ASSESSMENT OF GAIT RECOGNITION BASED ON THE LOWER PART OF THE HUMAN BODY

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ABSTRACT

This paper is focused on the assessment of gait recognition on a constrained scenario, where limited information can be extracted from the gait image sequences. In particular we are interested in assessing the performance of gait images when only the lower part of the body is acquired by the camera and just half of a gait cycle is available (SFootBD database). Thus, various state-of-the-art feature approaches have been followed and applied to the data. A comparison with a standard and ideal gait database (USF database) is also carried out using similar experimental protocols. Results show that good recognition performance can be achieved using such limited data information for gait biometric (around 85% of rank 5 identification rate and 8.6% of EER). The comparison with a standard database shows that different feature approaches perform differently for each database, achieving best individual results with MPCA and EGEI methods for the SFootBD and the USF database respectively.

Index Terms— Biometrics, gait recognition, surveillance

1. INTRODUCTION

Surveillance of public spaces is growing at an unprecedented pace in response to crime and global terrorism. For example, currently, in the UK there are reportedly more cameras per person than in any other country in the world [1]. Due to the computational improvement of the current technologies and the increase of this type of devices during these last few years in certain open areas or even closed places, the deployment of non-invasive biometric technologies becomes important for the development of automated visual surveillance systems as well as for forensic investigations. The biometric technologies more suitable for these scenarios are face and gait recognition. Others such as iris or even ear would work under more controlled conditions [2].

This paper is focused on gait recognition under limited data conditions. Gait is a relatively new biometric which utilizes the manner of walking to recognize an individual [3]. Compared to biometrics such as the iris or fingerprint recognition, this technique presents two main advantages: the recognition is performed at a distance and there is no need to cooperation from the users [4]. Both of these characteristics are also present in the case of face recognition, but gait has also the advantage of being able to work with low image resolution. On the other hand, the case of gait recognition is a very difficult task due to the huge amount of variability factors that can affect the gait recordings in real scenarios, such as persons walking to differ-

ent directions, occlusions due to other people or clothing, different lighting conditions, etc.

In this paper six state-of-the-art feature extraction approaches for gait recognition have been followed to compare their recognition performances using a limited gait database which contains only the lower part of the body, SFootBD database (Swansea University, UK). Then, these results were compared with a second and more ideal database used by many researchers, the USF database (University of South Florida, USA), where the gait images represent the whole body of the person. Finally, the best three individual feature approaches, GEI, EGEI and MPCA, were fused to increase the discrimination power of the systems obtaining an average rank 5 identification rate of 85% and 97% for the two gait databases respectively. This shows that even with limited gait information the results are very promising.

The remainder of the paper is organized as follows. Section 2 describes the two databases used to evaluate the performance. Section 3 describes the different feature approaches followed. Section 4 reports the experimental work and Section 5 draws the final conclusions.

2. GAIT DATABASES

Due to the importance of databases which are essential tools to evaluate the biometric recognition systems, in this paper we have carried out experimental work on two gait databases whose properties differ from one another allowing a comparative analysis of the results to be obtained.

The first database used is the SFootBD [5]. This database is comprised of four biometric modes: footstep, gait, face and speech, using only the gait mode in this case. This database was captured without supervision, therefore obtaining more realistic biometric samples (example shown in Figure 1(top)). This gait dataset is comprised of 130 users and 9893 gait image sequences but only having information for half of a gait cycle (left-right) and the lower half of the human body. The SFootBD is a much more limited database compared to the next database in terms of the amount of available information. Therefore, this database can be seen as a more realistic scenario for a gait application, e.g. a forensic case.

