Detecting age groups using touch interaction based on neuromotor characteristics

J. Hernandez-Ortega✉, A. Morales, J. Fierrez and A. Acien

A new parental control method to prevent unauthorised usage of touch devices by kids is proposed. The impact of rapidly advancing technology on the developing child has seen an increase exposition to new forms of danger. Studies reveal that 97% of US children under the age of four use mobile devices. A reliable and efficient method to prevent the use of touch devices by preschool children is proposed. The proposed method is based on the analysis of the neuromotor characteristics of the users according to the decomposition of simple drag and drop tasks using the kinematic theory of rapid human movements. The experimentation is conducted on a publicly available database with samples obtained from 89 children between 3 and 6 years old and 30 adults. The results are compared with an existent system based only on task time and accuracy. Finally, both systems are combined at score level to achieve better performances. The results, with correct classification rates over 96% in the combined system, show the discriminative ability of the proposed neuromotor-inspired features and the possibility of combining this system with others to improve their final performance.

Introduction: Touchscreen panels have changed the way users interact with new devices. They have increased their relevance because of their portability and ease of use. In this Letter, the classification of users according to their attributes is crucial for service personalisation (e.g. recommender systems, parental control, and security). 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 behaviour (e.g. browsing history, social network contents, and keystroke dynamics).

Early childhood is a crucial stage of life in terms of a child's physical, intellectual, emotional and social development. The study in [1] reveals that 97% of US children under the age of four use mobile devices, regardless of family income. Parental control tools are often a need as young children are not prepared for some types of contents (e.g. adult contents) or services (e.g. online shopping). These tools use to filter the contents being displayed or they can limit the access of children to the use of the devices [2]. ParentsAround is an example of these tools that filter web contents according to the topics that parents consider as sensible. Curbi is another example, with it, parents are able to block the access to the whole device or only to specific apps. Most of the times these parental control tools must be activated and deactivated by the parents manually (semi-supervised systems). The development of unsupervised automatic systems based on the analysis of the user's interaction is important to improve technologies in use nowadays.

The user activity can be monitored and used to detect age groups according to simple and fast touch tasks. In [3], researchers analysed 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 tasks of diverse complexity. In [4] tap tasks are used to extract time and precision-based features to classify users according to their age. They designed two different approaches, using only one tap for classification and using seven consecutive taps, with promising results of 86.5 and 99%, respectively.

Touch activities are highly dependent of neuromotor characteristics of each person. The difference between adults and children is mainly caused by the different grade of maturity of their anatomy and neuromotor system [5]. Because of that reason, we propose to use a model of the human neuromotor system to characterise the interaction of children and adults with touchscreen devices. The Sigma-Lognormal model is part of the kinematic theory of rapid human movements [6]. The goal of this model is to decompose 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 [7].

In this Letter, we propose a new method to detect preschool children usage of touch panels, using data from simple tasks performed in smartphones and tablets. Three use cases are: (i) locking content and/or applications when children are using the devices; (ii) as input for service providers so they can adapt their contents; and (iii) real-time interface adaptation.

We use information of simple drag and drop tasks collected from 119 people (89 children and 30 adults) interacting with a smartphone *ad-hoc* app. Drag and drop is one of the most popular actions performed in touch devices. It involves moving the cursor over an object, selecting it, and moving it to a new location.

The main contributions of this work can be summarised as follows: (i) a novel algorithm for age classification based on neuromotor characteristics obtained from simple and fast drag and drop tasks; (ii) our approach obtains the highest accuracy reported in the literature for individual actions based on touch tasks; and (iii) we propose a combination of our system and the one from [4] getting higher accuracy rates than the ones from the isolated systems.

Sigma-Lognormal model: We propose the Sigma-Lognormal model to decompose touchscreen interaction and detect the usage by preschool children. The Sigma-Lognormal model states [6, 8] 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 $\boldsymbol{v}_i(t)$ that has a lognormal shape

$$|\boldsymbol{v}_i(t)| = \frac{D_i}{\sqrt{2\pi\sigma_i\left(t - t_{0_i}\right)}}\exp\left(-\frac{\left(\ln\left(t - t_{0_i}\right) - \mu_i\right)^2}{2\sigma_i^2}\right) \tag{1}$$

where each of the parameters is described in Table 1. The complete velocity profile is modelled as a sum of the different individual stroke velocity profiles as

$$\boldsymbol{v}_r(t) = \sum_{i=1}^{N} \boldsymbol{v}_i(t) \tag{2}$$

where N is the number of lognormals of the entire movement.

