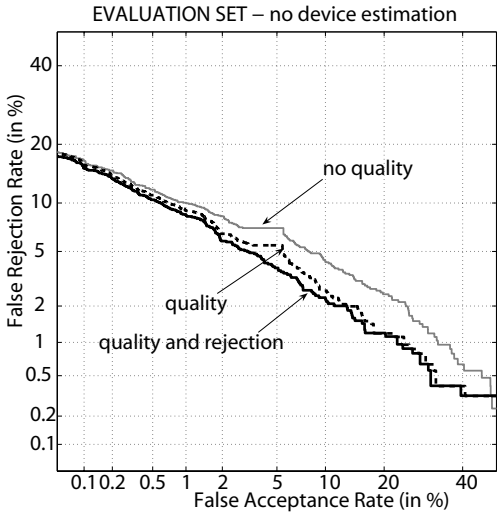


Figure 5.10: **Verification results of the proposed fusion incorporating quality information in the fusion stage (without device estimation).**

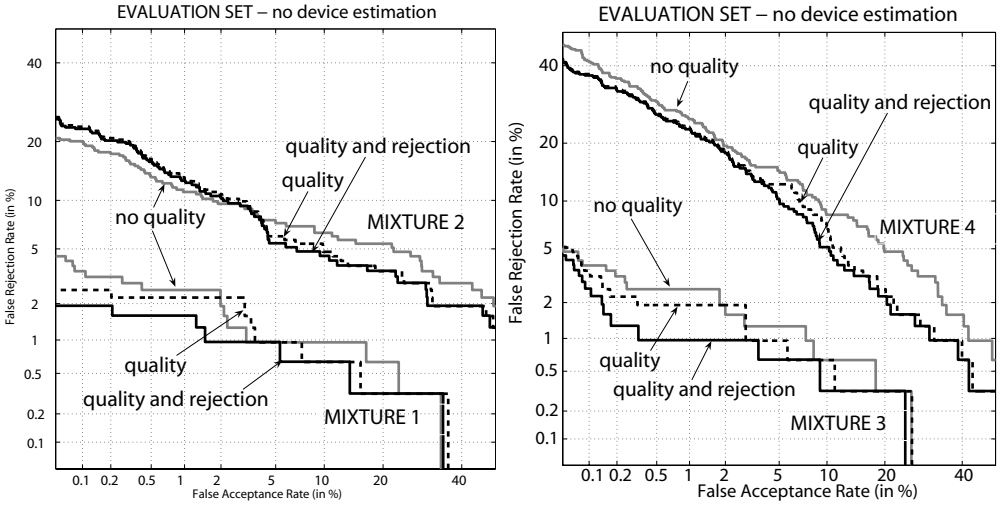


Figure 5.11: **Verification results of the proposed fusion for the different mixtures defined in Table 5.2 incorporating quality information in the fusion stage (without device estimation).**

5.5 Chapter summary and conclusions

As biometric technology is increasingly deployed, it will be a common situation to replace parts of operational systems with newer designs and/or to operate with information from different sources (Poh *et al.*, 2007). The recent *quality-based evaluation* of the BioSecure Multimodal Evaluation Campaign (BMEC, 2007; Poh and Bourlai, 2007) was aimed to compare the performance of different multi-modal biometric fusion architectures and algorithms when biometric signals are originated from heterogeneous face and fingerprint biometric devices in mismatched conditions. This evaluation operated at the matching score level, providing participants with different sets of scores which were obtained using several reference systems. Together with the scores, quality information of the associated biometric signals was also provided.

In this chapter we have described a fusion strategy submitted to this quality-based evaluation, developed in the framework of this Thesis (Alonso-Fernandez *et al.*, 2008b), which obtained very good results (2nd position in terms of Half Total Error Rate out of 13 participants (BMEC, 2007)). In our approach, output scores of the individual matchers are first mapped to log-likelihood-ratios by linear logistic regression, prior to the fusion stage. The proposed strategy allows to efficiently combine scores originated from different biometric sources (modalities, matchers, devices, etc.) since they are in a comparable domain, and it is generalizable to newer developments or additional modalities.

Quality-based conditional processing is carried out in two stages of the proposed strategy: by estimating the device used in each access in order to switch between different linear logistic regression modules, and by rejecting scores from low quality biometric samples. Worth noting, a considerable performance improvement has been obtained when applying the quality-based score rejection.

The proposed fusion approach is also able to cope easily with missing values of any modality. In the Biosecure *quality-based evaluation*, the robustness of the submitted algorithms against missing values was also evaluated, although it has not been studied in this chapter. The proposed fusion scheme also obtained remarkable results (BMEC, 2007), being the first in terms of HTER when the proportion of missing data was increased (i.e. higher than 20%).

This chapter presents novel contributions in the definition of a quality-based multibiometric architecture, the use of quality information to estimate the input device used in the acquisition of biometric data, and the use of a score-rejection scheme that only considers sources of enough quality in the fusion.

Chapter 6

Conclusions and Future Work

This PhD Thesis has studied the biometric sample quality assessment problem. After a summary of previous work related to this problem, it is explored in two particular traits: fingerprints and signature images. In anatomical traits like fingerprint, we can objectively define what quality is. But it is harder to do so in behavioral traits like signature, where proposed features for quality assessment are related to how a signer *decides* to sign. Several quality assessment methods are studied and compared for the two mentioned traits. Also, the incorporation of quality information in multibiometric systems is explored, showing its benefits.

6.1 Conclusions

Chapter 1 introduced the topic of biometric systems, biometric modalities, the motivation of the Thesis, and the contributions originated from this PhD Thesis. Chapter 2 summarized related works and detailed the motivations for this Thesis based on these previous works.

Chapter 3 studied the problem of quality assessment of fingerprint images. This chapter provided a taxonomy of existing approaches for fingerprint image quality assessment. It also compared a set of representative fingerprint quality measures by studying both their correlation and their *utility*. The impact of image quality in the performance of a minutiae- and a ridge-based matcher was evaluated with a multisession database acquired with three sensors of different technology. High correlation was observed between quality measures in most cases, with some differences depending on the sensor used. Regarding the utility, for the approach based on minutiae the highest performance improvement for good quality was obtained in the False Rejection

Rate, whereas for the ridge-based approach the highest improvement was observed in the False Acceptance Rate.

Chapter 4 studied the problem of quality assessment of signature images. Several measures to predict the performance of signature systems were proposed as contribution. They were aimed to predict features like signature legibility, complexity, stability, duration, etc. Also, one verification system based on local contour of signatures was presented. Among the most remarkable findings of this chapter, we have found that for skilled forgeries, the best performance is obtained with legible signatures. Also, performance is worsened with highly variable signatures, specially with few enrolment data, or with low variance of the pen pressure. For the other measures, different behavior was observed between the three matchers used.

Chapter 5 finally conducted a study of system adaptation to the quality of biometric systems. We have contributed with a new quality-based conditional-processing multibiometric architecture that is generalizable to biometric systems working with multiple sources of information. In the proposed approach, output scores of the individual sources are first mapped to log-likelihood-ratios, allowing an efficient combination since they are in a comparable domain. Quality is then used to switch between different system modules depending on the data source, and to consider only data of enough quality. The effectiveness to cope with signals originated from heterogeneous biometric sources was also demonstrated by the proposed approach in an standard benchmark test.

To summarize, the main results and contributions obtained from this Thesis are:

- The novel strategies for signature quality assessment and performance prediction.
- The novel quality-based conditional-processing multibiometric architecture aimed at combining biometric signals originated from heterogeneous sources.
- The individual system developed for off-line signature verification using local contour information of the signature.
- The multimodal biometric data acquired, which will be released for research purposes in the near future.
- The experimental evaluation of fingerprint and signature quality measures using different biometric sensors and matchers.

