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Modeling the Complexity of Signature and Touch-Screen Biometrics using the Lognormality Principle

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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.

1. 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.¹⁻⁴

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.⁵ The Sigma LogNormal model has been used in the past for several

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applications. One of the most successful ones has been the synthetic generation of handwriting, in particular signatures (two examples in⁶ and⁷). This model has recently been used in⁸ and⁹ not to generate synthetic signature samples, but to improve the performance of traditional signature verification systems. In⁸ the authors proposed a skilled forgery detector using some features extracted from the Sigma LogNormal model whereas in⁹ 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 others with very simple ones). Then, a specific signature verification system is developed for each complexity group achieving very significant improvements of verification performance.¹⁰ 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,¹¹ as the difference between adults and children is mainly caused by the different maturity of their anatomy and neuromotor system. These are less mature in children, so they have worse manual dexterity causing rougher movements.^{5,12}

The remainder of the paper is organized as follows. Sec. 2 describes the Sigma LogNormal model, used in this work to model the complexity of handwritten tasks. Sect. 3 describes the first case study focused on modeling the complexity of on-line signatures and its experimental results. Sect. 4 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. 5 draws the final conclusions and points out some lines for future work.

2. 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.^{5,13}

The Sigma LogNormal model decomposes the complex signals that describe the speed of muscular movements into simpler ones that can be explained by a few parameters. These parameters contain information about the activity itself and about the neuromotor skills of the person.¹⁴ In particular, the Sigma Log-

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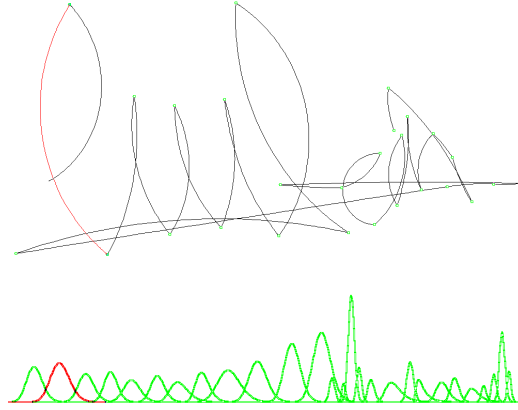


Fig. 1. Trace and velocity profile of one reconstructed on-line signature using the Sigma LogNormal model. A single stroke of the signature and its corresponding lognormal profile are highlighted in red colour. Individual strokes are segmented within the LogNormal algorithm.⁵

Normal 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 1. 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 1. Fig. 1 shows an example of the lognormal velocity profiles extracted for each stroke of one signature.

3. Case Study 1: On-Line Signature Complexity

Signature verification systems have been shown to be highly sensitive to signature complexity.¹⁵ In,¹⁶ Alonso-Fernandez *et al.* evaluated the effect of the complexity

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Table 1. 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.

and 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.^{17,18} In¹⁹ 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 in²⁰ a new metric known as “relative entropy” for classifying users into animal groups where skilled forgeries are also considered. Despite all the studies performed regarding on-line signature as a biometric 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.

3.1. Proposed System

The architecture of our proposed system is shown in Fig. 2. 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)²¹ 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 to²² (see Table 2). The most discriminative and robust time functions of each complexity level are selected using the Sequential Forward

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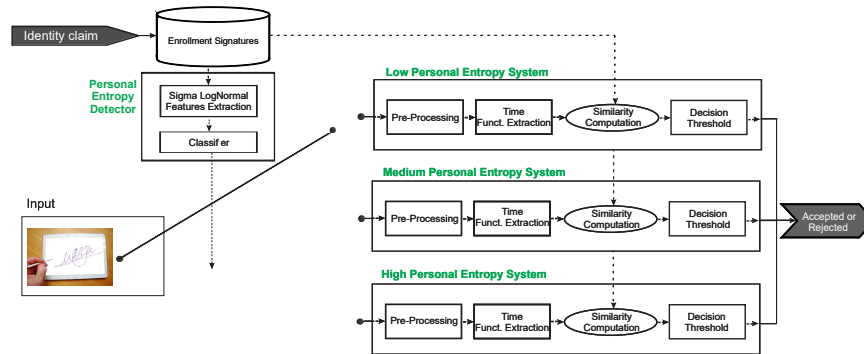


Fig. 2. Architecture of our proposed methodology focused on the development of an on-line signature verification system adapted to the signature complexity level.

