On the Design of Personal Digital Bodyguards: Impact of Hardware Resolution on Handwriting Analysis

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***Abstract*—Handheld touch-capable devices have become one of the most popular and fastest growing consumer products. It seems logical therefore to think of such devices as Personal Digital Bodyguards (PDBs) in charge for example of biometrical, biomedical, and neurocognitive monitoring by just inspecting the user's handwriting activity. However, it is unclear whether the hardware of today's devices is capable to handle this task. To this end, we conducted a comparative study regarding the capabilities of past and current tablets to allow for the design of PDBs based on the exploitation of the Kinematic Theory. Our study shows that, while some improvements are still necessary at the sampling frequency level, the conclusions drawn by the Kinematic Theory can be directly transferred to PDBs.**

I. Introduction

Many human motor control theories rely on the assumption that dynamic and kinematic information is encoded in one way or another in the user's neural activity. Although the specific underlying processes are still under investigation, from an engineering and computational perspective, this assumption provides practical guidelines for designing and implementing innovative devices and products for different applications. This is particularly true when it comes to handwriting and gesture-based interaction, for which the number of input devices has increased recently. Ergonomic handheld slate tablets and laptops trapped in tablet bodies, with styli or touch gestures replacing computer mice and keyboards, deliver a natural writing and drawing experience [1]. A similar breakthrough is underway in the smartphone industry.

In the forthcoming years, the ubiquity of smartphones and tablets, along with their increased computing power and sensing capabilities, will make it possible to convert these devices into Personal Digital Bodyguards (PDBs). Among other things, PDBs will leverage handwriting activity to monitor the user's motor control, being able to detect e.g. stress, aging, and health problems. In this context, PDBs provide an intelligent solution for biometrical, biomedical and neurocognitive monitoring and in fact are within reach [2]. However, the realization of this vision is a difficult challenge. Indeed, handwriting entails complex neuromotor skills. Producing a handwritten message requires the performance of numerous cognitive tasks leading to the production of words from the motor action plans that have been learned over the years. According to the Kinematic Theory of Human Movements [3], [4], these plans activate specific neuromuscular networks to produce a given pen tip trajectory by combining lognormal strokes, the fundamental units of handwriting movements [5].

Most of the research regarding this theory has been done in well-controlled protocols and experimental setups, using standard digitizers characterized by their stable sampling frequency and high spatial resolution. One practical question that emerges when it comes to making a technology transfer toward handheld devices (e.g. tablets, phablets, smartphones...) is the following. Is today's hardware ready for such a move?

In this context, it is far from being certain that the conclusions drawn by the Kinematic Theory can be directly transferred to PDBs, at least in the present status of the device development ecosystem, where the sampling frequencies are much smaller than those of the classical digitizers and often not stable. Furthermore, the spatial resolution is lower and the touchscreen sensitive area might not be homogeneous since this is not a requirement in most commonly used tasks like e.g. browsing the Web, sending an SMS, or operating a camera application.

In this paper, we present the results of a comparative study regarding the capabilities of past and current tablets to be used in the design of PDBs. Our study is mostly exploratory but firmly based on the exploitation of the Kinematic Theory. We show that, while some improvements are necessary at the sampling frequency level, the conclusions drawn by the Kinematic Theory can be directly transferred to PDBs.

II. Related Work

In the past, it has been argued that pen-based digitizers lack sufficient sensitivity [6]. However, this statement no longer holds true. For example, Elliott [7] sought to understand how the individual variables of handwriting vary across devices. It was found that there are significant differences

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in signature traits across devices, but these variables are not significantly different. Today, handwriting accuracy is a still matter of concern for tablet users (finger writing behavior), influenced by many factors including e.g. frequency sampling, the texture of the screen, or the responsiveness of the device.

Many researchers have focused on identifying the activities that the stylus is most beneficial for. Among other findings, device and task interactions have been largely confirmed, with the stylus identified as optimal for compound tasks, crossing tasks, radial steering, selection, stroke-based gestures, and shape tracing tasks [8]. Forlines et al. [9] investigated the differences between direct touch and mouse input on tabletop displays. They observed that for bimanual tasks performed, users benefit from direct-touch input. However, mouse input may be more appropriate for a single user working on tabletop tasks requiring only single-point interaction. In addition, Zabramski et al. [10], [11] compared the performance of mouse, pen, and touch input in a line-tracing task. It was observed that touch input was the worst performer in terms of accuracy but was the fastest in terms of speed.