6.2 Future work

Several research directions arise from the work proposed in this Ph.D. Thesis. We enumerate here some of them that we consider remarkable:

Application of the proposed evaluation framework to other biometric traits. The evaluation framework used in this Ph.D. Thesis (Grother and Tabassi, 2007) is applicable to any biometric trait and it is a clear future area of research. Apart from the two traits considered in this Ph.D. Thesis (fingerprint and signature), biometric algorithms have been also proposed for iris (Chen *et al.*, 2006a; Kalka *et al.*, 2005), voice (Garcia-Romero *et al.*, 2006) and face (Kryszczuk and Drygajlo, 2007). However, prior work on quality evaluation and sample quality analysis is limited. Biometric quality assessment is a current research challenge and it is not been until recent years when it has received specific attention from the research community (Benini and et al, 2006; BQW, 2007; Youmaran and Adler, 2006).

Combination of different approaches for quality estimation. Experiments have shown that there are quality measures better suited to specific situations (sensor technology, matching algorithm, etc.). Remarkable differences between quality measures are found in terms of behavior. Therefore, adaptive quality fusion methods that exploit these differences could improve the process of assessing the quality of biometric signals and therefore, the overall performance of the system, e.g. Fierrez-Aguilar *et al.* (2006); Fronthaler *et al.* (2008). This research line will be explored in the future.

Proposal of new quality measures. Many quality assessment algorithms have been developed, mainly for fingerprint images (Alonso-Fernandez *et al.*, 2007c). Other measures have also been recently proposed for iris, voice, face and signature. However, there is much research that still can be done in this field with the proposal of new quality measures to other biometric traits. Efforts are currently going towards an harmonized and universal interpretation of quality measures by defining the key factors that need to be assessed in each biometric trait.

Incorporation of quality measures in biometric systems. Some of the steps of the recognition system can be adjusted based on the estimated quality in order to improve the overall performance. There are recent works following this direction (Baker and Maurer, 2005; Chan *et al.*, 2006; Fierrez-Aguilar *et al.*, 2006;

Nandakumar *et al.*, 2006), in which quality measures are used to dynamically assigning weights to the outputs of individual matchers based on the quality of the samples. Other approaches (Chen *et al.*, 2005; Hong *et al.*, 1998; Shi *et al.*, 2004) exploit the signal quality in different steps of the recognition system in order to improve the feature extraction process.

Study of quality in new biometric scenarios. Chapter 5 of this Thesis has addressed the problem of biometric device replacement and the matching of biometric samples originated from different devices. These are common operational situations that will appear as biometric technology is deployed (Poh *et al.*, 2007). Other problems that could be a source of future work in this area are: impact of environmental variations in new applications requiring personal identification (over the Internet, with mobile platforms in indoor/outdoor environments, etc.), evaluation of new multibiometric scenarios (e.g. ePassport using face, fingerprint and iris), etc.

Use of "biometric information" to assess sample quality. Youmaran and Adler (2006) have developed an approach that measures the information content of biometric data from an information theoretic point of view. Intuitively, degradations to a biometric sample will reduce the amount of identifiable information available. They develop a mathematical framework to measure biometric information for a given system and set of biometric features using the concept of entropy (Duda *et al.*, 2004). Quantifying the biometric information in different systems individually also would allow to evaluate the potential gain from fusing them. There are other efforts related to this issue specifically focused on certain biometric traits, as Daugman (2003); Kholmatov and Yanikoglu (2008).

Effects of time variability in the quality of acquired signals and the implementation of **template selection and update** techniques. As biometric data is subject to natural variations across time, multiple templates that best represent this variability should be stored in the database. Also, stored templates should be updated with new acquisitions by replacing them with better quality samples captured subsequently. There are initial techniques following this direction (Ko and Krishnan, 2004; Uludag *et al.*, 2004).

Chapter 7

Resumen Extendido de la Tesis

Calidad de muestras biométricas y su aplicación en sistemas de autenticación multimodal

Se denomina *reconocimiento biométrico* al proceso que permite determinar la identidad de un individuo de forma automática mediante el uso de características personales de tipo conductual y/o anatómico, como las huellas, la cara, el iris, la voz, la firma, etc. (Jain *et al.*, 2006). El análisis científico de evidencias biométricas lleva usándose en el ámbito forense (judicial, policial y pericial) desde hace más de un siglo. Pero en los últimos años, con el desarrollo de la sociedad de la información y con un mundo cada vez más interconectado y globalizado, la demanda de aplicaciones que permitan la identificación de individuos de modo automático ha crecido enormemente. Es en este contexto donde el reconocimiento biométrico ha experimentado una investigación y desarrollo considerable.

Aunque el reconocimiento automático de personas se lleva estudiando más de treinta años (Atal, 1976; Kanade, 1973), hasta la última década no se ha establecido como un campo de investigación específico, con múltiples libros de referencia (Bolle *et al.*, 2004; Jain *et al.*, 1999, 2008; Li and Jain, 2004; Maltoni *et al.*, 2003; Nanavati *et al.*, 2002; Ratha and Bolle, 2004; Ross *et al.*, 2006; Wayman *et al.*, 2005; Zhang, 2002), conferencias específicas en el tema (AVBPA, 2005; BTAS, 2007; ICB, 2007; ICBA, 2004;

SPIE-BTHI, 2008), proyectos internacionales (BioSec, 2004; BioSecure, 2004; COST-2101, 2006; COST-275, 2003), esfuerzos de estandarización (BioAPI, 1998; CBEFF, 2001; INCITS M1, 2007; ISO/IEC JTC1 SC37, 2002) y el desarrollo de evaluaciones y pruebas comparativas (BMEC, 2007; FpVTE, 2003; FRVT, 2006; FVC2006, 2006; ICE, 2006; Mansfield and Wayman, 2002; NIST SRE, 2006; SVC, 2004; Wayman *et al.*, 2005). También ha habido un creciente interés institucional de gobiernos (DoD, 2007), industria (IBG, 2007), organismos de investigación (NIST-ITL, 2007) así como el establecimiento de consorcios internacionales específicamente dedicados a la biometría (BC, 2005; EBF, 2003).

Pero pese a la madurez de este campo de investigación, el reconocimiento biométrico sigue siendo un área muy activa de investigación, con numerosos problemas prácticos aún por solucionar (Jain *et al.*, 2004a). Estos problemas prácticos han hecho que, pese al interés de las aplicaciones biométricas, la introducción en el mercado de estas nuevas tecnologías sea más lenta de lo esperado.

Esta tesis se centra en el análisis de calidad de muestras biométricas, así como su aplicación en sistemas multimodales. En particular, se explora el problema en dos rasgos: huella y firma "offline". Al contrario que una imagen de huella, donde se puede definir su calidad de manera más o menos objetiva, en el caso de rasgos de comportamiento como la firma no es sencillo hallar una definición de calidad.

7.1 Introducción

El paradigma de la autenticación biométrica. El reconocimiento de personas se ha realizado históricamente asociando identidad y "algo que la persona posee" (por ejemplo, una llave o una tarjeta, que puede ser robado, perdido o duplicado), o bien "algo que la persona sabe" (por ejemplo, una palabra-clave o un PIN, que puede ser olvidado o revelado). El reconocimiento biométrico añade a este paradigma una nueva dimensión, asociando persona e identidad personal mediante "algo que la persona es (o produce)". "Algo que la persona es" nos indica una característica fisiológica asociada de forma inherente a la persona, mientras que "algo que la persona produce" nos indica una aptitud o acto previamente entrenado que la persona realiza como patrón de conducta.