On the other hand, the second gait database used in this paper is the USF database [6]. This database contains sequences of gait images from 122 users, 1870 with a half gait cycle (right-left) and the whole body shape. This database is comprised of 12 probes and 1 gallery with the persons walking under different conditions. In this paper only a subset of probe A was evaluated which is comprised of 71 users and 1458 gait sequences. This
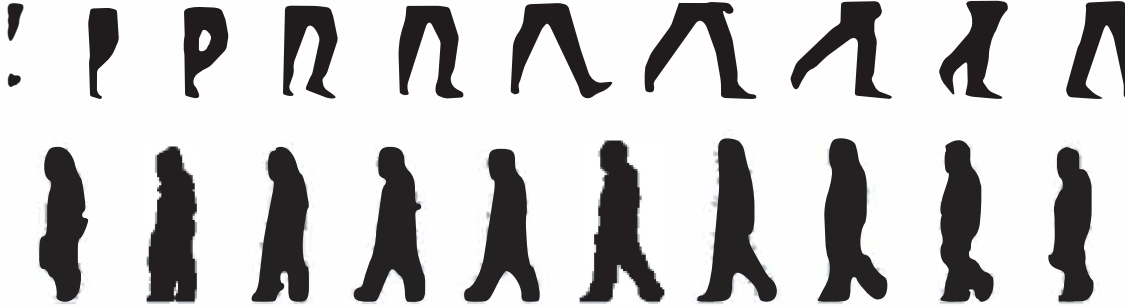
Figure 1: Examples of gait sequences of the two databases considered in this paper. SFootBD database on the top row and USF database on the bottom row.

dataset contains sequences with a certain type of shoe, walking over grass. Figure 1(bottom) shows an example gait sequence from this database.

Regarding image alignment for the different feature approaches, the USF database was aligned using the position of the head. For the case of the SFootBD, the images were aligned to a central position using the position of the waist.

3. FEATURE EXTRACTION

During the last few years, many algorithms have been developed to extract the discriminative information for gait recognition. In general, there are two main feature approaches: appearance-based and model-based [7]. Appearance-based approaches are focused on identifying persons using their silhouette, shape, geometrical measures, etc. On the other hand, model-based approaches are focused on identifying persons using the kinematic characteristics of the walking manner. The majority of the state-of-the-art approaches are appearance-based.

In this paper, an analysis of the state-of-the-art was conducted selecting six feature approaches, which were implemented and tested with different conditions. These algorithms are: Active Energy Image (AEI) [8], Multilinear Principal Component Analysis (MPCA) [9], Gait Flow Image (GFI) [3], Gait Energy Image (GEI) [10], Motion Silhouette Contour Template (MSCT) [3] and Enhance Gait Energy Image (EGEI) [11].

Results achieved for these six feature approaches are shown in Section 4. The three approaches obtaining best individual performance were: GEI, EGEI and MPA and are described in more detail next.

The first feature approach considered, one of the most popular to date, is called Gait Energy Image (GEI) [10]. In this case, a single image is obtained by averaging the binary silhouettes of a pedestrian over one gait cycle. Therefore, this method is an appearance-based approach. As Figure 2 shows, the image obtained represents by means of the intensity of each pixel, the frequency (energy) of body occurrence at the position of each pixel for a complete walking cycle. This algorithm was developed in 2006 [10] and although it is not as new as the other ones, the good results reflect the effectiveness of it. This method allows an easy implementation and reduces the time, storage and computational costs but it is heavily affected by factors such as the clothing and persons carrying objects.

The second feature approach considered, called Enhanced Gait Energy Image (EGEI) [11], is based on enhancing the previous GEI method. For this, an averaged GEI image represent-
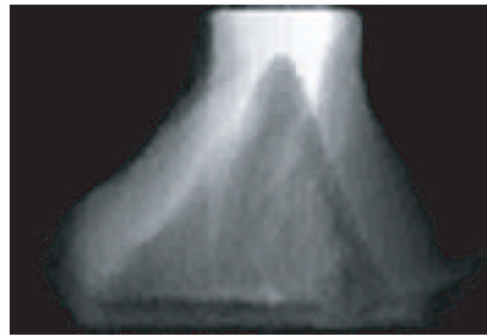

Figure 2: Example of Gait Energy Image (GEI) for SFootBD database.

ing each user class is used to construct a dynamic weight mask (DWM) by variance analysis. This mask is applied to the original GEI images to obtain the EGEI images. Finally, this method uses a Gabor filter bank in order to emphasize the most discriminative parts of the body image as shown in Figure 3. This technique is computationally more expensive than the GEI method, but allows to improve the results in cases of having much noisier environments.
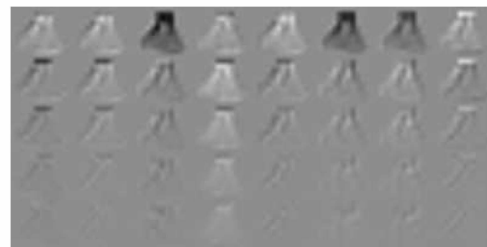

Figure 3: Example of Enhanced Gait Energy Image (EGEI) for SFootBD database.