Table 1: Sigma-Lognormal parameters description

Parameter	Description
D_i	Covered distance when executed isolated
t_{0i}	Initialisation time. Displacement in the time
μ_i	Logtemporal delay
σ_i	Response time of the neuromotor system
θ_{si}	Initial angular position of the stroke
θ_{ei}	Final angular position of the stroke

An action controlled by the neuromotor system can be decomposed into a summation of these lognormals, each one characterised by different values for the six parameters in Table 1. The parameters of the Sigma-Lognormal model are used to calculate the 18 different features described in [8]. 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.

In Fig. 1, an example of the velocity profile of a drag and drop task is presented, for both children and adults. As can be seen in the figure, children's speed signals are usually composed by a higher number of strokes than the adults' signals. The higher maturity on the neuromotor skills of adults produces soft velocity profiles that reveal a fine control of movements.

Experiments: The experimental protocol is based on the publicly available database presented in [9]. It contains tasks captured in both smartphones and tablets. In this work, we have analysed separately the data from smartphones and the data from tablets. The total number of drag and drop tasks is 2912 for children and 1157 for adults (see [9] for more details). The parameters of the model (see Table 1) for all tasks were extracted using the Script Studio software [6].

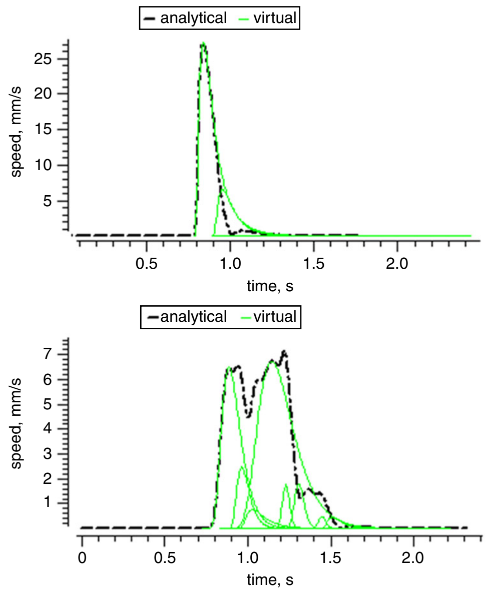

Fig. 1 *Comparison between Sigma-Lognormal speed profiles: adult (up) and child (down). Task is the same in both profiles. Virtual signals are the decomposition of the speed profile into individual strokes*

This software provides the $6 \times N$ parameters for each drag and drop task, where 6 denotes the parameters in Table 1, and N is the number of strokes of each task. The 18 features from [8] are computed for each stroke and each parameter is averaged across strokes. The 18 averaged parameters are augmented with task time and the number of strokes to generate the final feature vector of size 20.

As a classifier we use support vector machines (SVM) 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. The next process has been performed for training and testing the classifier: *Step 1:* 15 children and 15 adults are chosen randomly from all users in the database. Then, the SVM is trained with all the drag and drop tasks from those users. *Step 2:* 1 child and 1 adult are chosen randomly from the remaining users. Only 1 task from each one is selected to test the classifier and obtain a score. *Step 3:* For each iteration of *steps 1*, *2* is repeated 100 times. *Step 4: Step 1* is repeated 100 times. This makes a total number of $100 \times 100 \times 2 = 20{,}000$ classification scores. We have chosen this protocol as it is the same from [4] and guarantees a fair comparison between both approaches.

Results: Table 2 shows the classification accuracies obtained for the method proposed in [4], the system proposed in the present work and the combination of both systems at score level (by sum of scores). They are presented in terms of correct classification accuracy (percentage of samples from both classes correctly classified). Table 2 also shows the superior performance of our model and how the combination of the proposed approach with the system in [4] improves the performance up to 96.3%. The improvement in the accuracy rate can be associated to the better discrimination of users due to the characterisation of their neuromotor characteristics, while in [4] their criterion was based in features related basically with the precision. Second, it has been proved that both approaches are complementary, as we achieve the best accuracy rate using the combined scores of both systems.