Sistemas biométricos. El reconocimiento biométrico es un término genérico para denominar a los dos modos de funcionamiento de los sistemas biométricos. De forma más precisa, se denomina *identificación* biométrica a la tarea que pretende asociar una muestra biométrica a uno de los N patrones o modelos disponibles del conjunto cono-

cido de individuos registrados. Por este motivo, a esta tarea también se la conoce como comparación uno-contra-muchos o uno-contra-N. La salida de los sistemas que funcionan bajo este modo suele ser una lista ordenada de candidatos, estando ligado el criterio de ordenación al grado de similitud entre muestra de prueba y patrón registrado. Por el contrario, la *verificación* (o *autenticación*) biométrica es la tarea que pretende decidir si una determinada muestra de entrada coincide o no con un usuario específico (denominado usuario "solicitado", o "pretendido"). Esta tarea es conocida como problema uno-contra-uno, y la salida será una decisión binaria (aceptado/rechazado) basada en la comparación del grado de similitud (en forma de puntuación o *score* entre la muestra de entrada y el modelo de usuario pretendido) respecto a un determinado umbral de decisión. En esta Tesis nos centramos en el modo de verificación, cuyas dos etapas, registro (*enrollment*) y verificación (*verification*), se muestran esquemáticamente en la Figura 1.1.

El objetivo en la verificación biométrica es decidir entre dos clases, cliente o impostor. Dependiendo del rasgo biométrico que se trate, los impostores pueden conocer y utilizar información del rasgo imitado para facilitar el acceso, por ejemplo, la forma de la firma en el caso de verificación de firma escrita. Por ello se suelen considerar dos tipos de impostores: 1) *impostores casuales* (que producen *falsificaciones aleatorias*), cuando no se conoce información del rasgo imitado, y 2) *impostores reales* (que producen *falsificaciones entrenadas*), cuando se conoce y utiliza información del rasgo imitado.

Modalidades biométricas. Hay una serie de modalidades fisiológicas que pueden ser consideradas como tecnológicamente "maduras", a saber, la huella dactilar, el iris, la cara, la geometría de los dedos y/o la mano, o la huella palmar. En relación con las modalidades conductuales, rasgos como la voz, la escritura y la firma manuscrita, o el modo de andar (marcha), son modalidades objeto de grandes esfuerzos de investigación. La Figura 1.2 muestra algunos ejemplos de rasgos biométricos (Jain *et al.*, 2006). En teoría, cualquier característica humana puede ser considerada como un rasgo biométrico siempre que satisfaga las siguientes propiedades:

- *universal*, que indica que toda persona debe poseer dicho rasgo;
- *distintivo*, que se refiere a que dicho rasgo debe ser lo suficientemente diferente para diferentes personas;
- *permanente*, que indica que dicho rasgo debe poseer una representación que se mantenga a lo largo del tiempo;

- *mensurable*, que se refiere a la habilidad de medir dicho rasgo cuantitativamente.

Otras propiedades deseables de cara al uso de rasgos biométricos en sistemas de autenticación incluyen:

- *rendimiento*, que se refiere a la eficiencia, precisión, velocidad, robustez, y uso de recursos de las implementaciones prácticas basadas en dicho rasgo;
- *aceptabilidad*, que indica el grado en el que la gente está dispuesta a usar dicho rasgo y en qué términos;
- *seguridad*, que se refiere a la dificultad de burlar un sistema basado en dicho rasgo con métodos fraudulentos;
- *manejo de excepciones*, referido a la capacidad de completar el reconocimiento de modo manual en el caso de que ciertas personas no sean capaces o no puedan usar alguna modalidad biométrica;
- *coste*, referido al coste económico del sistema para su uso normal.

Si se analiza el estado del arte de los sistemas basados en diferentes rasgos biométricos, podremos observar que no existe ningún rasgo individual que maximice todas las propiedades indicadas. Algunos rasgos biométricos son altamente distintivos pero son difícilmente mensurables (p.ej., el iris, con dispositivos caros y difíciles de utilizar), mientras que otros se adquieren fácilmente pero no son tan distintivos (p.ej., la cara). No obstante, cuando se consideran varios rasgos simultáneamente, prácticamente todas las propiedades se satisfacen ampliamente, hecho que pretenden explotar los sistemas multibiométricos.

Sistemas biométricos multimodales. En dichos sistemas se utilizan varios rasgos biométricos simultáneamente con objeto de compensar las limitaciones de rasgos individuales (Ross *et al.*, 2006). Como resultado, las tasas de error en verificación suelen disminuir, el sistema resultante es más robusto frente a fallos de los sistemas individuales y frente a ataques externos, y el número de casos donde el sistema no es capaz de dar una respuesta se reduce (p.ej., debido a la mala calidad de una muestra biométrica de uno de los rasgos individuales).

A grandes rasgos, se pueden definir dos niveles de fusión: fusión *antes* de la comparación, y fusión *después* de la comparación. Fusión antes de la comparación incluye fusión a nivel de sensor y fusión a nivel de características, mientras que después de la

comparación tenemos a nivel de puntuaciones y a nivel de decisión. Esta clasificación se basa en el hecho de que tras la comparación, la cantidad de información disponible para fusionar se reduce enormemente.

Entre todos estos tipos de fusión, la mayoría de estrategias para la combinación de rasgos biométricos existentes en la literatura se basan en la fusión de las puntuaciones o medidas de similitud proporcionadas por los sistemas individuales, por la mayor facilidad de acceso a las mismas (Fierrez-Aguilar, 2006; Ross *et al.*, 2006). Como resultado de esta fusión, tenemos una nueva puntuación o medida de similitud, que será lo que usemos para el reconocimiento. A su vez, los métodos de fusión a nivel de puntuación se clasifican en tres categorías: métodos basados en densidades, métodos basados en transformaciones y métodos basados en clasificadores (Ross *et al.*, 2006).

En los *métodos basados en densidades*, las funciones de densidad conjunta $p(\mathbf{s}|\omega_0)$ y $p(\mathbf{s}|\omega_1)$ correspondientes a las clases "usuario genuino" (ω_0) e "impostor" (ω_1) se estiman para un vector de puntuaciones dado $\mathbf{s} = [s_1, s_2, \cdots, s_R]$, donde R es el número de comparadores. A continuacion, se aplica la regla de decisión de Bayes (Duda *et al.*, 2004):

$$\begin{array}{c} \text{Asignar} \quad \mathbf{s} \rightarrow \omega_i \quad \text{si} \\ \frac{p(\mathbf{s}|\omega_i)}{p(\mathbf{s}|\omega_j)} > \tau, i \neq j \quad \text{y} \quad \text{i,j} = \{0,1\} \end{array} \tag{7.1}$$

donde $p(\mathbf{s}|\omega_i)/p(\mathbf{s}|\omega_j)$ es un *cociente de verosimilitud* y $\tau = P(\omega_j)/P(\omega_i)$ es un umbral predeterminado que depende de las probabilidades *a priori* de observar las clases ω_j and ω_i[1]. La estimación de la densidad $p(\mathbf{s}|\omega_i)$ se hace usando un conjunto de entrenamiento de vectores de medidas de similitud mediante técnicas paramétricas o no paramétricas. En la literatura se han propuesto varias estrategias siguiendo estos métodos (Dass *et al.*, 2005; Kittler *et al.*, 1998; Ross *et al.*, 2006). Para estimar de modo preciso las funciones de densidad, normalmente se necesita un conjunto grande de muestras de entrenamiento, sobre todo si la dimensionalidad del vector $\mathbf{s}$ es alta.