The third approach considered in this paper, called Multilinear Principal Component Analysis (MPCA) [9], is an extension of the popular algorithm PCA. As can be seen in Figure 4, the data is arranged in several dimensions to form a tensor. In our case, four dimension tensors are used: two spatial dimensions of the images, a time dimension and another dimension for the different data examples. Once the tensor is ready, MPCA can drastically reduce the high dimensionality of the original

data into low dimension feature vectors which are used in the classification stage.
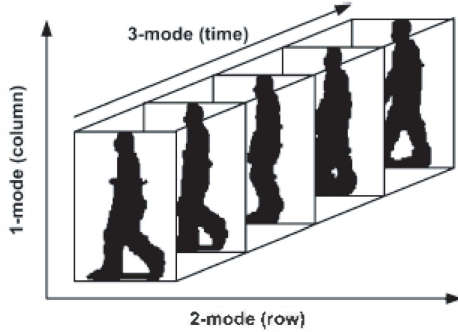

Figure 4: Example of Multilinear Principal Component Analysis (MPCA), extracted from [9]

4. EXPERIMENTAL WORK

4.1. Experimental Protocol

To carry out the experimental work to study the discriminative power of different gait recognition systems using limited data, both databases considered were divided into training and test sets. In both cases, the number of gait sequences per user in the training set was set to 10, being 59 and 71 the number of users present in the training set for the SFootBD and USF databases respectively. It is worth mentioning that SFootBD is comprised of 130 users which are all present in the test set, so in this configuration data from 71 users comprises a set of impostor tests, which makes this an open-set scenario, more challenging than the case of the USF database.

Reduction of feature dimensionality was performed over the six feature approaches considered. Firstly, principal component analysis (PCA) was applied, analysing different number of principal components (PC). The case of MPCA did not require to use PCA. Later, linear discriminant analysis (LDA) was used to further extract the most relevant information. Finally, support vector machine (SVM) with a RBF kernel was employed as the classifier to obtain the recognition results.

Experiments are carried out for both identification (1 vs. all) and verification (1 vs. 1) working modes. In the first case, top rank identification performance is obtained using cumulative match characteristic (CMC) curves, and for the case of verification the equal error rate (EER) is given as a performance measure.

4.2. Evaluation of Results

The first experiment was set to compare the individual performance of the six feature approaches considered (AEI, MSCT, GFI, GEI, EGEI and MPCA) over the two gait databases. Results are shown in Table 1, and give the optimum number of PCA components found for each feature approach and for each database. It is interesting to analyse that the number of PCA components is smaller in all cases but one (MPCA) for the SFootBD compared to the USF database, most likely for the lower amount of information contained (approximately a quarter of the information as only half of the gait cycle is visible for the lower part of the body).

As can be seen in Table 1, the GEI, EGEI and MPCA approaches obtained much better individual performance compared to AEI, MSCT, GFI, for both identification (rank 1 and 5) and verification (EER) experiments.

The second experiment was the fusion of the best three feature approaches in order to further improve the recognition performance of the system for a limited gait database. The fusion was carried out at the score-level using a simple product rule.
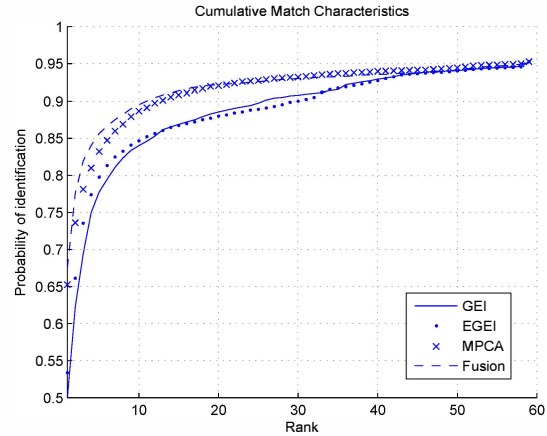
(a) SFootBD
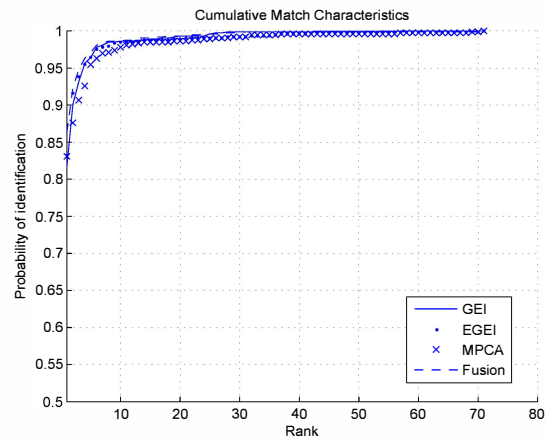
(b) USF DB