Other researchers have focused on the effect of the device on the usability and user experience of digital handwriting. For example, Ward and Phillips [12] found several misunderstood performance characteristics of tablet digitizer that many impact the usability of interactive applications. Also, Annett [8] found that latency, unintended touch, and stylus accuracy have a significant impact on the user experience.

Overall, high writing resolution is achieved with higher sampling rates on the capturing device. However, researchers have shown that some applications do not need such a high sampling rates to achieve good results in practice. For example, Junker et al. [13] found that there is almost no loss in accuracy for sampling rates greater than 20 Hz and resolutions greater than 2 bits. Vatavu [14] analyzed the effect of sampling rate on the performance of template-based stroke gesture recognizers. It was found that as few as 6 sampling points per gesture example are sufficient to attain competitive recognition accuracy.

Despite the fundamental research conducted in previous works, to the best of our knowledge, a systematic examination of hardware resolution on handwriting analysis is lacking in the research literature. Therefore, a study like the one we conducted in this paper is both timely and necessary.

III. Kinematic Theory

The Kinematic Theory is aimed at explaining the generation and control of human movements. This theory has been proved in the past years to be one of the best approaches to describe the global properties of the neuromuscular networks involved in a synergistic action [15], [16]. It proposes explanations about the emergence of the basic kinematic relationships and psychophysical laws that have been consistently reported in the studies dealing with human movements [15].

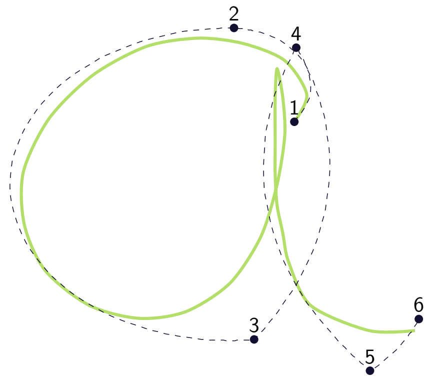

Figure 1. A handwritten letter ‘a’. The handwriting trajectory (green thick line) is described by the temporal overlap of a series of strokes (black dashed arcs). Each stroke is described by a lognormal equation.

The basic idea behind the Kinematic Theory is that the neuromuscular network involved in the production of a human movement can be considered as a linear system made up of a large number of coupled subsystems [3], [17], [4]. For example, when writing on a paper sheet we use from the shoulder down to the joints of the fingers, each of which must be controlled by the muscle groups attached to them. The resulting velocity profile of a specific neuromuscular system converges toward a lognormal function, that is:

$$\|\vec{v}(t)\| = D\Lambda(t; t_0, \mu, \sigma^2) \tag{1}$$

being

$$\Lambda(t; t_0, \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}(t - t_0)} e^{\frac{-[\ln(t-t_0)-\mu]^2}{2\sigma^2}} \tag{2}$$

where D describes the amplitude of the input command; t_0 is the time occurrence of the input command; μ is the neuromuscular system time delay and σ is the neuromuscular system response time.

There are many models derived from this *lognormal* paradigm, among which the Sigma-Lognormal model ($\Sigma\Lambda$M) is the latest and more complete representation [18]. Unlike previous models, the $\Sigma\Lambda$M does not assume that the involved neuromuscular systems are working in precisely opposite directions. The synergy emerging from the interaction and coupling of many of these neuromuscular systems results in the generation of any complex movements, not limited to a single stroke.

According to the $\Sigma\Lambda$M, the velocity of a complex movement (Figure 1) is described by the temporal overlap of the velocities $\vec{v}_i(t)$ of each involved stroke [19]:

$$\vec{v}(t) = \sum_{i=1}^{N} \vec{v}_i(t) = \sum_{i=1}^{N} \begin{bmatrix} \cos\phi_i(t) \\ \sin\phi_i(t) \end{bmatrix} D_i \Lambda(t; t_{0_i}, \mu_i, \sigma_i^2) \tag{3}$$

where N represents the number of strokes and $\phi_i(t)$ is the direction profile for each stroke, described by an error function:

$$\phi_i(t) = \theta_{s_i} + \frac{\theta_{e_i} - \theta_{s_i}}{2}\left[1 + \mathrm{erf}\left(\frac{\ln(t - t_{0_i}) - \mu_i}{\sigma_i\sqrt{2}}\right)\right] \quad (4)$$

where θ_{s_i} is the starting direction and θ_{e_i} is the ending direction of the i-th stroke.

