Modeling the Complexity of Biomechanical Tasks using the Lognormality Principle: Applications to Signature Recognition and Touch-Screen Children Detection

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***Abstract*—This paper focuses on modeling the complexity of biomechanical tasks through the usage of the Sigma LogNormal model of the Kinematic Theory of rapid human movements. The Sigma LogNormal model has been used for several applications, in particular related to modeling and generating synthetic handwritten signatures in order to improve the performance of automatic verification systems. In this paper we report experimental work for the usage of the Sigma LogNormal model to predict the complexity of biomechanical tasks on two case studies: 1) on-line signature recognition in order to generate user-based complexity groups and develop specific verification systems for each of them, and 2) detection of age groups (children from adults) using touch screen patterns. The results achieved show the benefits of using the Sigma LogNormal model for modeling the complexity of biomechanical tasks in the two case studies considered.**

***Index Terms*—On-line signature verification, user profiling, neuromotor model, signature complexity, age prediction, touch dynamics, biometrics**

I. Introduction

On-line signature verification and other handwritten tasks (drawings, touch patterns, etc.) are experiencing a high development recently due to the technological evolution of digitizing devices, including smartphones and tablets. Such handwritten data can be applied to many applications in different sectors such as security, e-government, healthcare, education, user profiling, advertising or banking [1], [2].

This work has been supported by project TEC2015-70627-R MINECO/FEDER and by UAM-CecaBank Project. Ruben Tolosana is supported by a FPU Fellowship from Spanish MECD, and Javier Hernandez by a FPI Fellowship from UAM.

This paper focuses on modeling the complexity of handwritten information, which can be a very important factor in different applications related to handwriting. We propose to model the complexity of handwritten tasks through the usage of the Sigma LogNormal model of the Kinematic Theory of rapid human movements [3]. The Sigma LogNormal model has been used in the past for several applications. One of the most successful ones has been the synthetic generation of handwriting, in particular signatures (two examples in [4] and [5]). This model has recently been used in [6] and [7] not to generate synthetic signature samples, but to improve the performance of traditional signature verification systems. In [6] the authors proposed a skilled forgery detector using some features extracted from the Sigma LogNormal model whereas in [7], a new set of features based on the Sigma LogNormal model was proposed achieving very good performance.

In this paper we report experimental work for the usage of the Sigma LogNormal model to predict the complexity of biomechanical tasks on two case studies: 1) The first one describes its application to on-line signatures in order to generate user-based complexity groups (as there are users with very complex signatures and other with very simple ones). Then, a specific signature verification system is developed for each complexity group achieving very significant improvements of verification performance [8]. 2) On the other hand, the second one describes its application to detect age groups (children from adults) in touch dynamic tasks performed on smartphones or tablets [9], as the difference between adults and children is mainly caused by the different maturity of their anatomy and

TABLE I
SIGMA LOGNORMAL PARAMETERS DESCRIPTION

Parameter	Description
D_i	Input pulse: covered distance when executed isolated.
t_{0i}	Initialization time. Displacement in the time axis.
μ_i	Logtemporal delay.
σ_i	Impulse response time of the neuromotor system.
θ_{si}	Initial angular position of the stroke.
θ_{ei}	Final angular position of the stroke.

neuromotor system. These are less mature in children, so they have worse manual dexterity causing rougher movements [10] [3].

The remainder of the paper is organized as follows. Sec. II describes the Sigma LogNormal model, used in this work to model the complexity of handwritten tasks. Sect. III describes the first case study focused on modeling the complexity of on-line signatures and its experimental results. Sect. IV describes the second case study focused on modeling the complexity of touch dynamic information in order to detect age groups and its experimental results. Finally, Sec. V draws the final conclusions and points out some lines for future work.

II. THE SIGMA LOGNORMAL MODEL

Many models have been proposed to analyze human movement patterns in general and handwriting in particular. These models allow the analysis of features related to motor control processes and the neuromuscular response, providing complementary features to the traditional *X* and *Y* coordinates related to handwriting tasks. One of the most well known writing generation models is the Sigma LogNormal model [3] [11].