Table 2: Classification accuracies of the systems as the percentage of samples from both classes correctly classified

Accuracy, %	Our implementation of [4]	Our approach	Combined system
Smartphone	86.5	91.4 (↓36%)	95.8 (↓68%)
Tablet	90.5	95.4 (↓52%)	96.3 (↓61%)

We show the accuracies reached with data from smartphones and tablets separately. In brackets we show the percentage of error reduction with respect to [4]

Conclusion: In this Letter, we have presented a new algorithm for age group classification with application to parental control of preschool children using touch devices. We propose a feature extraction based on the parameters of the Sigma-Lognormal model. These features illustrate the neuromotor skills of users, which enable to discern between children and adults.

An evaluation of its performance has been made, using a public database with touchscreen activity of children and adults. The classification rates are over 95% for our system, and over 96% for the combination of the proposed system with an existing approach.

As future improvements of this system, two main aspects can be considered. First, the patterns used are this work are obtained from single and short strokes. Better classification rates may be achieved by considering more complex tasks or continuous monitoring. The maturity of the neuromotor skills is the key to recognise children using the method proposed in this work, which is focused in preschool children under 6 years. However, how to recognise age groups with mature neuromotor skills (from 10 years old onwards) is a challenging task and new models and methodologies should be proposed for that purpose in the future. Finally, age classification of older users using the Sigma-Lognormal model is also a possibility as it is demonstrated that fine motor control abilities decay with the age, affecting to the use of computers (including touchscreen devices) and their interfaces [10].

Acknowledgments: This work was funded by the project CogniMetrics (TEC2015-70627-R) and JdC contract (JCI-2012-12357) from MINECO/FEDER.

Submitted: *15 February 2017*
doi: 10.1049/el.2017.0492
One or more of the Figures in this Letter are available in colour online.

J. Hernandez-Ortega, A. Morales, J. Fierrez and A. Acien (*ATVS – Biometric Recognition Group, Escuela Politecnica Superior, Universidad Autonoma de Madrid, 28049 Madrid, Spain*)

✉ E-mail: javier.hernandezo@uam.es

References

1 Kabali, H.K., Irigoyen, M.M., Nunez-Davis, R., *et al.*: 'Exposure and use of mobile media devices by young children', *Pediatrics*, 2015, **136**, (6), pp. 1044–1050, doi: 10.1542/peds.2015-2151
2 GetParentalControls.org: 'Parental controls product guide, 2010 edition', Available at https://filteringfacts.files.wordpress.com/2010/03/productguide2010.pdf, accessed November 2016
3 Aziz, N.A.A., Batmaz, F., Stone, R., *et al.*: 'Selection of touch gestures for children's applications'. Science and Information Conf., London, October 2013, pp. 721–726
4 Vatavu, R.D., Anthony, L., and Brown, Q.: 'Child or adult? inferring smartphone users' age group from touch measurements alone'. Human-Computer Interaction, 2015, pp. 1–9, doi: 10.1007/978-3-319-22723-8_1
5 Piaget, J., and Inhelder, B.: 'The psychology of the child' (Basic books, 1966)
6 O'Reilly, C., and Plamondon, R.: 'Development of a Sigma–Lognormal representation for on-line signatures', *Pattern Recognit.*, 2009, **42**, (12), pp. 3324–3337, doi: 10.1016/j.patcog.2008.10.017
7 Duval, T., Rémi, C., Plamondon, R., *et al.*: 'Combining sigma-lognormal modeling and classical features for analyzing graphomotor performances in kindergarten children', *Hum. Mov. Sci.*, 2015, **43**, pp. 183–200, doi: 10.1016/j.humov.2015.04.005
8 Fischer, A., and Plamondon, R.: 'A dissimilarity measure for on-line signature verification based on the Sigma-Lognormal model'. 17th Conf. of the Int. Graphonomics Society, Guadeloupe, June 2015
9 Vatavu, R.D., Cramariuc, G., and Schipor, D.M.: 'Touch interaction for children aged 3 to 6 years: experimental findings and relationship to motor skills', *Int. J. Human-Comput. Studies*, 2015, **74**, pp. 54–76, doi: 10.1016/j.ijhcs.2014.10.007
10 Hawthorn, D.: 'Possible implications of aging for interface designers', *Interact. Comput.*, 2000, **12**, (5), pp. 507–528, doi: 10.1016/S0953-5438(99)00021-1