Finally, the $x(t)$ and $y(t)$ Cartesian coordinates can be calculated integrating $\vec{v}(t)$:

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} + \sum_{i=1}^{N} \int_{t_{0_i}}^{t} \vec{v}_i(\tau)\,\mathrm{d}\tau \quad (5)$$

or alternatively, $x(t)$ and $y(t)$ can also be computed directly from the Sigma-Lognormal parameters [20]:

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} + \sum_{i=1}^{N} \frac{D_i}{\theta_{e_i} - \theta_{s_i}} \begin{bmatrix} \sin\phi_i(t) & - & \sin\theta_{s_i} \\ -\cos\phi_i(t) & + & \cos\theta_{s_i} \end{bmatrix} \quad (6)$$

The generation of these complex movements obeys the *lognormality principle* [21]. This principle states that a user in total control of his movements produces the minimum number of perfect lognormal strokes in order to generate the intended hadwriting trajectory. In contrast, when the user is not in full control, the produced strokes will not be ideal lognormals or she will use a large number of these to produce the movement. Therefore, the lognormality of velocity profiles can be interpreted as reflecting the behavior of users who are ideal motion planners.

In sum, the $\Sigma\Lambda$M provides a solid framework to study the generation of complex human movements, as defined by the control parameters (t_0, D, θ) and the peripheral parameters (μ, σ) provided by the model. Our evaluation is performed by tapping into this model, as discussed in the next section.

IV. Evaluation

Participants were told to write a series of words on three different devices. Then, each word was reconstructed according to the $\Sigma\Lambda$M. Finally, the performance of each device was assessed through a number of assessment measures derived from the $\Sigma\Lambda$M. Below we describe the experimental setup and the evaluation procedure.

A. Apparatus

Each participant tested three devices, see Figure 2: a Wacom Bamboo Pen & Touch digitizer, an Apple iPad mini 2, and a Lenovo ThinkPad 1st gen. We used the first one as a baseline device against which the other devices should be compared, since previous works have used the Wacom for $\Sigma\Lambda$M analysis [22]. Table I summarizes the technical specifications of these devices.

Table I
Device specifications.

Manufacturer	Device	Size	Resolution	Input
Wacom	Bamboo	6.1”	2 540 LPI*	Pen/Touch[1]
Apple	iPad mini	7.9”	326 PPI	Touch
Lenovo	ThinkPad	10.1”	215 PPI	Pen/Touch[2]

* 1 PPI $\approx$ 2 LPI
[1] Touch input was disabled.
[2] Pen input was disabled.

We developed an HTML5 application that rendered a web canvas on which participants could write. The application captured both pen and touch coordinates via event listeners, together with the timestamp in which the event occurred. This way, each word was encoded as an on-line sequence of {x, y, t} tuples. No restriction was placed to the sampling frequency, thereby obtaining the maximum sampling frequency possible for each device.[1]

B. Participants

We recruited 12 participants aged 23–46 (M=28, SD=2.3) using our University's mailing lists. We intentionally wanted a rather broad sample and recruited participants with many different backgrounds; e.g. Mechanical Engineering, Computer Science, or Physics. There was no economic compensation for the participants, who just provided us with raw handwritten data.

C. Design and Procedure

We used a repeated measures within-subjects design, i.e., all participants tested all devices. Each participant had to handwrite ten common English words, extracted from the list of “Most common words in English,” according to the Oxford English Dictionary.[2] Words were chosen at random from this list, with the only restriction that they should be at least three characters long. Each participant entered each word ten times, in order to control for variability, resulting in 100 samples per participant and device (see Figure 2), 3 600 samples in total. We used Latin squares (pseudo-random condition assignments) to counterbalance the order in which devices would be tested, and to mitigate possible learning effects between trials.