The Sigma LogNormal model states that the velocity profile of human hand movements can be decomposed into strokes. Moreover, the velocity of each of these strokes, i, can be described with a speed signal $v_i(t)$ that has a lognormal shape:

$$|v_i(t)| = \frac{D_i}{\sqrt{2\pi\sigma_i(t - t_{0i})}} \exp\left(-\frac{(\ln(t - t_{0i}) - \mu_i)^2}{2\sigma_i^2}\right) \quad (1)$$

where each of the parameters are described in Table I. The complete velocity profile is modelled as a sum of the different individual stroke velocity profiles as:

$$v_r(t) = \sum_{i=1}^{N} v_i(t) \quad (2)$$

where *N* is the number of lognormals of the entire movement. A complex action, like a handwritten signature or touch task, is a summation of these lognormals, each one characterized by different values for the six parameters in Table I. Fig. 1 shows an example of the lognormal velocity profiles extracted for each stroke of one signature.

III. CASE STUDY 1: ON-LINE SIGNATURE COMPLEXITY

Signature verification systems have been shown to be highly sensitive to signature complexity [12]. In [13], Alonso-Fernandez *et al.* evaluated the effect of the complexity and

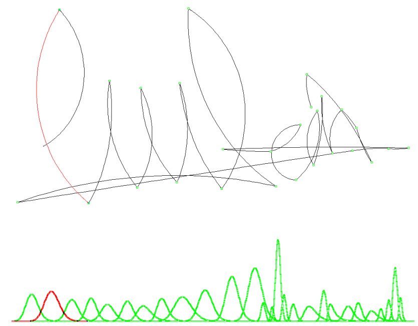

Fig. 1. Trace and velocity profile of one reconstructed on-line signature using the Sigma LogNormal model. A single stroke of the signature and its corresponding lognormal profile are highlighted in red colour. Individual strokes are segmented within the LogNormal algorithm [3].

legibility of the signatures for off-line signature verification (i.e. signatures with no available dynamic information) pointing out the differences in performance for several matchers. Signature complexity has also been associated to the concept of entropy, defining entropy as the inherent information content of biometric samples [14], [15]. In [16] a "personal entropy" measure based on Hidden Markov Models (HMM) was proposed in order to analyse the complexity and variability of on-line signatures regarding three different levels of entropy. In addition, the same authors have recently proposed in [17] a new metric known as "relative entropy" for classifying users into animal groups where skilled forgeries are also considered. Despite all the studies performed in the on-line signature trait, none of them have exploited, as far as we are aware, the concept of complexity in order to develop more robust and accurate on-line signature verification systems.

A. Proposed System

Based on the parameters of the Sigma Lognormal model, we propose to use the number of lognormals (N) that models each signature as a measure of the complexity level of the signature. Once this parameter is extracted for all available genuine signatures of the enrolment phase, the user is classified into a complexity level using the majority voting algorithm (low, medium and high complexity levels). Only genuine signatures are considered in our proposed approach for measuring the complexity level. The advantage of this approach is that the signature complexity detector can be performed off-line thereby avoiding time consuming delays and making it feasible to apply in real time scenarios.

Then, after having classified a given user into a complexity group, a specific on-line signature verification module based on time functions (a.k.a. local system) [18] has been adapted to each signature complexity level. For each signature acquired, signals related to *X* and *Y* pen coordinates are used to extract a set of 23 time functions, similar to [19]. The most discriminative and robust time functions of each complexity level are selected using the Sequential Forward Feature Selection algorithm (SFFS) enhancing the signature verification system in terms of EER. A DTW algorithm [20] is used to compute the similarity between the time functions from the input and training signatures.

