# Velocity-Based Signal Features for the Assessment of Parkinsonian Handwriting

Donato Impedovo, *Senior Member, IEEE*

***Abstract*—This letter investigates different velocity-based signal processing techniques to the aim of Parkinson's disease classification through handwriting. It is showed that combining new velocity-based features with classic features improves state-of-the-art performance on the PaHaW dataset.**

***Index Terms*—Parkinson's disease, computer aided diagnosis, handwriting, drawing, velocity signal, micrographia, tremor.**

## I. Introduction

PARKINSON'S DISEASE (PD) is one of the most common neurodegenerative disorders, it results in a progressive cognitive, functional and behavioural decline [1], [2]. Different successful Computer Aided CAD systems have been already proposed and based on behavioral biometrics as for example speech [3]. These systems exhibit very performing accuracy in the healthy/pathologic classification being non-invasive techniques. It is well known that handwriting problems are related to this disease as well as to its severity, so changes in writing can be considered a prominent biomarker [1], [2]. Handwriting, in fact, is a complex activity entailing cognitive, kinesthetic and perceptual-motor components [3], whose changes can be used for the evaluation of PD [4]–[6] as well as Alzheimer's Disease [7].

In this context, handwriting acquisition is performed using tablet to acquire position ($x$, $y$), pressure, azimuth (i.e., angle of the pen in the horizontal plane), altitude (i.e., angle of the pen with respect to the vertical axis) and their time stamps. In air movements can also be acquired. From a signal processing perspective, the acquired trait is represented as a sequence $\{S(n)\}_{n=0,1,\ldots,N}$, where $S(n)$ is the signal value sampled at time $n\Delta t$ of the writing process ($0 \leq n \leq N$), $\Delta t$ being the sampling period.

A crucial step in designing a handwriting-based decision support system concerns the choice of the most appropriate features.

This letter investigates a wide set of velocity-based features for the PD/HC discrimination (being HC the set of Healthy Controls). More specifically, the sigma log-normal model, the Maxwell-Boltzmann distribution and transform based features are presented, justified and tested on the PaHaW dataset [8]. Experiments have been performed to compare the use of a standard (state of the art) system based on a wide set of features (more than 200), and the previous one extended with features here proposed. Results obtained clearly outperform the current state of the art.

The letter is organized as follows. Section II sketches conventional velocity-based features currently adopted, Section III illustrates new velocity-based features. Section IV describes experiments and results. Section V concludes the letter.

## II. Conventional Velocity-Based Features

PD motor deficits include: akinesia (impairment of voluntary activity), bradykinesia (slowness of movement), micrographia (reduction in writing size), and rigidity and tremor [1]. Many different features can be considered to describe these symptoms, however velocity-based features play a crucial role. In fact, it has been demonstrated that PD patients results in slower movements then HC while writing meanders, circle, star, spiral, sentence/name as well as on copying tasks [4], [9]–[11].

Tremor/Jerk has been observed on meanders, horizontal, straight forward and backward slanted lines, circles drawing and sentence writing [11]–[13]. It is quite evident that tremor/jerk is correlated to the velocity signal, in fact tremor/jerk is characterized by rapid changes of the velocity signal. Up to date, velocity has been evaluated as the derivative of spatial features or in terms of task or stroke execution duration. More specifically, velocity function features have been computed as derivatives of movements in the *x*- and *y*-direction or considering the derivative of the displacement (i.e., the distance between two consecutive points in the *x*-*y* plane). Tremor/Jerk has been evaluated in terms of Number of Changes in Velocity (NCV) and/or in Acceleration (NCA) and/or as the derivative of the acceleration signal. Function features have been extended by evaluating statistical parameters of the function feature set (e.g., mean, median, standard deviation, 1st percentile, 99th percentile, etc.) [2]. Parameter features have been normalized considering the total task/stroke duration [2].

## III. Extended Velocity-Based Features

### A. Sigma-Lognormal Model

The Sigma-Lognormal model theory "*describes a stroke velocity profile as the output of a system made up of two neuromuscular systems, one agonist (acting in the direction of the*

Manuscript received January 22, 2019; revised February 26, 2019; accepted February 28, 2019. Date of publication March 4, 2019; date of current version March 18, 2019. This work was supported by the Italian Ministry of Education, University and Research within the PRIN2015—Handwriting Analysis against Neuromuscular Disease—HAND Project under Grant H96J16000820001. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Monica F. Bugallo.

The author is with Department of Computer Science, University of Bari Aldo Moro, Bari 70125, Italy (e-mail: donato.impedovo@uniba.it).