1) $\Sigma\Lambda$M Reconstruction Procedure: Given that strokes are “hidden” inside a handwriting movement, a $\Sigma\Lambda$M reconstruction is needed to perform a “reverse engineering” process, in order to uncover the values of the stroke parameters that best explain the observed velocity profile. For this, we used the procedure presented in [23]. As discussed later, a good reconstruction is expected to have the following properties: (1) the reconstruction quality should be higher than a preset threshold and (2) for a given reconstruction, the smallest number of strokes is preferable.

[1] The Wacom digitizer achieved 120 Hz of temporal resolution on average, whereas both tablets achieved around 60 Hz.

[2] http://www.oxforddictionaries.com

Figure 2. Experimental setup. From left to right: Wacom digitizer, iPad tablet, and ThinkPad tablet.

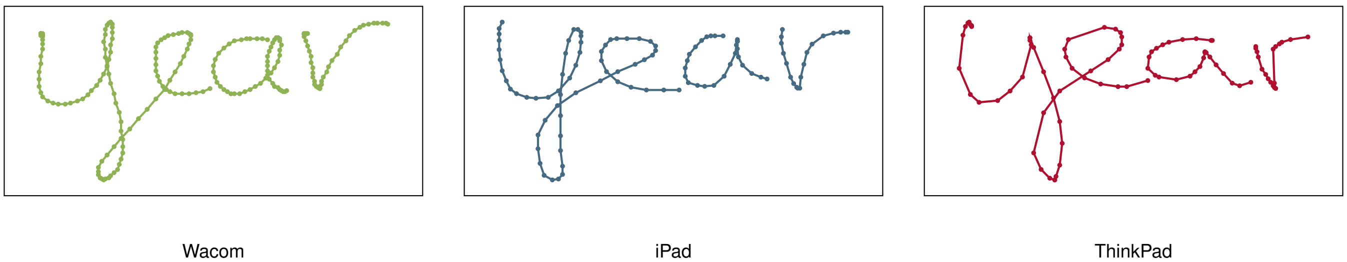

Figure 3. The word “year” written by one of the participants using the different devices.

2) Assessment Measures: We estimate the quality of a reconstruction using three standard measures. The first measure is the signal to noise ratio (SNR) between the original and the reconstructed velocity profile:

$$\mathrm{SNR} = 10 \log \left(\frac{\sum_{t=1}^{T} \|\vec{\mathrm{v}}(t)\|^2}{\sum_{t=1}^{T} \|\vec{\mathrm{v}}(t) - \vec{v}(t)\|^2} \right) \tag{7}$$

where $\vec{v}(t)$ is the analytic velocity, $\vec{\mathrm{v}}(t)$ is observed velocity and T is the duration of the handwriting movement. Previous works suggest that different SNR thresholds can be used to quantify what is considered as a good reconstruction [23], [24], here 25 dB will be used as upper bound.

The second measure is the number of lognormal strokes, nbLog—or N in Equations (3), (5) and (6)—used in the reconstruction. As previously commented, the smaller this number the better.

Finally, the third measure evaluates the reconstruction quality according to the lognormality principle, by calculating the ratio between SNR and nbLog. The higher this ratio, the better. Overall, given two reconstructions with the same number of strokes, a bigger SNR is always preferable. And if both reconstructions achieve the same SNR, a smaller number of lognormal strokes is desirable.

D. Results

First, we measured the average writing duration per device. As shown in Figure 4, writing on the handheld devices is slower. In particular, it is half slower on the iPad and two times slower on the ThinkPad.

Next, we looked at the $\Sigma\Lambda$M reconstruction quality measures; see Figures 5 to 7. Unsurprisingly, in terms of SNR, the Wacom digitizer achieves the highest value, followed by the iPad and the ThinkPad. However, with respect to the number of lognormals (nbLog), both the Wacom digitizer and the iPad tablet achieve similar values, and the samples written on the ThinkPad tablet have 60% more lognormals on average than the other devices. Finally, regarding the ratio between SNR and nbLog, the Wacom digitizer achieves the highest value, followed by the iPad (14% less) and the ThinkPad (32% less).