En los *métodos basados en transformaciones*, las puntuaciones se combinan directamente mediante operadores sencillos como la suma, la regla del máximo, etc. (Kittler *et al.*, 1998). En este caso, normalmente es necesario un proceso de normalización que transforme las distintas puntuaciones a un rango común (Jain *et al.*, 2005).

Los *métodos basados en clasificadores* utilizan las puntuaciones de los diferentes comparadores como entrada de un clasificador entrenado (Duda *et al.*, 2004) para de-

[1]La regla de Bayes, tal como se expresa aquí, asume que el coste de cada error de clasificación es el mismo para todas las clases posibles (Duda *et al.*, 2004). Puesto que esta particularización no se considera en esta Tesis, no introducimos aquí términos de coste de errores de clasificación por claridad.

terminar directamente la clase (usuario genuino o impostor), en lugar de devolver otra puntuación. En este caso, las puntuaciones normalmente no es necesario transformarlas a un rango común antes de la clasificación, aunque sí será necesario un conjunto grande de muestras de entrenamiento para el clasificador. En la literatura biométrica se han propuesto múltiples clasificadores para la combinación de puntuaciones: redes hyper BF (Brunelli and Falavigna, 1995), k-vecino más cercano (Verlinde and Chollet, 1999), árboles de decisión (Ben-Yacoub *et al.*, 1999; Ross and Jain, 2003; Verlinde and Chollet, 1999), regresión logística lineal (Verlinde and Chollet, 1999), k-media and fuzzy clustering (Chatzis *et al.*, 1999), Máquinas de Vector Soporte (SVM) (Ben-Yacoub *et al.*, 1999; Fierrez-Aguilar *et al.*, 2005a,e; Garcia-Romero *et al.*, 2003), perceptrones multicapa (Ben-Yacoub *et al.*, 1999), discriminantes de Fisher (Ben-Yacoub *et al.*, 1999; Wang *et al.*, 2003), clasificadores Bayesianos (Ben-Yacoub *et al.*, 1999; Bigun *et al.*, 1997) y redes neuronales (Wang *et al.*, 2003).

Calidad en sistemas biométricos. Existen múltiples algoritmos de medida de calidad principalmente para huellas (Alonso-Fernandez *et al.*, 2007c) y más recientemente para iris (Chen *et al.*, 2006a; Kalka *et al.*, 2005), voz, (Garcia-Romero *et al.*, 2006; Richiardi and Drygajlo, 2008; Richiardi *et al.*, 2007), cara (Kryszczuk and Drygajlo, 2007) y firma (Alonso-Fernandez *et al.*, 2007a; Muller and Henniger, 2007). Muchos de estos trabajos demuestran que la calidad influye decisivamente en el rendimiento de los sistemas. Es por ello que el análisis de calidad en biometría es un área actual de intensa actividad investigadora (BQW, 2007; Grother and Tabassi, 2007). También hay importantes esfuerzos encaminados a estandarizar la información de calidad biométrica así como su incorporación a estructuras de datos existentes (Benini, 2007; Benini and et al, 2003, 2006).

Los roles de la calidad en sistemas biométricos son múltiples (Benini, 2007; Grother and Tabassi, 2007):

- como herramienta de monitorización y estadística para detectar fuentes de datos erróneos (Ko and Krishnan, 2004);
- como herramienta para recapturar muestras a la entrada hasta cumplir un mínimo de calidad;
- como mecanismo de ajuste de partes del sistema según la calidad de las señales capturadas (*procesado de calidad condicional*).

Este último rol ha sido fuente de numerosos trabajos recientes para sistemas monomodales (Alonso-Fernandez *et al.*, 2007c, 2008; Chen *et al.*, 2005, 2006a; Fronthaler *et al.*, 2008;

Grother *et al.*, 2005; Kang *et al.*, 2003; Sickler and Elliott, 2005). La incorporación de calidad en mecanismos de fusión multimodal también está siendo un área de trabajo importante (Fierrez-Aguilar *et al.*, 2006, 2005e; Fronthaler *et al.*, 2008; Garcia-Romero *et al.*, 2006; Kryszczuk and Drygajlo, 2008; Nandakumar *et al.*, 2006; Poh *et al.*, 2007).

Tipos de errores en verificación. El modo de verificación puede ser considerado como una tarea de detección, comportando un compromiso entre dos tipos de errores: 1) Falso Rechazo (FR), que se produce cuando un usuario auténtico (lo que se conoce también por usuario genuino o cliente) es rechazado por el sistema, y 2) Falsa Aceptación (FA), que sucede cuando un impostor es aceptado por el sistema como si fuera un usuario auténtico. Estos dos tipos de errores tienen relación inversa entre sí, pudiéndose obtener diversos puntos de funcionamiento del sistema en función del umbral de decisión elegido. El punto de trabajo en cada caso dependerá de cada aplicación en particular. Por esta razón la caracterización de los sistemas biométricos se realiza mediante las curvas completas que relacionan ambos tipos de error. Por esta razón también, en el caso de caracterizar el rendimiento de un sistema de verificación con tasas numéricas, se suele optar bien por un par (FA,FR) o por el punto en donde coinciden ambas tasas, esto es, el punto de igual error (*Equal Error Rate* –EER).

Representación del funcionamiento en verificación. Tradicionalmente se han venido usando para representar el rendimiento de los sistemas biométricos en modo de verificación las curvas ROC (*Receiver-* o *Relative- Operating Characteristic*), en las que se representa la probabilidad de FA frente a la probabilidad de FR para los diferentes puntos de trabajo (esto es, umbrales de decisión) del sistema. En las curvas ROC, la zona de interés se concentra en la esquina inferior izquierda de la gráfica, que se corresponde con la zona en la que los dos tipos de error se minimizan conjuntamente. El problema de este tipo de representación ocurre cuando los sistemas producen bajas tasas de error, puesto que, en estos casos, las curvas que describen los sistemas tienden a concentrase, impidiéndose de esta forma una visualización comparativa clara de sistemas competitivos. Con el objeto de solventar este problema, más recientemente, se han propuesto las denominadas curvas DET (*Detection Error Tradeoff*) (Martin *et al.*, 1997), que representan también los dos tipos de error pero aplicando una transformación de ejes. Dicha escala produce un efecto de separación de las gráficas de sistema que en las ROC se concentraban en la esquina inferior izquierda, y además consigue que dichas curvas tiendan a ser líneas rectas para distribuciones de puntuaciones Gaussianas, haciendo así que las comparaciones entre sistemas competitivos sean directas y

sencillas. En la Figura 1.3 se muestra una comparación entre curvas ROC y DET de dos sistemas hipotéticos de verificación A y B.

Motivación para la Tesis. Según hemos mencionado, el rendimiento de sistemas biométricos se ve fuertemente afectado por la calidad de las señales biométricas. Esta tesis se centra en este problema así como en su aplicación a sistemas multibiométricos. Más particularmente, se basa en las siguientes observaciones de la literatura:

- El trabajo previo en evaluación de calidad biométrica es relativamente limitado (Grother and Tabassi, 2007). La comunidad investigadora se ha venido centrando principalmente en el desarrollo de sistemas reconocedores, perfeccionando los mecanismos de extracción de características biométricas y de reconocimiento. Igualmente, aunque hay múltiples algoritmos de medida de calidad biométrica, todos han sido evaluados individualmente y bajo marcos de evaluación heterogéneos. Solo recientemente se ha formalizado el concepto de calidad en biometría y se han propuesto marcos comparativos para su evaluación (Grother and Tabassi, 2007; Youmaran and Adler, 2006).