B. Database and Experimental Protocol

In this case, BiosecurID database [21] is considered. Signatures were acquired from a total of 400 users using a Wacom Intuos 3 pen tablet with a resolution of 5080 dpi and 1024 pressure levels. The database comprises 16 genuine signatures and 12 skilled forgeries per user, captured in 4 separate acquisition sessions. Each session was captured leaving a two month interval between them, in a controlled and supervised office-like scenario. Signatures were acquired using a pen stylus. The available information within each signature is: X and Y pen coordinates and pressure. In addition, pen-up trajectories are available.

The experimental protocol has been designed to allow the study of different signature complexity levels in the system performance. Two main experiments are carried out: 1) evaluation of the signature complexity detector proposed in this work in order to classify users into different complexity levels, and 2) evaluation of the proposed approach based on a separate on-line signature verification system adapted to each signature complexity level.

For the first experiment, our proposed signature complexity detector is analyzed using all available users from BiosecurID. For the second experiment, the BiosecurID database is split into development dataset (40% of the users) and evaluation dataset (the remaining 60% of the users). The development dataset is considered in order to select the most discriminative and robust time functions for each signature complexity level using the SFFS algorithm whereas the evaluation dataset is considered for the evaluation of the proposed system. Both skilled and random forgeries are considered using the 4 signatures from the enrolment session as reference signatures and the remaining 12 genuine signature and 12 skilled forgeries signature as the test. The final score is obtained after performing the average score of the four one-to-one comparisons.

C. Results

The first experiment was designed to evaluate the proposed approach for signature complexity detection. For this, the signature complexity detector was performed in two different steps. First, each user of the BiosecurID database was manually labelled in a signature complexity level (low, medium, high). This process was carried out seeing the image of just one genuine signature per user and it was performed by two annotators and two times each in order to keep consistency on the results. Three different complexity levels were considered based on previous works [17]. Users with signatures longer in writing time and with an appearance more similar to handwriting were labelled as high-complexity users whereas those users with signatures shorter in time and with generally simple flourish with no legible information were labelled as low-complexity users. This first stage served as a ground truth. Following this stage, the Sigma LogNormal parameter N was extracted for each available genuine signature of the BiosecurID database (i.e. a total of $400 \times 16 = 6400$ genuine signatures). Then, we represented for each complexity level their corresponding distribution of lognormals according to the ground truth performed during the first stage. Fig. 2 shows the distributions of the number of lognormals obtained for each complexity level using all genuine signatures of the BiosecurID database. The three proposed complexity-dependent decision thresholds are highlighted by black dashed lines and were selected in order to minimize the number of misclassifications between different signature complexity levels. Signatures with lognormal values equal or less than 17 are classified as low-complexity signatures whereas those signatures with more than 27 lognormals are classified into the high-complexity group. Otherwise, signatures are categorized into medium-complexity level. Fig. 3 shows some of the signatures classified into each complexity level.

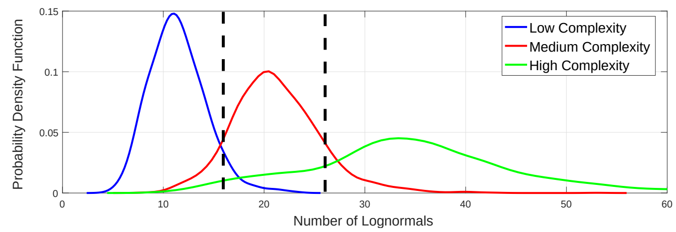

Fig. 2. Probability density function of the number of lognormals for each complexity level using all genuine signatures of the BiosecurID database. The three proposed complexity-dependent decision thresholds are highlighted by black dashed lines.