Digital Object Identifier 10.1109/LSP.2019.2902936

*movement) and the other antagonist (acting in the opposite direction)*" [14]. This model has been used with successful results in many practical applications: on-line signature verification [15], graphomotor performance evaluation in kindergarten children [16] and for studying handwriting in Alzheimer's disease patients [17]. The main advantage of this approach is that it considers not only the rapidity, fluency and regularity of the handwriting movement, but also physical body characteristics such as the state of the neuromuscular system responsible for the generation of the action plan.

The model considers strokes as primitives from which complex patterns are built and the velocity profile of each stroke *j* as having a lognormal shape $\Lambda$ scaled by a command parameter $D$ and time-shifted by the time occurrence of the command $t_0$:

$$\left|\overrightarrow{v_j}\left(t;P_j\right)\right| = D_j\Lambda_j\left(t_{0j};\mu_j,\sigma_j^2\right) = \frac{D_j}{\sigma_j\left(t-t_{0j}\right)\sqrt{2\pi}}exp\left(-\frac{\left[\ln\left(t-t_{0j}\right)-\mu_j\right]^2}{2\sigma_j^2}\right)$$

In the formula, $P_j = [D_j, t_{0j}, \mu_j, \sigma_j]$ is the vector of $\Sigma\Lambda$ parameters, described as follows:

- $D_j$ amplitude of the input command;
- $t_{0j}$ time occurrence of the input command, i.e., the starting time of the stroke;
- $\mu_j$ log-time delay, i.e., the time delay of the neuromuscular system expressed on a logarithmic time scale;
- $\sigma_j$ log-response time, which is the response time of the neuromuscular system expressed on a logarithmic time scale.

Moreover, the model assumes each stroke as happening around a pivot, with respect to a starting angle $\theta_{sj}$ and an ending angle $\theta_{ej}$. In this context, handwriting can be viewed as the output of a generator that produces a set of individual strokes superimposed in time. Hence, the resulting complex trajectory can be modeled as summation of lognormal components:

$$\vec{v}\left(t\right) = \sum_{i=1}^{N}\overrightarrow{v_j}\left(t;t_{0j},\mu_j,\sigma_j^2\right),$$

where $N$ is the number of lognormal strokes in which the handwritten trait is decomposed.

The reconstruction error of a velocity profile using the $\Sigma\Lambda$ parameters can be evaluated through the Signal-to-Noise Ratio (SNR) between the reconstructed pattern and the original one:

$$10log\left(\frac{\int_{t_s}^{t_e}\left[v_{ox}^2\left(t\right)+\ v_{oy}^2\left(t\right)\right]dt}{\int_{t_s}^{t_e}\left[\left(v_{ox}\left(t\right)-\ v_{oy}\left(t\right)\right)^2+\ \left(v_{oy}\left(t\right)-\ v_{ry}\left(t\right)\right)^2\right]dt}\right),$$

where the global effect of the distortions is computed using the horizontal and vertical components $v_x(t)$ and $v_y(t)$ from the starting time $t_s$ to the ending time $t_e$ in the Cartesian space.

Note that the sub-index *o* refers to the original velocity profile (*x* or *y*), while *a* is the artificially reconstructed functions.

Fig. 1(a) shows a single sigma-lognormal component on the velocity profile (red-coloured) of an handwritten specimen, while Fig. 1(b) shows the corresponding stroke on the $(x, y)$ plane. Note that according to the standard definition of a stroke, the entire specimen of Fig. 1 corresponds to a single component

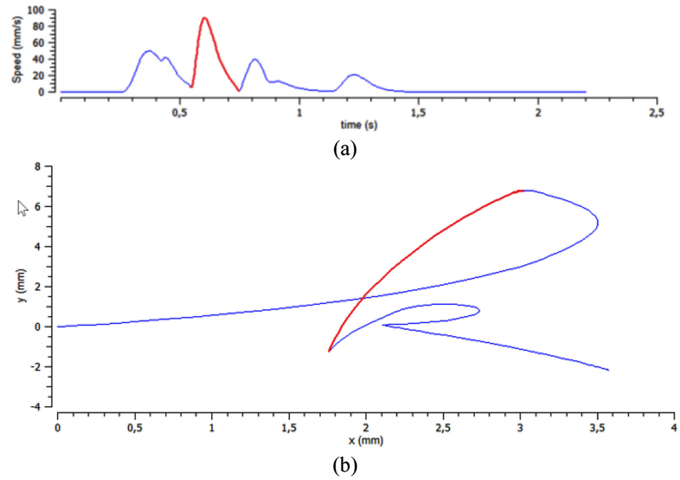


Fig. 1. Sigma log-normal components in the velocity domain (a) and in the spatial domain (b).

since there is just a pen-down and a pen. After the computations, the *j*-th single stroke (component) is represented by six components: $t_{0j}$, $D_j$, $\mu_j$, $\sigma_j$, $\theta_{sj}$ and $\theta_{ej}$. This set is extended considering the number of components of the handwriting trial. To some extent, the number of components can be a complexity measure of the trait, so that a higher number of components can be related to tremor.