- Para el caso de las huellas dactilares, se ha observado que los dos mecanismos de reconocimiento por excelencia (minucias y texturas) no sufren de la misma manera los efectos de la calidad (Fierrez-Aguilar *et al.*, 2006). Algunos estudios también se han enfocado al tipo de sensor utilizado (Grother *et al.*, 2005; Kang *et al.*, 2003; Sickler and Elliott, 2005). Estos resultados no obstante, han sido llevados a cabo en marcos limitados, sin efectuar pruebas comparativas extensas entre varios algoritmos de calidad y/o diferentes tecnologías de sensores de huella.

- En rasgos de comportamiento como la firma, es difícil definir el concepto de calidad. Algunos estudios proponen la complejidad o la variabilidad de la firma (Allgrove and Fairhurst, 2000; Fierrez-Aguilar *et al.*, 2005d) así como otras características locales (Muller and Henniger, 2007). También hay trabajos relacionados con la voz (Garcia-Romero *et al.*, 2006). No obstante, el análisis de calidad en rasgos de comportamiento es aún muy limitado.

- Una fuente de problemas adicionales es cuando el sensor de captura se cambia por otro (Poh *et al.*, 2007), o cuando las muestras a comparar provienen de diferentes sensores y/o algoritmos extractores de características (Grother *et al.*, 2005). Estos problemas de *interoperabilidad*, que normalmente reducen sustancialmente el rendimiento (Alonso-Fernandez *et al.*, 2005c, 2006c; Grother *et al.*, 2005; Ross

and Jain, 2004), no han sido específicamente tratados. Por desgracia, a medida que las aplicaciones biométricas se vaya extendiendo, será bastante común cambiar el sensor por diseños más recientes (o cuando se rompa o deteriore), así como intercambiar información con otros sistemas desarrollados por otras compañías (Poh *et al.*, 2007).

- La incorporación de medidas de calidad en sistemas multibiométricos es otro reto actual (BMEC, 2007; BQW, 2007). Se ha demostrado que estos sistemas son más robustos a variaciones en la calidad (Fierrez-Aguilar *et al.*, 2006; Nandakumar *et al.*, 2006) y puede ser una fuente adicional de mejora (BQW, 2007; Fierrez-Aguilar *et al.*, 2005e; Grother and Tabassi, 2007). Algunas estrategias que se proponen consisten en combinar de modo adaptativo las salidas de los diferentes comparadores en función de la calidad de las muestras de entrada (fusión dependiente de calidad) o en modificar las etapas de procesamiento del sistema (procesado dependiente de la calidad) (Chen *et al.*, 2005).

La Tesis. En esta Tesis se evalúa en primer lugar el impacto de la calidad de las señales biométricas en el rendimiento del sistema bajo un marco comparativo. Dicho estudio se lleva a cabo para dos rasgos particulares: huella y firma. También se lleva a cabo un estudio práctico de adaptación de sistemas multibiométricos a la calidad de las señales. Dentro de este objetivo, se propone una arquitectura de sistema generalizable a cualquier sistema biométrico que trabaje con diferentes fuentes de información heterogéneas.

La Disertación. En primer lugar se introducen los sistemas biométricos y multibiométricos, la evaluación del rendimiento de sistemas biométricos, la motivación de la Tesis, una expresión breve de la Tesis, la organización de la Disertación, y las contribuciones de investigación relacionadas con la Tesis.

Después se hace un análisis extenso del estado del arte en calidad biométrica, abordando los distintos factores que pueden afectar la calidad, cómo asegurar buena calidad de señal, o cuales son los roles de la misma en un sistema biométrico.

La parte experimental de la Disertación comienza con el estudio de la calidad en imágenes de firma. Se contribuye con una taxonomía de medidas de calidad existentes y se lleva a cabo un estudio comparativo de un conjunto representativo de medidas de calidad seleccionadas.

En el caso de verificación basada en firma, se proponen varias características enfocadas a medir la calidad y a predecir el comportamiento de los sistemas de re-

conocimiento. En esta parte, se introduce un nuevo sistema de verificación basado en características del contorno de la firma.

Finalmente, se lleva a cabo un estudio de la adaptación de un sistema multi-biométrico a la calidad de las señales biométricas. Se propone una arquitectura de procesado condicional basado en calidad que es capaz de integrar señales biométricas procedentes de diferentes fuentes. La calidad en este caso se utiliza para conmutar entre diferentes etapas del sistema así como para no incluir en la combinación señales que no cumplan con una mínima calidad.

La dependencia entre capítulos se ilustra en la Figure 1.4. Nótese que los capítulos experimentales, que están sombreados en la Figure 1.4, contienen referencias a los métodos utilizados de capítulos anteriores. De esta manera, y asumiendo conocimientos generales en sistemas biométricos (Jain *et al.*, 2008) y fusión multimodal (Ross *et al.*, 2006) los capítulos experimentales se pueden leer independientemente. También sería deseable el conocimiento de técnicas generales de reconocimiento de patrones (Duda *et al.*, 2004; Theodoridis and Koutroumbas, 2003) y de procesado de imagen (Gonzalez and Woods, 2002).

Contribuciones de la Tesis. Las contribuciones de la Tesis se pueden clasificar como sigue a continuación (nótese que algunas publicaciones se repiten en puntos diferentes de la lista):

- **Revisiones del estado del arte**. Taxonomía de medidas de calidad de huella (Alonso-Fernandez *et al.*, 2007c, 2005b). Estado del arte en verificación de huella (Alonso-Fernandez *et al.*, 2008a).

- **Métodos originales**. Métodos para medida de calidad y predicción del rendimiento con firmas *off-line* (Alonso-Fernandez *et al.*, 2007a,b). Métodos para verificación multimodal basada en calidad con diferentes fuentes de información (Alonso-Fernandez *et al.*, 2008b).

- **Nuevos sistemas biométricos**. Nuevo sistema de verificación de firma *off-line* basado en características del contorno de la firma (Gilperez *et al.*, 2008), desarrollado conjuntamente con Pecharroman-Balbas (2007).

- **Nuevos estudios experimentales**. Evaluación comparativa de medidas de calidad de huella en función del sensor utilizado y del tipo de comparador (Alonso-Fernandez *et al.*, 2007c, 2008; Fierrez-Aguilar *et al.*, 2005b). Estudio del impacto de la legibilidad y del tipo de firma en sistemas de verificación de firma

off-line (Alonso-Fernandez *et al.*, 2007b). Estudio del rendimiento de sistemas de verificación de firma *off-line* en función de nuevas medidas calidad propuestas (Alonso-Fernandez *et al.*, 2007a). Estudio de la combinación de diferentes características del contorno de la firma para verificación (Gilperez *et al.*, 2008). Estudio de la adaptación de sistemas a la calidad de señales biométricas procedentes de diferentes fuentes, incluyendo fusión y procesado adaptado a la calidad (Alonso-Fernandez *et al.*, 2008b).

- **Nuevos datos biométricos**. Una nueva base de datos biométricos ha sido adquirida en el marco de trabajo de la Tesis incluyendo cara, voz, firma, huella, mano e iris de más de 650 individuos (Alonso-Fernandez *et al.*, 2008b). Dicha base de datos es única en el sentido de que incluye tres nuevos escenarios simultáneos (Internet, PC en entorno oficina, y dispositivos móviles en entornos exteriores). Parte de esta base de datos se usa en los experimentos del Capítulo 5.