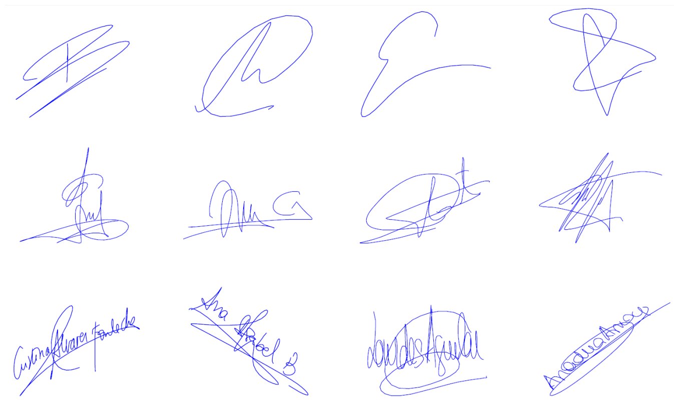

Fig. 3. Signatures categorized for each complexity level using our proposed signature complexity detector. From top to bottom: low, medium and high complexity.

We now analyse each resulting complexity level following the same procedure proposed in [17]: analysing the system performance for different complexity groups considering only X and Y pen coordinates. It is important to remark that each user is classified into a complexity level applying the majority voting algorithm to all available enrolment signatures of the user. Table II shows the system performance for each complexity level in terms of EER(%). The results show different system performance regarding the signature complexity level. Users with a high complexity level have an absolute improvement

TABLE II

EXPERIMENT 1: SYSTEM PERFORMANCE RESULTS (EER IN %) OF THE BIOSECURID DATABASE OF EACH PERSONAL COMPLEXITY LEVEL.

	Low C.	Medium C.	High C
Skilled forgeries	22.2	21.7	17.9
Random forgeries	3.6	2.4	2.6

of 4.3% compared to users categorized into a low complexity level for skilled forgeries.

Then, the second part of the experimental work was focused on developing a specific verification system for each group of signature complexity. For this, the SFFS algorithm was applied to the development dataset in order to find the most discriminative time functions for each complexity group. Then, the evaluation of the proposed system was compared to a baseline system based on DTW and the same system (same time functions) for all complexity groups, similar to the baseline system presented in [6].

Table III shows the evaluation results achieved considering our proposed approach based on personal entropy on-line signature verification systems. Analysing the results obtained, our Proposed Systems achieve an average absolute improvement of 2.5% EER compared to the Baseline System for the case of skilled forgeries. It is important to note that for the most challenging users (users with high personal entropy level), our proposed approach achieves an absolute improvement of 3.7% EER compared to the Baseline System. Analysing the results obtained for the random forgery cases, our Proposed Systems also achieves improvements for all personal entropy levels. For this case, the improvement has been lower than for skilled forgery cases due to its low values and the way that the SFFS algorithm was applied during the training of the systems (focused on skilled forgery cases). Results obtained after applying our proposed approach based on personal entropy on-line signature verification systems outperform the results of the state-of-the-art for the BiosecurID database. In [6], the authors achieved an absolute improvement of 1.0% EER for skilled forgery cases whereas our proposed approach achieves an average absolute improvement of 2.5% EER compared to the same Baseline System.

IV. CASE STUDY 2: PREDICTING AGE GROUPS FROM TOUCH PATTERNS

Age groups prediction based on handwritten touch patterns acquired from touchscreen devices such as smartphones or tables is a recent and important challenge. Touchscreen panels have changed the way users interact with new devices. The touchscreen enables an intuitive experience of use that allows a direct interaction with what is being displayed. In the last years there has been a huge spread of the use of this kind of devices by young children. The study in [22] reveals that 97% of US children under the age of four use mobile devices, regardless of family income. The age is a key attribute in user profiling with direct application on several automatic systems (e.g. parental control, recommender systems, advertising, etc.).

In this case study we propose the use of the Sigma LogNormal model to detect age groups as simple application of the model to drag and drop touch tasks showed large differences between adults and children velocity profiles. In Figure 4, an example of these types of profiles is presented, consisting in performing a drag and drop task in both cases. A visual comparison between children and adults velocity profiles shows that children's signals are usually composed by a higher number of strokes than the adults' ones, and therefore have a higher degree of complexity.