## B. Maxwell-Boltzmann Distribution

The kinetic molecular model theory is generally used to describe the velocity of a molecule of an ideal gas under a set of conditions. The velocity probability distribution indicates which velocity are more likely: a particle will have a speed belonging to the distribution and it will be more probably to be within a specific range than another. The basic idea here is to use the Maxwell-Boltzmann distribution to model the handwriting velocity profiles. In other words, it is expected that PD patients and HC will exhibit different distributions. This theory has been recently and successfully adopted for controlling the selectivity of the firing neurons in the hidden layers of a deep neural network suited for the task of handwritten digits recognition [18].

In this letter, apart for some constants, the Maxwell-Boltzmann distribution has been used to determine a set of parameters according to the following formula:

$$mb_j = v_j^2 e^{-v_j^2}.$$

## C. Discrete Transformations

The well-known Discrete Fourier Transform (DFT) has been applied to the velocity profile obtaining a set of coefficients which represent, in a nutshell, the distribution of occurrences of different velocities which are expected to be different among the PD and the HC population. Moreover, the real cepstrum of the velocity profile has been also computed as follow:

$$rcep = IDFT\left\{log\left[\left|DFT\left(v_j\right)\right|\right]\right\},$$

Being *IDFT* the Inverse Discrete Fourier Transform. In other words, the spectrum contains harmonics whose magnitude decreases as frequency increases (in the case of HC), the *log* of the spectrum compresses the dynamic range re-organizing frequencies so that components with slow variations are compressed near to the 0 of the abscissa's axis. Moreover, if the velocity profile has an underlining stationary quasi-periodic evolution (i.e., constant tremor pattern of PD) a peak and periodic repetitions of it are localized in the cepstrum at higher quefrencies.

## IV. Experiment

Experimental evaluation has been performed on the PaHaW dataset [8]. It includes 37 PD patients and 38 HC. Each participant completed 8 handwriting tasks: 1. drawing the Archimedes spiral; 2. writing in cursive the letter "*l*", 3. the bigram "*le*" and 4. the trigram "*les*"; 5. writing in cursive the words "*lektorka*" (female teacher in Czech), 6. "*porovnat*" (to compare) and 7. "*nepopadnout*" (to not catch); 8. writing in cursive the sentence "*Tramvaj dnes uz nepo-jede*" (The tram won't go today).

It is worth noting that task 1 is a Simple Drawing task generally used in literature for trajectory, tremor, dimension (size), velocity and acceleration evaluations [2]. The second task (repetition of "*l*") is a very popular one also recently used for Alzheimer Disease patients vs. HC discrimination [15]. In general tasks 2 to 8 are Simple Writing tasks, but repetition of the "*e*" and "*l*" characters, according to the Lognormal Kinematic Theory, are very interesting pattern, in fact "*l*" and "*e*" are constituted by just two velocity strokes. Moreover, the use of "*l*" and "*e*" involves the handwriting of the same character scaled in amplitude. The last task requires more simultaneous processing if compared to others and it allows the capturing in-air movements between words as well as the effect of fatigue while writing (which is typically conveyed in speed).

The raw data captured by the device are the $x$- and $y$-coordinates of the pen position and their timestamps. Moreover, measures of pen inclination, i.e., azimuth and altitude, and the pressure were recorded. The last signal concerns the so-called button status, which is a binary variable evaluating 0 for pen-up state (in-air movement) and 1 for pen-down state (on-surface movement).

### A. Standard Signal Processing Techniques - Baseline

Table I summarizes features adopted by state-of-art approaches, more detail on their implementation can be found in [2]. Function-based features have been extended by evaluating statistical parameters (e.g., mean, median, standard deviation, 1st percentile, 99th percentile, etc.). In this letter, all the features reported in Table I have been implemented and their use represents the baseline system.

### B. Experiments

The new set of velocity-based features (proposed in this letter) has been computed to extend the set of Table I. All features have been normalized before classification to have zero mean and unit variance. Successively, simple performance-based feature selection strategy has been employed. More specifically, each feature has been used separately to evaluate its classification performance thus having a measure of the most performing to verify the validity of the new set. This schema is the same used by other authors on the same dataset [8].