Otras contribuciones relacionadas con la Tesis no incluidas en el presente volumen incluyen:

- *Revisiones del estado del arte.* Estado del arte en firma manuscrita (Garcia-Salicetti *et al.*, 2008). Estado del arte en bases de datos y evaluaciones de firma y huella (Alonso-Fernandez and Fierrez, 2008; Garcia-Salicetti *et al.*, 2008). Revisión de aplicaciones biométricas (Alonso Fernandez *et al.*, 2008).

- *Nuevos sistemas biométricos.* Sistema de reconocimiento de iris basado en características de Gabor, desarrollado conjuntamente con Tome-Gonzalez (2008).

- *Nuevas aplicaciones biométricas.* Uso del reconocimiento de firma en dispositivos portátiles tipo Table PC y PDA (Alonso-Fernandez *et al.*, 2005a, 2006a; Martinez-Diaz *et al.*, 2007).

- *Métodos originales.* Esquema adaptativo de fusión multialgoritmo de huella basado en calidad (Fronthaler *et al.*, 2008). Mecanismo de normalización de score dependiente de usuario en función de la calidad (Alonso-Fernandez *et al.*, 2006b).

- *Nuevos datos biométricos.* Una nueva base de datos de firma dinámica de 53 sujetos capturada con Tablet PC (**?**) (Alonso-Fernandez *et al.*, 2005a). Una nueva base de datos incluyendo voz, iris, cara, firma, huella, mano y tecleo de 400 sujetos en 4 sesiones capturada en el marco del proyecto nacional BiosecurID (Galbally *et al.*, 2007).

- *Nuevos estudios experimentales.* Verificación multialgoritmo de huella y firma (Alonso-Fernandez *et al.*, 2008a, 2007d; Garcia-Salicetti *et al.*, 2007, 2008). Estudio de la capacidad discriminativa de medidas de calidad de huella (Alonso-Fernandez *et al.*, 2005b, 2007e, 2008). Estudio de ataques a sistemas de huella (Galbally-Herrero *et al.*, 2006; Martinez-Diaz *et al.*, 2006) e iris (Ruiz-Albacete *et al.*, 2008). Estudio de interoperabilidad y fusión de sensores de huella y firma (Alonso-Fernandez *et al.*, 2005c, 2006c). Estudio del efecto de la calidad en el rendimiento de los usuarios individuales en huella (Alonso-Fernandez *et al.*, 2006b).

- *Nuevas aplicaciones biométricas.* Uso de verificación de firma dinámica en Tablet PC y PDA (Alonso-Fernandez *et al.*, 2005a, 2006a; Martinez-Diaz *et al.*, 2007).

7.2 Medidas de calidad en sistemas biométricos

Hasta fechas recientes, no había consenso acerca de qué es calidad de una muestra biométrica. A grandes rasgos, podemos decir que una muestra es de buena calidad si es adecuada para el reconocimiento. Más formalmente (Benini and et al, 2006) se han establecido tres puntos de vista diferentes, mostrados en la Figura 2.1: *i*) *carácter*, referido a la calidad inherente al rasgo en términos de si es adecuado de por sí para el reconocimiento (por ejemplo, un dedo quemado no lo sería); *ii*) *fidelidad*, referido al grado de similitud entre la muestra capturada y el rasgo original, atribuible a las distintas fases de procesado del sistema; y *iii*) *utilidad*, referido al impacto de la muestra en el rendimiento del sistema. El *carácter* de la fuente y la *fidelity* de la muestra procesada contribuyen a la *utilidad* de dicha muestra. Generalmente se acepta que la *utilidad* es la propiedad mas importante, a la que deben orientarse las medidas de calidad , por tanto, una muestra a la que se la asigna una calidad alta necesariamente debería conducir a una mejor identificación. No obstante, hay que considerar que no todos los sistemas o algoritmos se comportan igual ni se ven afectados por los mismos factores, de modo que una medida de calidad suele estar ligada a un algoritmo o a un grupo de algoritmos particulares.

Existen múltiples factores que pueden afectar a la calidad, resumidos en la Figura 2.2. Distinguimos entre cuatro tipos principales:

- Factores ligados únicamente al usuario, entre los cuales tenemos los anatómicos y los de comportamiento (Tablas 2.2 y 2.3). Suelen ser los más difíciles de controlar y/o evitar (a veces incluso son inevitables).

- Factores ligados a la interacción usuario-sensor, entre los cuales se distinguen los de entorno y los de operación (Tablas 2.4 and 2.5). Son más fáciles de controlar que los anteriores, aunque siguen implicando al usuario y por ello no siempre es posible o recomendable. Podremos tener control sobre estos factores en tanto en cuanto controlemos el entorno o la operación de captura del rasgo biométrico.

- Factores ligados al sensor utilizado en la captura.

- Factores ligados al sistema de procesado y reconocimiento.

El primer tipo de factores mencionado tiene impacto en lo que hemos llamado *carácter* de una muestra biométrica, mientras que el resto afectan a la *fidelidad*.

Conocidos los factores que afectan a la calidad de señales biométricas, se definen una serie de medidas que podemos aplicar para asegurar una buena calidad de las mismas (las cuales se resumen en la Figura 2.3):

- Actuación en el punto de captura: supervisión, sensor adecuado, interacción adecuada del usuario, entorno apropiado, mantenimiento del puesto de captura, etc.

- Actuación en el propio sistema de reconocimiento: incluir algoritmos de tratamiento de calidad adecuados, incluir herramientas de monitorización de calidad, etc.

- Actuación mediante el propio algoritmo de medida de calidad: cálculo en tiempo real, fiabilidad, posibilidad de recaptura de muestras, etc.

En todo el proceso de aseguramiento de calidad es muy importante la adhesión a los estándares existentes, obteniendo así gran flexibilidad, modularidad y rápida adaptación a cambios tecnológicos y nuevos avances.

Para la evaluación de medidas de calidad, se han propuesto recientemente diferentes mecanismos para medir la *utilidad* (Grother and Tabassi, 2007) y la *fidelidad* (Youmaran and Adler, 2006) de las muestras. En esta Tesis, nos centraremos en la utilidad. El primer mecanismo consiste en dividir las muestras en L niveles de acuerdo con su calidad y calcular L curvas DET ordenadas. Otro mecanismo, el utilizado en esta Tesis, consiste en pintar las llamadas curvas de error-vs-rechazo. Esta curva modela el caso donde se rechazan las muestras de menor calidad con el objetivo de mejorar el rendimiento. Un buen algoritmo de calidad debería mejorar su rendimiento a medida que se rechazan las peores muestras.

Los roles de la calidad en sistemas biométricos son múltiples (Benini, 2007; Grother and Tabassi, 2007; Ko and Krishnan, 2004), los cuales se detallan en la Figura 2.6:

- Como mecanismo de recaptura hasta obtener una muestra que satisfaga una mínima calidad.
- Como mecanismo de invocación de intervención humana, en caso de que no sea posible obtener una muestra de un usuario con calidad suficiente.
- Para procesado, comparación de modelos y/o fusión de sistemas dependiente de calidad, modificando adecuadamente las etapas del sistema en función de la misma.
- Para actualización de las plantillas de registro de los usuarios con nuevas plantillas de mejor calidad.
- Como herramienta de monitorización y estadística para detectar fuentes de datos erróneos.

Por último, destacar los esfuerzos estandarizadores que se están llevando a cabo recientemente para la incorporación de medidas de calidad a las estructuras de datos biométricos existentes (Benini, 2007; Benini and et al, 2006).

7.3 Análisis de calidad en imágenes de huella

Este primer capítulo experimental se basa en las publicaciones Alonso-Fernandez *et al.* (2008a, 2007c, 2005b, 2008); Fierrez-Aguilar *et al.* (2005b).