Moreover, there are previous studies like [23], which have proved that the Sigma LogNormal model can be used to characterize children handwriting. They conclude that there are two main groups of children separable by looking at their learning stage. Children's neuromotor skills become more similar to the adults' skills when they grow up, namely, when they finish their preoperational stage. At age 10 children know how to activate each little muscle properly to produce determinate fine movements [24]. As they are based on the same neuromotor skills, the principles applied to handwriting models can be also used to model touchscreen patterns.

A. Proposed System

In this case, a more complex system was developed compared to Case Study 1 in order to predict age groups from drag and drop touch tasks, as the main focus here was to optimize the final classification result.

The parameters of the Sigma LogNormal model (as described in Sect. II) were used to calculate 18 different features per lognormal as described in [25]. These features can be classified into two groups: space-based and time-based. Space-based features are those that give information about the spatial distribution of the strokes, such as D_i, μ_i, σ_i, and other features based in θ_{si} and θ_{ei} (see Table I). Time based features are composed by the values of speed at some relevant points of the strokes like their maximum or inflexion points; and the time-offsets between those points. The task time and the number of lognormals in each task have been added as additional features.

It is worth noting that the lognormals with amplitude value lower than a threshold were discarded. Then, the 18 features from [25] are computed for each stroke, and each parameter is averaged across strokes. The 18 averaged parameters are augmented with the task time and the number of strokes to generate the final feature vector of size 20.

As a classifier we use a SVM (Support Vector Machine) with a RBF (Radial Basis Function) kernel because of its good general performance in binary classification tasks and the few number of parameters to configure.

B. Database and Experimental Protocol

The database used is publicly available and was presented in [24]. It is comprised with data from touchscreen activity of both children and adults performing predesigned tasks in an ad-hoc app. In the present work, we have used the data from singletouch and multitouch drag and drop activities. Drag and

TABLE III
EXPERIMENT 2: SYSTEM PERFORMANCE RESULTS (EER IN %) ON THE EVALUATION DATASET FOR EACH SIGNATURE COMPLEXITY LEVEL.

	Low C.		Medium C.		High C.	
	Baseline	Proposed	Baseline	Proposed	Baseline	Proposed
Skilled forgeries	13.8	10.1	7.5	5.2	6.2	4.6
Random forgeries	1.5	1.3	0.7	0.5	0.9	0.9

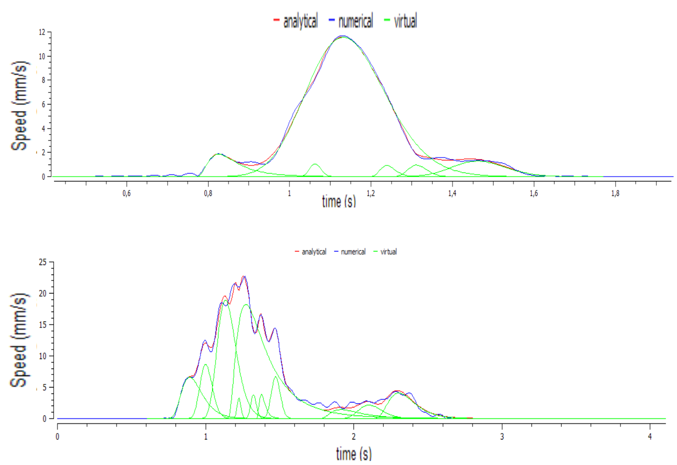

Fig. 4. Comparison between Sigma LogNormal speed profiles for (a) an adult and (b) a child following the same task.

drop activities consist of picking one object on the device screen and moving it to a target area. Multidevice information is available as the users have completed the tasks both in a smartphone and in a tablet. Both single-sensor and cross-sensor tasks are analyzed.

The dataset is composed by 89 children between 3 and 6 years old and 30 young adults under 25 years old. The mean age of the children is 4.6 years. The total number of drag and drop tasks is 2912 for children and 1157 for adults (see [24] for more details).