Feature Selection algorithm (SFFS) enhancing the signature verification system in terms of EER.

The local system considered in this work for computing the similarity between the time functions from the input and training signatures is based on DTW algorithm.²³ Scores are obtained as:

$$score = e^{-D/K} \quad (3)$$

where D and K represent respectively the minimal accumulated distance and the number of points aligned between two signatures using DTW algorithm.

3.2. Database and Experimental Protocol

In this case, BiosecurID database²⁴ 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

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Table 2. Set of time functions considered in this work.

#	Feature
1	x-coordinate: x_n
2	y-coordinate: y_n
3	Pen-pressure: z_n
4	Path-tangent angle: θ_n
5	Path velocity magnitude: v_n
6	Log curvature radius: ρ_n
7	Total acceleration magnitude: a_n
8-14	First-order derivate of features 1-7: $\dot{x}_n, \dot{y}_n, \dot{z}_n, \dot{\theta}_n, \dot{v}_n, \dot{\rho}_n, \dot{a}_n$
15-16	Second-order derivate of features 1-2: \ddot{x}_n, \ddot{y}_n
17	Ratio of the minimum over the maximum speed over a 5-samples window: v_n^r
18-19	Angle of consecutive samples and first order difference: α_n, α'_n
20	Sine: s_n
21	Cosine: c_n
22	Stroke length to width ratio over a 5-samples window: r_n^5
23	Stroke length to width ratio over a 7-samples window: r_n^7

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 signatures and 12 skilled forgeries signatures as the test. The final score is obtained after performing the average score of the four one-to-one comparisons.

3.3. Results

3.3.1. Analysis of the Signature Complexity Detector:

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

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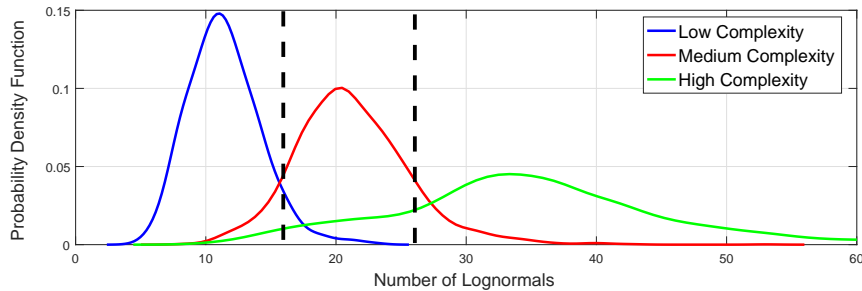


Fig. 3. Probability density function of the number of lognormals for each complexity level using all genuine signatures of the BiosecurID database. The three proposed complexity-dependent decision thresholds are highlighted by black dashed lines.

was carried out by manually labelling the image of just one genuine signature per user. This 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.²⁰ 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 Log-Normal 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. 3 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. 4 shows some of the signatures classified into each complexity level.

We now analyse each resulting complexity level following the same procedure proposed in:²⁰ 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 3 shows the system

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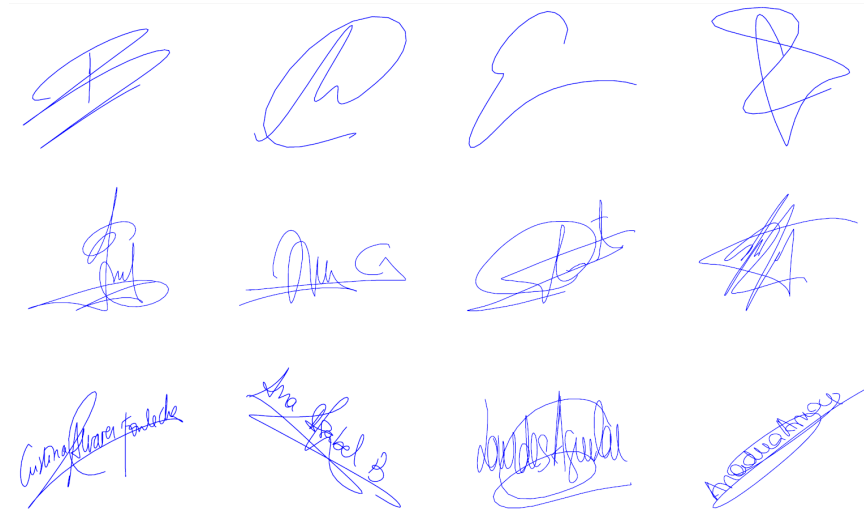


Fig. 4. Signatures categorized for each complexity level using our proposed signature complexity detector. From top to bottom: low, medium and high complexity.