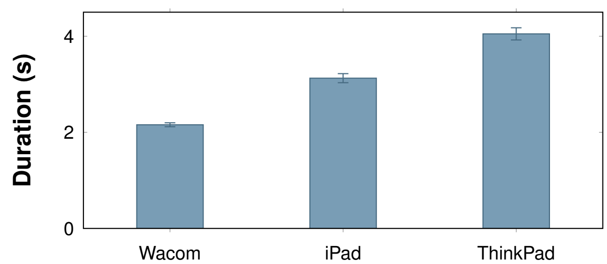

Figure 4. Differences in average writing duration (the lower the better). Error bars denote 95% CIs.

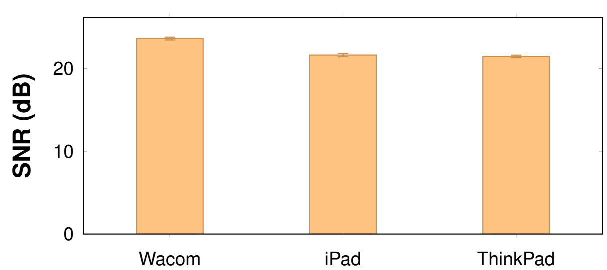

Figure 5. Differences in SNR (the higher the better). Error bars denote 95% CIs.

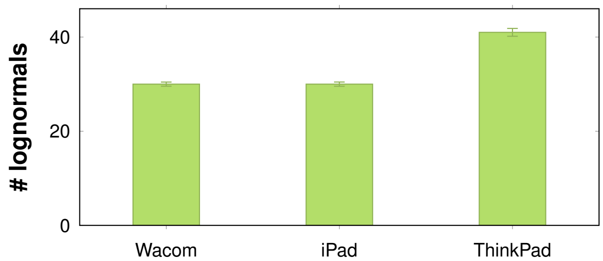

Figure 6. Differences in the number of lognormals (the lower the better). Error bars denote 95% CIs.

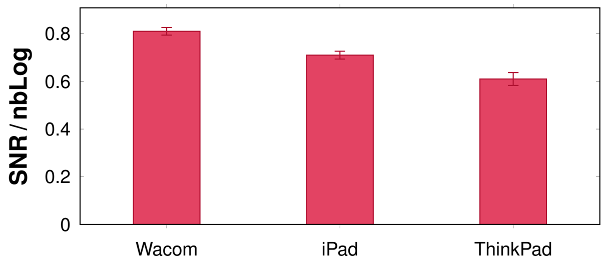

Figure 7. Differences in SNR/nbLog (the higher the better). Error bars denote 95% CIs.

To analyze better the differences between these devices we performed an Analysis of Variance (ANOVA) for each quality measure. The ANOVA test revealed statistical significance in all cases excepting the ratio between SNR and nbLog: writing duration [$F_{2,33} = 9.76, p < .001, \eta_p^2 = 0.37$], SNR [$F_{2,33} = 3.94, p = .029, \eta_p^2 = 0.19$], nbLog [$F_{2,33} = 3.47, p = .042, \eta_p^2 = 0.17$], and SNR/nbLog [$F_{2,33} = 3.03, p = .062, \eta_p^2 = 0.15$]. Effect sizes suggest small to moderate practical significance of the results.

Therefore, we conducted post-hoc pairwise t-tests (two tails, Bonferroni-Holm corrected for multiple comparisons) where the ANOVA test reported statistical significance. The post-hoc tests provide specific information on which devices perform significantly different from each other.

In terms of writing duration, the differences between the Wacom digitizer and the ThinkPad tablet are statistically significant ($p < .001$). Thus, the ThinkPad tablet performs significantly worse than the Wacom digitizer in this regard. In terms of SNR, the differences between the ThinkPad and iPad tablets are not statistically significant ($p > .05$). However, the Wacom digitizer performs significantly better than both tablets in this regard ($p = .027$). Finally, in terms of nbLog, the differences between all devices are not statistically significant ($p > .05$), suggesting that all devices achieve equally similar performance in this regard. Other comparisons were not found to be statistically significant.

V. Discussion and Future Work

As it can be seen from the above results, all of the studied devices could be used in the context of the Kinematic Theory since, among other findings, the handwritten trajectories can be reproduced with SNR higher than 20 dB (see Figure 5), which is considered to be appropriate for human movement analysis [25].