El objetivo es comparar varias medidas de calidad representativas mediante el estudio de su correlación y de su utilidad. Se evalúa su impacto en el rendimiento de los dos algoritmos más utilizados en reconocimiento de huella: minucias y texturas.

Medidas de calidad en huella. La calidad en huella puede definirse como la claridad de sus crestas y valles, así como la "extractabilidad" de las características usadas para el reconocimiento (Chen *et al.*, 2005). En huellas de buena calidad, las crestas y los valles fluyen de modo suave, siguiendo una dirección que localmente se puede considerar constante (Hong *et al.*, 1998).

Son múltiples los factores que específicamente contribuyen a degradar la calidad de las huellas, dando lugar a múltiples perturbaciones (algunos ejemplos se muestran el la Figura 3.14): bajo solapamiento entre distintas adquisiciones, rotación, desplazamiento, huella incompleta, baja definición, ruido de capturas previas, distorsión, etc. Para detectar los distintos factores de baja calidad, los algoritmos existentes analizan

las siguientes propiedades de las huellas: direccionalidad o "fuerza" de las crestas, continuidad de las mismas, claridad, integridad de las estructura cresta-valle, o rendimiento estimado al usar dicha muestra. Para ello, se utilizan múltiples fuentes de información: ángulo local a partir del campo de orientación, filtros de Gabor, intensidad de gris de los píxeles, espectro de potencia, o clasificadores. El análisis de calidad puede ser local (dividiendo la imagen en bloques solapados o no), global (analizando la imagen en conjunto), o a partir de clasificadores.

Sistemas y base de datos utilizada. En el estudio de este capítulo se utiliza un comparador de minucias desarrollado por en NIST americano (Watson *et al.*, 2004), de libre obtención, y un comparador basado en texturas desarrollado por el Grupo de Reconocimiento Biométrico - ATVS (Fierrez-Aguilar *et al.*, 2005b). La base de datos utilizada es el corpus BioSec baseline (Fierrez *et al.*, 2007), que incluye 19,200 imagenes de huella de 200 individuos capturados en 2 sesiones y con 3 sensores de diferente tecnología, mostrados en la Figura 3.28: un sensor de tipo capacitivo, un sensor de tipo térmico y un sensor de tipo óptico. Estas tres tecnologías de sensores son las más utilizadas en la actualidad.

Resultados. Para los experimentos de este capítulo, se ha seleccionado un grupo de medidas de calidad representativo de las distintas fuentes de información mencionadas. En concreto, se ha elegido una medida que hace uso de información de dirección, otra de intensidad de gris, otra del espectro de potencia y otra basada en clasificadores.

Se ha observado que en general existe una correlación entre las medidas de calidad estudiadas (ver Figura 3.31), aunque se observan algunas diferencias en función del sensor, sugiriendo que su funcionamiento es diferente en cada uno de los mismos. En cuanto a la utilidad de las medidas (ver Figuras 3.32- 3.35, se observa que para el comparador basado en minucias, el mayor incremento en el rendimiento cuando se rechazan muestras de baja calidad se obtiene para el Falso Rechazo (Figura 3.34). Esto se debe a que se observa una clara correlación entre las medidas de similitud de usuarios genuinos y su calidad (Figura 3.32), no siendo así para las medidas de similitud de impostores. Por otro lado, para el comparador basado en texturas, la mayor mejora se observa en la Falsa Aceptación (Figura 3.35), debido a que en este caso la mayor correlación se observa entre las medidas de similitud de imposores y su calidad (Figura 3.33).

7.4 Análisis de calidad en imágenes de firma

Este segundo capítulo experimental se basa en las publicaciones Alonso-Fernandez *et al.* (2007a,b); Gilperez *et al.* (2008).

El objetivo es presentar nuevas medidas para la predicción del rendimiento de sistemas de verificación de firma *off-line*. La utilidad de las medidas propuestas se evalúa en tres algoritmos de reconocimiento, uno de los cuales basado en características locales de contorno es una contribución en esta Tesis.

Medidas de calidad en firma. Si bien en imágenes de huella podemos definir de modo objetivo la calidad a partir de la estructura de crestas, en rasgos de comportamiento tales como la firma resulta más complicado. Algunos estudios proponen le estabilidad o la complejidad como parámetros para medir la calidad (Allgrove and Fairhurst, 2000; Brault and Plamondon, 1993; Muller and Henniger, 2007). No obstante, estos son factores que dependen totalmente de cómo el usuario decide firmar, por lo que si rechazamos una firma en función de ellos, es posible que la siguiente vuelva a "sufrirlos". En este caso la estrategia deberá ser, una vez extraídos los parámetros de calidad, adaptar el sistema acorde a ellos.

En este capítulo se presentan varias medidas encaminadas a predecir el comportamiento de un sistema de firma a partir de imágenes *off-line*:

- Dos medidas, legibilidad y tipo de firma, que se extraen de modo manual (ver Figuras 4.7 y 4.8). El objetivo aquí es valorar si el hecho de que las firmas posean letras legibles, rúbricas sencillas o complejas, etc. puede afectar al rendimiento del sistema. El hecho de asignar estas medidas de modo manual es factible en un entorno de firma *off-line*, donde la captura se lleva a cabo con un escáner o una cámara.

- Una medida que calcula automáticamente el área de la imagen donde hay varios trazos cruzándose, y por tanto donde no existe una dirección o trazo predominante para el análisis (ver Figura 4.9). Esta medida podría considerarse como una medida de complejidad.

- Una medida que calcula la variabilidad de un conjunto dado de firmas, con el objetivo de medir su estabilidad.

- Tres medidas geométricas a partir de las cuales se calcula la varianza de la presión ejercida con el lápiz al firmar, la duración de la firma, y su área.

Sistemas y base de datos utilizada. En este capítulo se utilizan tres sistemas de verificación. El primero de ellos se basa en análisis global de la imagen y en un clasificador de mínima distancia (Fierrez-Aguilar *et al.*, 2004; Lee and Lizarraga, 1996). El segundo, se basa en análisis local de la imagen y en un comparador basado en Modelos Ocultos de Markov (Fierrez-Aguilar *et al.*, 2004; Justino *et al.*, 2001; Lee and Lizarraga, 1996). El tercero está basado en análisis local del contorno de la firma (Bulacu and Schomaker, 2007), desarrollado en el marco de esta Tesis conjuntamente con Gilperez *et al.* (2008).

La base de datos utilizada es un subcorpus de la base de datos bimodal MCYT (Ortega-Garcia *et al.*, 2003b), que incluye imágenes de huella dactilar y firma escrita de 330 individuos. La información dinámica de las firmas escritas fue capturada con una tableta digitalizadora Wacom Intuos A6 haciendo uso de un bolígrafo especial con tinta sobre papel común. Este procedimiento permitió capturar por un lado la información dinámica, en forma de trayectorias, presión y ángulos de inclinación del bolígrafo respecto al tiempo (ver Figura 4.1); y por el otro lado la información estática impresa en las hojas, que posteriormente fue digitalizada a 600 puntos por pulgada para un conjunto total de 2250 firmas de 75 individuos. Cada firma fue escrita en una rejilla de tamaño 3.75 cm $\times$ 1.75 cm (ancho $\times$ alto). En el conjunto de firmas digitalizadas, cada usuario posee 15 firmas auténticas y 15 falsificaciones realizadas por otros usuarios.