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 of 4.3% compared to users categorized into a low complexity level for skilled forgeries. Therefore, the idea of considering a different optimal on-line signature verification system for each signature complexity level is analysed in next sections in order to select the most discriminative and robust time functions for each complexity group and reduce the system performance.

3.3.2. Time-Functions Selection for the Complexity-based Signature Verification System:

First we analyse which are the most discriminative and robust time functions for each signature complexity level using the SFFS algorithm over the development dataset. The following three cases are studied:

- (1) Time functions selected for all three signature complexity levels.
- (2) Time functions selected only for medium and high signature complexity levels.
- (3) Time functions selected only for low and medium signature complexity levels.

For the first case, the time functions z_n , a_n and v_n^r (see Table 2) have been

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Table 3. 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

selected in all systems as robust time functions regardless of the signature complexity level. These time functions are the variation of pressure, variation of acceleration and ratio of the minimum over the maximum speed and provide general and valuable information to all signature verification systems about the knowledge and speed of the users performing their signatures. For the second case, the time functions v_n , \ddot{y}_n and α_n have been selected for both medium and high signature complexity levels. These time functions provide information related to the variation of the velocity, vertical acceleration and variation of angle, time functions more related to the geometry of characters and therefore, with the handwriting. Finally, the time function c_n is the only one selected for the third case and provides information related to the angles as signatures with low and medium complexity level are usually categorized for having simple flourishes with no legible information. It is important to highlight that the time function \ddot{y}_n is not selected for users with low signature complexity level. In other studies such as,²⁵ this time function was selected in most optimal systems. However, the vertical acceleration seems not to be very discriminative for users with low signature complexity level as their signatures are usually simpler and not related to handwriting.

3.3.3. *Experimental Results of the Complexity-based Signature Verification System:*

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.⁸

Table 4 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

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Table 4. 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

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,⁸ 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.

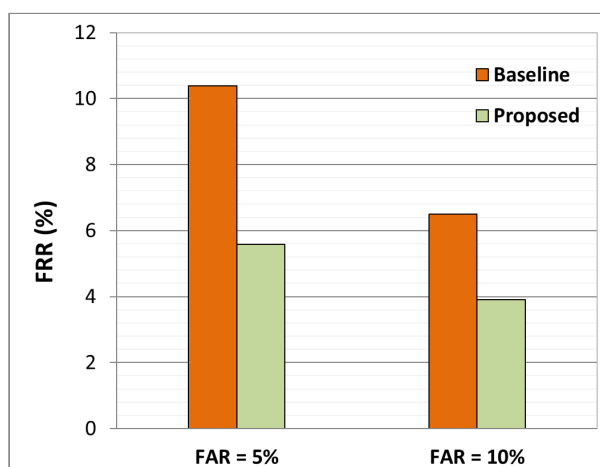


Fig. 5. **Experiment 2:** Analysis of the False Rejection Rate (FRR) at different values of False Acceptance Rate (FAR) for both Proposed and Baseline Systems on the whole evaluation dataset.

For completeness, Fig. 5 shows the performance of the Baseline and Proposed Systems considering all personal entropy levels together in terms of the false rejection rate (FRR) at different values of false acceptance rate (FAR). Our Proposed

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Systems achieve a final value of 5.8% FRR for a FAR = 5.0% and 3.9% FRR for a FAR = 10.0%. These results show the importance of considering different signature verification systems for each personal entropy level in order to enhance the verification systems with more robust time functions.