Figure 5: CMC Curves for both SFootBD and USF databases comparing the three best feature approaches and their fusion at the score-level.

Figure 5 shows four CMC curves for the three selected feature approaches and the fusion for the SFootBD and USF databases respectively. For both databases, the CMC curves improve fast having a knee point around rank 10 for the SFootBD and around rank 6 for the USF database, saturating after these values. The saturation is much faster for the USF database compared to the SFootBD.

As can see in Figure 5(a), the approach which provides better results for the case of the SFootBD is MPCA (83.21% of rank 5 identification rate). The fusion of the three approaches achieved also a small improvement in terms of identification rate (85.64% for rank 5) and EER (8.61%). Table 1 shows an overview of the main results achieved. In contrast to these results Figure 5(b) shows results for the case of the USF database where the three feature approaches provide very similar identi-

		SFootBD				USF DB			
		PCs	Rank1	Rank5	EER	PCs	Rank1	Rank5	EER
a	AEI	100	41.56	69.08	16.4219	150	65.06	85.56	9.2160
b	MSCT	50	46.89	75.11	13.5498	150	67.26	88.31	7.9780
c	GFI	100	45.10	72.58	14.3508	150	65.47	85.97	9.6286
d	GEI	100	49.98	77.77	12.71	100	81.71	96.42	3.99
e	EGEI	50	53.37	79.75	11.94	100	83.22	96.42	4.12
f	MPCA	300	65.26	83.21	9.84	200	83.08	95.46	5.36
	FUSION (d,e,f)	-	67.50	85.64	8.60	-	86.38	97.11	3.58

Table 1: Results achieved for both SFootBD and USF databases, with rank 1 and rank 5 identification rate and EER both in %. Also, number of principal components (PC) is given for each feature approach.

fication rates, achieving a slightly better performance for EGEI (96.42% of rank 5 identification rate). The fusion of the three approaches achieves a small improvement obtaining 97.11% rank 5 identification rate and 3.58% EER. In all cases results achieved for USF are much better than those for SFootBD due to the limited data information. It is interesting to note a previous study by Veres *et. al.* [12] that analysed the discriminative power of the different parts of the silhouette for gait recognition, concluding that the most static parts (upper part of the body and head) where the most discriminative. In this paper, we can affirm that the lower part of the silhouette, which correspond to the most dynamic part, also contains discriminative information which can be used for person recognition.

Another interesting result is that CMC curves shown in Figure 5(a) do not achieve a 100% of identification rate for the SFootBD. This is because the case of the SFootBD is a more realistic scenario (open-set identification) where there are test trials (from 71 persons in this case) that do not belong to any of the users in the training set.

5. CONCLUSIONS

In this paper, an evaluation of gait recognition systems over data with limited information (SFootBD) has been carried out. For this, six state-of-the-art feature approaches (AEI, MSCT, GFI, GEI, EGEI and MPCA) have been applied to the gait data. Similar experimental work has been followed over an ideal gait database (USF database) in order to compare results. In both cases best individual performance has been achieved for GEI, EGEI and MPCA feature approaches and a fusion of the three has been carried out at the score-level. As expected, there are significant differences in the performance of these approaches over the two databases, but more than acceptable results (85.64% of rank 5 identification rate and 8.60% of EER) have been achieved over the limited gait database, showing that using only the lower part of the body provides significant discriminative information for person recognition.

6. ACKNOWLEDGEMENTS

7. REFERENCES

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