Resultados. De los resultados experimentales extraemos que con imitadores entrenados, se obtiene mejor rendimiento usando firmas legibles, a pesar de que cabría esperar que este tipo de firmas son más fáciles de imitar. En cuanto a la legibilidad para el caso de imitadores casuales, se obtiene un comportamiento diferente para cada comparador, mostrando una fuente útil de complementariedad entre ellos que puede ser explotada.

Otro resultado destacable en este apartado concerniente a la medida de variabilidad propuesta es que el rendimiento cae considerablemente con conjuntos de firmas muy variables, especialmente si se usan pocas firmas de entrenamiento.

Finalmente, para las medidas geométrica propuestas, algunas conclusiones son que: en general es mejor alta varianza en la presión ejercida con el lápiz al firmar, y que las firmas de mayor duración son por lo general más resistentes a imitadores entrenados.

7.5 Procesado y fusión multibiométrica dependiente de calidad

Este último capítulo experimental se basa en la publicación Alonso-Fernandez *et al.* (2008b).

El objetivo es analizar el efecto de combinar señales procedentes de distintos sensores biométricos para una misma modalidad. Se propone una arquitectura de procesado condicional donde la calidad se utiliza para conmutar entre diferentes etapas del sistema, así como para no incluir en la combinación señales que no cumplan con una mínima calidad. El sistema aquí descrito se utilizó para participar en la Evaluación Multimodal BioSecure (BMEC, 2007; Poh and Bourlai, 2007), con muy buenos resultados (segunda posición en términos de Tasa Media de Error Total entre trece participantes).

Calibración y fusión en sistemas biométricos. En el sistema propuesto, se hace uso de fusión basada en regresión logística lineal (Brummer *et al.*, 2007; Pigeon *et al.*, 2000), de manera que las medidas de similitud a la salida estén *calibradas*. Calibradas quiere decir que han sido convertidas al logaritmo del cociente de verosimilitudes (LLR), de tal modo que la medida representa un grado de apoyo con sentido probabilístico a las hipótesis de aceptación o rechazo del individuo. Así, se puede combinar de modo fácil y eficiente las medidas de similitud proporcionadas por diferentes fuentes.

Sistemas y base de datos utilizada. Como base de datos en este capítulo, se usa el conjunto de medidas de similitud empleado en la Evaluación Multimodal BioSecure, llevada a cabo en 2007 (BMEC, 2007; Poh and Bourlai, 2007). Las medidas de similitud que incluye proceden de comparaciones con imágenes de cara y de huella extraídas de la base de datos BioSecure, capturada en el marco de esta Tesis (Alonso-Fernandez *et al.*, 2008b). Las imágenes de cara se capturaron con dos cámaras de diferente resolución, y las de huella con un sensor óptico y uno térmico (los sensores junto con ejemplos de muestras capturadas se muestran en la Figura 5.1). Se considera también el caso de comparar imágenes de un sensor con imágenes capturadas con el otro. Junto con las medidas de similitud, se proporcionan una serie de medidas de calidad de las imágenes. Para las comparaciones, se utilizaron sistemas estándar de reconocimiento (Martinez and Kak, 2001; Watson *et al.*, 2004). Se consideran dos conjuntos de medidas de similitud diferentes, uno de desarrollo (proporcionado a los participantes antes de la evaluación) y uno de prueba (utilizado para la evaluación y hecho público tras la misma).

Estimación del sensor usando medidas de calidad. De acuerdo con el protocolo de la Evaluación Multimodal BioSecure, no se proporciona información referente al sensor utilizado en las capturas, por lo que es necesario estimarlo. Para ello, en el sistema propuesto, se hace uso de una función discriminante cuadrática con densidades normales multivariable (Duda *et al.*, 2004). Los parámetros que modelan las densidades son las medidas de calidad proporcionadas, o parámetros derivados directamente de ellas.

Se observa en los resultados la estimación del sensor de cara funciona correctamente en el conjunto de desarrollo, no confirmado en el conjunto de prueba, lo cual podría deberse al tamaño pequeño del conjunto de desarrollo proporcionado. Por otro lado, el sensor de huella no es posible estimarlo de modo fiable con este mecanismo en ninguno de los conjuntos de datos.

Interoperabilidad de sensores. Se estudia en este apartado la capacidad del sistema propuesto para combinar señales de diferentes fuentes biométricas. Para ello, se analizan las diferentes combinaciones disponibles del uso de sensores en cada modalidad (4 en total). Se compara asimismo con un conjunto de reglas sencillas de fusión. Los resultados de este estudio se muestran en la Tabla 5.6 y en la Figura 5.6. Se observa que cuando se comparan imágenes de un sensor con imágenes capturadas con el otro, el sistema propuesto funciona considerablemente mejor que las reglas sencillas de fusión. Asimismo, el rendimiento global del sistema también es sustancialmente mejor.

Fusión dependiente de calidad. Por último, en este apartado, se analiza el caso de rechazar muestras de baja calidad, de manera que en la fusión se consideren solamente las de buena calidad disponibles. Los resultados de este estudio se muestran en la Tabla 5.8 y en las Figuras 5.10 y 5.11.

Se observa que el rendimiento del sistema mejora considerablemente al incorporar esta política de rechazo (hasta un 24%). Una ventaja añadida muy importante es que en un número considerable de accesos donde uno de los rasgos (huella o cara) es de baja calidad, aún es posible utilizar el otro.

7.6 Líneas de Trabajo Futuro

Se proponen las siguientes líneas de trabajo futuro relacionadas con el trabajo desarrollado en esta Tesis:

- **Aplicación del estudio realizado a otros rasgos biométricos.** Se han

propuesto en la literatura medidas de calidad para otros rasgos aparte de los considerados en esta Tesis: iris (Chen *et al.*, 2006a; Kalka *et al.*, 2005), voz (Garcia-Romero *et al.*, 2006) y cara (Kryszczuk and Drygajlo, 2007). Una vez obtenido un consenso acerca de qué es la calidad y cómo evaluarla (Benini and et al, 2006; BQW, 2007; Youmaran and Adler, 2006), un trabajo futuro es llevarlo a cabo para todos estos rasgos.

- **Combinación de varias medidas de calidad**, una vez que se ha observado que algunas se comportan de manera diferente en función de varios factores, explotando dichas diferencias, e.g. Fierrez-Aguilar *et al.* (2006); Fronthaler *et al.* (2008).

- **Propuesta de nuevas medidas de calidad** que complementen a las existentes o en rasgos donde apenas se ha trabajado este tema.

- **Incorporación de medidas de calidad en sistemas biométricos.** Análisis del ajuste de etapas del sistema (Chen *et al.*, 2005; Hong *et al.*, 1998; Shi *et al.*, 2004) o de mecanismos de fusión como el propuesto aquí (Baker and Maurer, 2005; Chan *et al.*, 2006; Fierrez-Aguilar *et al.*, 2006; Nandakumar *et al.*, 2006).

- **Efecto de la calidad en nuevos escenarios**, como resultado de nuevas necesidades que se van planteando con el desarrollo de la biometría: sustitución de sensores, comparación de muestras procedentes de distintas fuentes, reconocimiento con sensores móviles personales, etc.

- **Análisis de calidad desde el punto de vista de teoría de la información.** Existen algunos esfuerzos encaminados a relacionar la calidad de muestras biométricas con la cantidad de información discriminativa contenida en la misma (Daugman, 2003; Kholmatov and Yanikoglu, 2008; Youmaran and Adler, 2006), la cual constituye un área interesante de trabajo futuro.

- **Efecto del paso del tiempo** en la calidad de las señales capturadas así como desarrollar mecanismos de **selección y actualización de plantillas** siguiendo criterios de calidad. Algunos trabajos iniciales son Ko and Krishnan (2004); Uludag *et al.* (2004).

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