On the other hand, we observed that participants wrote much more carefully on the ThinkPad tablet to avoid handwritten words looking "wobbly" due to the low screen resolution. This fact may explain to a great extent the significant higher number of lognormals required to reconstruct each handwritten trajectory on average (see Figure 6).

However, even when the writing duration is higher than usual (see Figure 4), it can be observed that all devices achieved a comparative performance in terms of SNR/nbLog (see Figure 7). The differences among these ratios suggest that high-quality reconstruction is still achievable in finger writing. This result is especially important because it confirms previous works' findings that showed that the Kinematic Theory was not limited to pen-based handwriting, but could be used in a more general context. For example, reproducing wrist movement and eye saccades [4], 2D and 3D arm movements [26], and more recently, stroke gestures [24].

It must be pointed out that the use of a stylus greatly improves performance, as compared to finger writing. Also, the friction is one of the major factors in determining the accuracy of handwritten text, but unfortunately modern tablets like the ones we used in our study do not allow to control this factor. However, despite of these observations, our findings open up the possibility of using the Kinematic Theory in numerous applications like games or gesture-based applications. For biomedical applications, one question remains to be investigated and in fact this will be the topic of a follow up study. Do the $\Sigma\Lambda$M parameters extracted from the trajectories differ greatly form one device to another? In preliminary experiments we have observed that the peripheral parameters—μ and σ in Equations (1) to (4)—do not vary too much from device to device for the same participant. For example, the user in Figure 2 has $\overline{\mu}_{\text{Wacom}} = -1.52$, $\overline{\mu}_{\text{iPad}} = -1.58$, $\overline{\mu}_{\text{ThinkPad}} = -1.80$, and $\overline{\sigma}_{\text{Wacom}} = 0.3$, $\overline{\sigma}_{\text{iPad}} = 0.28$, $\overline{\sigma}_{\text{ThinkPad}} = 0.28$. However, these experiments are outside the scope of this paper and will be the subject of study in future work. Eventually, the answer to such a question will be particularly determinant when it comes to track the neuromotricity of a person from different types of devices. We also plan to test more devices that cover different variabilities in e.g. size, resolution, and sampling frequency. All in all, this work should be seen as one corner stone of a broad series of potential applications of the PBS concept.

VI. Conclusion

This study is the very first to address fundamental questions regarding the interoperability of handheld devices based on the exploitation of the Kinematic Theory. Previous research in the context of this theory has been done in well-controlled protocols and experimental setups, using standard digitizers characterized by their stable and high sampling frequency and spatial resolution.

So far, we can anticipate that improvements will be necessary at the sampling frequency level. However, our study has shown that today's hardware is ready to make a technology transfer toward handheld devices. With this, the PDB concept and ideas become finally realizable. Looking forward, we believe this paper will inform researchers and practitioners about the design of PDBs. Now we can be confident that it is possible to derive practical guidelines for implementing innovative devices in charge of active neurocognitive monitoring.

Acknowledgments

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References

[1] F. Matulic and M. Norrie, "Empirical evaluation of uni- and bimodal pen and touch interaction properties on digital tabletops," in *Proc. Intl. Conf. on Interactive Tabletops and Surfaces (ITS)*, 2012, pp. 143–152.

[2] R. Plamondon, "Personal digital bodyguards for e-security, e-health and e-learning," in *Proc. Biennial Conf. of the Int. Graphonomics Society*, 2015, keynote opening lecture.

[3] ——, "A kinematic theory of rapid human movements. Part I: Movement representation and control," *Biol. Cybern.*, vol. 72, no. 4, pp. 295–307, 1995.

[4] ——, "A kinematic theory of rapid human movements. Part II: Movement time and control," *Biol. Cybern.*, vol. 72, no. 4, pp. 309–320, 1995.

[5] A. Woch and R. Plamondon, "Using the framework of the kinematic theory for the definition of a movement primitive," *Motor Control*, vol. 8, no. 4, pp. 547–557, 2004.

[6] R. J. Elble, R. Sinha, and C. Higgins, "Quantification of tremor with a digitizing tablet," *Journal of Neuroscience Methods*, vol. 32, no. 3, pp. 193–198, 1990.

[7] S. J. Elliott, "Differentiation of signature traits vis-à-vis mobile- and table- based digitizers," *ETRI Journal*, vol. 26, no. 6, pp. 641–646, 2004.