4. Case Study 2: Predicting Age Groups from Touch Patterns

Age groups prediction based on handwritten touch patterns acquired from touch-screen devices such as smartphones or tables is a recent and important challenge. Touchscreen devices provide mobile access to an unlimited number of digital contents and services (e.g. more than a half of YouTube visits come from mobile devices and this percentage is increasing²⁶). Digital services are used by people from everywhere, all ages, all ethnicities and all socioeconomic status. In this context, the classification of users according to geographic and demographic attributes is crucial for service personalization (e.g. recommender systems, parental control, security).²⁷ Some of these attributes can be obtained from metadata associated to the device (e.g. IP address, language selection, GPS location) or can be inferred from the user behavior (e.g. browsing history, social network contents, and keystroke dynamics).²⁸ We want to highlight the spread of the use of this kind of devices by young children. The study in²⁹ reveals that 97% of US children under the age of four use mobile devices, regardless of family income.

In this case study we analyze a way to classify users of touch panels according to two age groups (children and adults). The age is a key attribute in user profiling with direct application on several automatic systems (e.g. parental control, recommender systems, advertising). Three examples of use cases are: i) locking content and/or applications: locking some services in tablets and smartphones when children are using them, i.e. buying new applications or sensitive content; ii) user's age study by service providers: this way service providers could develop new content that fits better to their actual audience; iii) real-time interface adapting: as children have worse control of their fine movements than adults, changing default interfaces to special tailored ones could be beneficial.

The most popular method to reveal the age of the user is based on an online questionnaire in which the user directly answers questions about his age. However, this solution assumes: i) honesty on the response of the users, and ii) users can read. Both assumptions cannot be guaranteed because of many practical reasons. Besides the fact that people lie, nowadays children start to use digital platforms and services before learning to read.

In the existing literature, there are many experiments exploring the use of technology by children, seeking how to improve the design of adapted interfaces and

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applications.³⁰ However, modeling and characterizing mathematically how children interact with touch devices and how their conduct differs from the adult's one is a field that has not been studied deeply enough. A work related to this topic is³¹ where they analyzed different types of touching tasks like tap, rotate or drag and drop, and they found that children have different success rates when trying to perform different tasks. Simple tasks - for example tapping - can be done by all children without any problem, but the more complex ones are very difficult to be completed by very young children.

In,³² they measured the touch patterns of children and compared it to patterns from adults. They discovered that children have a larger miss rate than adults when trying to hit small targets. In³³ tap tasks are used to extract time and precision-based features. They designed two different approaches, using only one tap for classification and using 7 consecutive tasks. They get high accuracy rates: 86.5% in the one tap approximation, and 99% of accuracy using 7 consecutive taps to combine their scores. Even though they get good results using tap tasks, we decide to use drag and drop tasks because the differences between the neuromotor development of users can be manifested in a better way. The direct comparison between approaches is not fair because we are using different tasks/information to classify users. However, in our work we demonstrate that using a very common and fast action (e.g. unlock screen based on drag and drop) we can achieve higher classification rates than those achieved in³³ for the one task approach (the second approach has not been implemented yet). In our opinion, both approaches are complementary, have very different nature, and can be combined to achieve higher performances.

The difference between adults and children is mainly caused by the different maturity of their anatomy and neuromotor system. These are less mature in children, so they have worse manual dexterity causing rougher movements.^{12,34}

In order to characterize the interaction of children and adults with touchscreen devices, we propose to use a model of the human neuromotor system. The Sigma LogNormal theory of rapid human movements represents complex movements with an analytic model that describes some physical and cognitive features of human beings.^{35,36} Studies like¹⁴ 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.³⁷ As they are based on the same neuromotor skills, the principles applied to hand-

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Table 5. Sigma LogNormal features extracted.

Space-based features	Time-based features
$f_1 = D_i$	$f_8 = \Delta t_0 = t_{0i} - t_{0i-1}$
$f_2 = \mu_i$	$f_9 = v_2 = v_i(t_{2i}) $
$f_3 = \sigma_i$	$f_{10} = v_3 = v_i(t_{3i}) $
$f_4 = \sin(\theta_{si})$	$f_{11} = v_4 = v_i(t_{4i}) $
$f_5 = \cos(\theta_{si})$	$f_{12} = \delta t_{05} = t_{5i} - t_{0i}$
$f_6 = \sin(\theta_{ei})$	$f_{13} = \delta t_{15} = t_{5i} - t_{1i}$
$f_7 = \cos(\theta_{ei})$	$f_{14} = \delta t_{13} = t_{3i} - t_{1i}$
	$f_{15} = \delta t_{35} = t_{5i} - t_{3i}$
	$f_{16} = \delta t_{24} = t_{4i} - t_{2i}$
	$f_{17} = \Delta t_1 = t_{1i} - t_{1i-1}$
	$f_{18} = \Delta t_3 = t_{3i} - t_{3i-1}$

writing models can be also used to model touchscreen patterns.