As the experimental protocol, the database was divided randomly into training (60%) and testing (40%). The random selection was repeated 50 times and the final performance is presented in terms of averaged correct classification accuracy.

C. Results

Table IV shows the accuracies obtained according to the different scenarios. They are presented in terms of correct classification accuracy (percentage of samples from both classes correctly classified).

The mean value of accuracy having into account all the evaluated scenarios is 92.8%. The classification rates are over 96% in a single-sensor setting and over 95% in a cross-sensor scenario. The best results are obtained with tablets as sensors, while using smartphone's data slightly degrades the results.

Compared with [26] where they get an accuracy rate of 86.5% using one tap task for classification and with a single-sensor aproximation (using smartphone's data), our system performs better, getting a 93.6% of accuracy using only data from smartphones, and over 96% using data from tablets. Another conclusion that can be extracted of Table IV is that the data obtained from multitouch tasks get worse results than the singletouch cases. The best multitouch scenario is obtained using tablet's data for both training and testing, with a 94.6% of accuracy, compared with its singletouch counterpart that gets a 96.3%. This may be caused by the less developed control of the left hand by right-handed people and vice versa. The main reason for using the Sigma LogNormal model is that adults have a better control of fine movements than children, what is translated to different values for the model parameters [24].

The cross-sensor scenarios get results not too far from the single-sensor scenarios. The results obtained using smartphone singletouch data for training, and tablet singletouch data for testing (95.9% of accuracy) are quite similar to those obtained using only tablet singletouch data (96.3% of accuracy). This fact makes this type of systems very suitable for real applications due to its high independence of the device used.

Due to the higher number of children in the database compared to adults, selecting a percentage of the total users make the two scenarios unbalanced. Experiments balancing the number of both classes in training and testing have been made. The results show small variations around 1% of accuracy with respect to the presented results.

V. CONCLUSIONS

This work has reported experimental results on modeling the complexity of biomechanical tasks through the usage of the Sigma LogNormal model of the Kinematic Theory of rapid human movements. Two different case studies have been analyzed.

The first case study has focused on applying the Sigma LogNormal model to develop an on-line signature complexity detector. Just by using the number of strokes of the signatures was enough to obtain very good results differentiating between three different signature complexity groups (low, medium and high). As a second stage, a specific signature verification system was developed for each signature complexity group by carrying out a time functions selection process. Very significant improvements of recognition performance have been shown when comparing the proposed system with a baseline, being both based on DTW and time functions as features. For future work, the approach considered in this work will be further analysed using the e-BioSign public database [27] in order to consider new scenarios such as the case of using the finger as the writing tool. Also, novel systems based on the usage of Recurrent Neural Networks (RNNs) [28] and the fusion of different systems [29] will be considered .

TABLE IV

ACCURACY RESULTS FOR THE 20 LOGNORMAL FEATURES. THE ACCURACY IS MEASURED AS THE RATE OF CORRECT CLASSIFICATIONS CONSIDERING BOTH CLASSES.

		Testing samples			
		Phone Singletouch	Tablet Singletouch	Phone Multitouch	Tablet Multitouch
Traning samples	Phone Singletouch	93.6%	95.0%	88.0%	92.1%
	Tablet Singletouch	93.7%	96.3%	88.9%	94.0%
	Phone Multitouch	94.1%	95.9%	88.0%	92.8%
	Tablet Multitouch	93.0%	96.3%	87.9%	94.6%

On the other hand, the second case study has focused on age group prediction (children from adults) from handwritten touch patterns acquired from touchscreen devices such as smartphones or tables. Applying the Sigma LogNormal model to some examples of drag and drop tasks from children and adults showed that children had a more complex velocity profiles with a larger number of sigma LogNormals. The proposed approach is based on 20 features extracted from the model, and results achieved were very promising with classification rates over 96% in a single-sensor setting and over 95% in a cross-sensor scenario.

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