[8] M. K. Annett, "The fundamental issues of pen-based interaction with tablet devices," Ph.D. dissertation, University of Alberta, 2014.

[9] C. Forlines, D. Wigdor, C. Shen, and R. Balakrishnan, "Direct-touch vs. mouse input for tabletop displays," in *Proc. SIGCHI Conf. on Human Factors in Computing Systems (CHI)*, 2007, pp. 647–656.

[10] S. Zabramski, "Careless touch: A comparative evaluation of mouse, pen, and touch input in shape tracing task," in *Proc. Australian Computer-Human Interaction Conference (OzCHI)*, 2011, pp. 329–332.

[11] S. Zabramski and W. Stuerzlinger, "The effect of shape properties on ad-hoc shape replication with mouse, pen, and touch input," in *Proceeding of the 16th International Academic MindTrek Conference*, 2012, pp. 275–278.

[12] J. R. Ward and M. J. Phillips, "Digitizer technology: Performance characteristics and the effects on the user interface," *IEEE Computer Graphics and Applications*, vol. 7, no. 4, pp. 31–44, 1987.

[13] H. Junker, P. Lukowicz, and G. Troster, "Sampling frequency, signal resolution and the accuracy of wearable context recognition systems," in *International Symposium on Wearable Computers (ISWC)*, 2004, pp. 176–177.

[14] R.-D. Vatavu, "The effect of sampling rate on the performance of template-based gesture recognizers," in *Proc. Intl. Conf. on Multimodal Interaction (ICMI)*, 2011, pp. 271–278.

[15] R. Plamondon and A. Alimi, "Speed/accuracy tradeoffs in target directed movements," *Behav. Brain Sci.*, vol. 20, no. 2, pp. 279–349, 1997.

[16] W. Guerfali and R. Plamondon, "A new method for the analysis of simple and complex planar rapid movements," *J. Neuroscience Methods*, vol. 82, no. 1, 1998.

[17] C. Ghez and J. Krakauer, "Voluntary movement," *Principles of neural science*, vol. 3, pp. 622–624, 1991.

[18] R. Plamondon and M. Djioua, "A multi-level representation paradigm for handwriting stroke generation," *Hum. Mov. Sci.*, vol. 25, no. 4–5, pp. 586–607, 2006.

[19] R. Plamondon and W. Guerfali, "The 2/3 power law: When and why?" *Acta psychologica*, vol. 100, no. 1, pp. 85–96, 1998.

[20] C. O'Reilly and R. Plamondon, "Development of a Sigma-Lognormal representation for on-line signatures," *Pattern Recogn.*, vol. 42, no. 12, pp. 3324–3337, 2009.

[21] R. Plamondon, C. O'Reilly, C. Rémi, and T. Duval, "The lognormal handwriter: learning, performing, and declining," *Front. Psychol.*, vol. 4, no. 1, pp. 945:1–945:14, 2013.

[22] C. O'Reilly and R. Plamondon, "Can computer mice be used as low-cost devices for the acquisition of planar human movement velocity signals?" *Behav. Res. Methods*, vol. 43, no. 1, pp. 229–238, 2011.

[23] D. Martín-Albo, R. Plamondon, and E. Vidal, "Improving sigma-lognormal parameter extraction," in *Proc. Intl. Conf. on Document Analysis and Recognition (ICDAR)*, 2015.

[24] L. A. Leiva, D. Martín-Albo, and R. Plamondon, "Gestures à go go: Authoring synthetic human-like stroke gestures using the kinematic theory of rapid movements," *ACM T. Intel. Syst. Tec.*, vol. 7, no. 2, 2015.

[25] A. Fischer, R. Plamondon, C. O'Reilly, and Y. Savaria, "Neuromuscular representation and synthetic generation of handwritten whiteboard notes," in *Proc. Intl. Conf. on Frontiers in Handwriting Recognition (ICFHR)*, 2014, pp. 222–227.

[26] N. Leduc and R. Plamondon, "A new approach to study human movements: The three dimensional Delta-Lognormal model," in *Proc. Biennial Conf. of the Intl. Graphonomics Society (IGS)*, 2001, pp. 98–102.