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 particular, this case study is focused in age classification of users into two groups: children under 6 years old and adults. We use information of simple touch tasks collected from 119 people (89 children and 30 adults) using two different types of devices: a smartphone and a tablet. Single-sensor and cross-sensor scenarios have been evaluated. The results show accuracies over 90% in several scenarios with top correct classification rate of 96% for the data obtained from tablets.

4.1. 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. 2) were used to calculate 18 different features per lognormal (see Table 5) as described in.³⁵ 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 1). 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 from³⁵ are computed for each stroke, and each parameter is averaged across strokes. The 18 averaged parameters are

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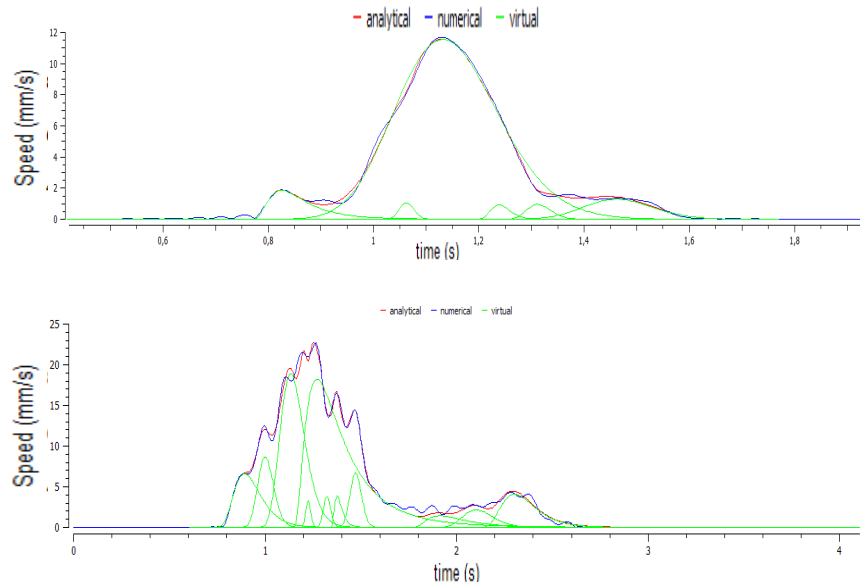


Fig. 6. Comparison between Sigma LogNormal speed profiles for (a) an adult and (b) a child following the same task.

augmented with the task time and the number of strokes to generate the final feature vector of size 20.

Regarding the classification of the age of the user, quite often it is possible to differentiate between children and adults by simply looking at the velocity profile of a touch screen task. In Figure 6, 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.

Figures 7(a) and 7(b) show the histograms of two features (Covered distance f_1 , and Logtemporal delay f_2) for children and adults. These two features are highly discriminative as their histograms are clearly separated, showing differences between both classes and therefore suggesting the potential for the classification task.

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.

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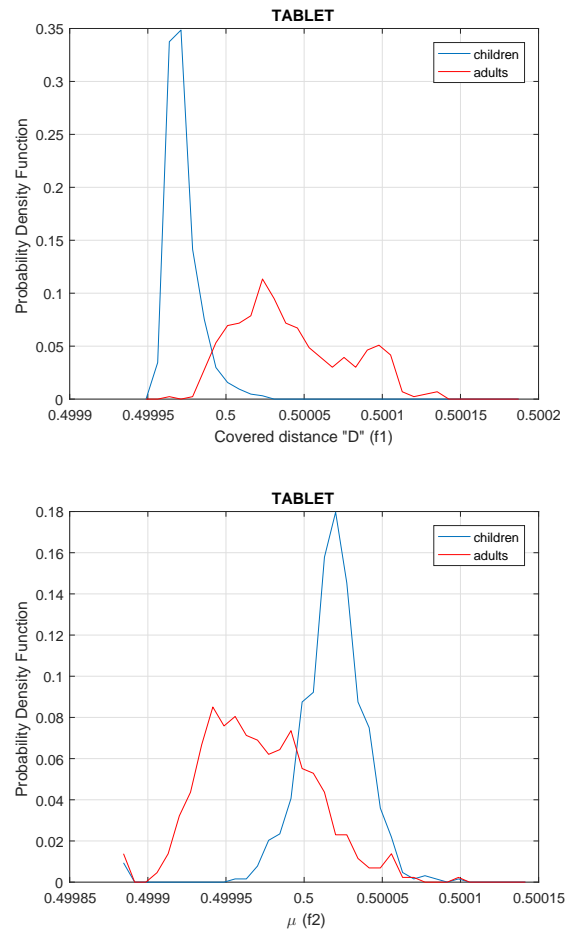


Fig. 7. Probability Density Functions for two features (f_1 and f_2). These are highly discriminative features as histograms are separated.

4.2. Database and Experimental Protocol

The database used is publicly available and was presented in.³⁷ It is comprised with data from touchscreen activity of both children and adults performing pre-designed 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 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

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Table 6. 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%

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 (see³⁷ 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.

4.3. Results

Table 6 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 with³³ where they get an accuracy rate of 86.5% using one tap task for classification and with a single-sensor approximation (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 from Table 6 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.³⁷

The cross-sensor scenarios get results not too far from the single-sensor sce-

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narios. 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.

Figure 8 shows histograms of the scores calculated in the classification process. It can be seen that the scores from children and adults are visibly separated into two different zones, making possible to obtain high accuracy rates (over 96%). There are also other zones where the scores distributions overlap. These regions are the source of incorrect classifications. Combining scores from several tasks of the same user could make possible to reduce the overlap areas, increasing even more the accuracy rate.

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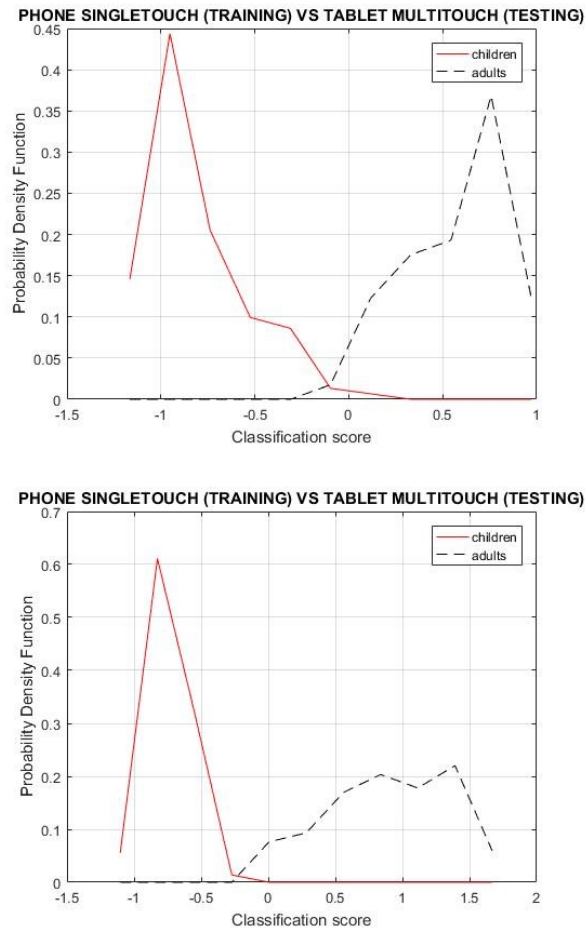


Fig. 8. Histograms of scores using the Sigma LogNormal model features. Left figure represents the scores for single-sensor scenario, using tablet single-touch data for both training and testing. Right figure shows the histogram for a cross-sensor scenario, using phone single-touch data for training and tablet multi-touch data for testing the classifier.

5. 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.

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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 database³⁸ in order to consider new scenarios such as the case of using the finger as the writing tool. Novel systems based on the usage of Recurrent Neural Networks (RNNs)³⁹ and the fusion of different systems⁴⁰ will be considered. Also, different types of presentation attacks to signature recognition systems⁴¹ will be considered analysing how signatures with different complexity levels are affected.

On the other hand, the second case study has focused on age group prediction (children from adults) from handwritten touch patterns acquired from touch-screen 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. Future work includes the analysis of touchscreen data to continuously monitor the user behaviour.⁴²

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