TABLE I
Baseline Features

| Feature Name | Description |
|---|---|
| Position | Position in terms of s(x,y) |
| Button Status | Movement in the air: b(t)=0<br>Movement on the pad: b(t)=1 |
| Pressure | Pressure of the pen on the pad |
| Azimuth | Angle between the pen and the vertical plane on the pad |
| Altitude | Angle between the pen and the pad plane |
| Displacement | $d_i = \begin{cases} \sqrt[2]{(x_{i+1}-x_i)^2+(y_{i+1}-y_i)^2}, & 1 \le i \le n-1 \\ d_n - d_{n-1}, & i = n \end{cases}$ |
| Velocity | $v_i = \begin{cases} \frac{d_i}{t_{i+1}-t_i}, & 1 \le i \le n-1 \\ v_n - v_{n-1}, & i = n \end{cases}$ |
| Acceleration | $a_i = \begin{cases} \frac{v_i}{t_{i+1}-t_i}, & 1 \le i \le n-1 \\ a_n - a_{n-1}, & i = n \end{cases}$ |
| Jerk | $j_i = \begin{cases} \frac{a_i}{t_{i+1}-t_i}, & 1 \le i \le n-1 \\ j_n - j_{n-1}, & i = n \end{cases}$ |
| x / y displacement | Displacement in the x / y direction |
| x / y velocity | Velocity in the x / y direction |
| x / y acceleration | Acceleration in the x / y direction |
| x / y jerk | Jerk in the horizontal/vertical direction |
| NCV | Number of Changes in Velocity, NCV has been also normalized to writing duration |
| NCA | Number of Changes in Acceleration, NCA has been also normalized to writing duration |
| NCP | Number of Changes in Pressure, NCP has been also normalized to writing duration |
| Stroke number | Number of strokes |
| Dimensions | Length and height of the trait in terms of samples both at task and at stroke level |
| Durations | Stroke duration, in-air time, on-surface time, total task time, Ratio of time spent in-air/on-surface |
| Speeds | Dimensions on related times (e.g. stroke dimension on stroke time, etc.) |
| Entropy | Shannon and Rény operators applied on (x,y) |
| Energy | Teager-Kaiser energy |
| SNR | Signal-to-noise ratio of the horizontal/vertical component of the pen position |
| EMD | Empirical Mode Decomposition |

Although a wide set of classifiers have been successfully tested, for the sake of simplicity, results related to the use of SVM with a linear kernel have been here reported. A 10-fold cross-validation has been employed and the splitting has stratified (i.e., each fold contained roughly the same number of subjects from each diagnostic group). The entire procedure has repeated ten times, until each fold has been used as test set.

### C. Results

The baseline system adopting standard features achieved an accuracy of 88.33%. Successively, the set of standard features has been extended with those here proposed.

The first interesting result deals with features selection. When it has been performed at global level (i.e., considering all

TABLE II
TASK BASED PERFORMANCE

| Task | Accuracy |
|---|---|
| **1 – spiral** | **97.33** |
| **2 – "*lll*"** | **97.47** |
| 3 – "*le le le*" | 95.12 |
| 4 – "*les les les*" | 93.17 |
| **5 – "*lektorka*"** | **96.79** |
| 6 – "*porovnat*" | 95.96 |
| 7 – "*nepopadnout*" | 96.76 |
| 8 – "*tramvaj dnes uz nepo-jede*" | 92.05 |

TABLE III
ACCURACY PERFORMANCE

| Features | Accuracy |
|---|---|
| Baseline (all tasks) | 88.33% |
| Present Work (all tasks) | 93.79% |
| Mucha et al. 2018 [19] | 97.14% |
| **Present work (selection of the best three tasks)** | **98.44%** |

the writing tasks available within the dataset), the Maxwell-Boltzmann and the Sigma-Lognormal features have been observed within the set of the 10 most relevant/performing. In this case an accuracy of 93.79% has been achieved. This result clearly confirm that velocity-based features play a fundamental role in HC/PD classification.

The classification has been also performed at a single task level (i.e., using features related to each single task). Table II summarizes results. As it can be observed, 6 tasks out 8 are able to outperform the global result already obtained. The popular task of "lll" gets 97.47% of accuracy. Results also confirm that in-air features convey very useful information since they offer the possibility to evaluate difficulties in executing and planning an activity [2]. Moreover, it must be also considered that tremor is more evident on in-air movements than on-pad movements and the velocity-based features here proposed are able to numerically exploit it. In fact, the sigma-lognormal and the Maxwell-Boltzamnn features were always in the set of the 10 most relevant features, as well as all the other velocity-based features were in the set of the top 20. Regarding the spiral drawing task, the result here obtained is in line with recent literature which highlights its importance [19]–[21], while with baseline features it resulted not relevant for classification aims [8].

As previously mentioned, a specific task could be better than another for discrimination aim. The best three tasks are very different each other [2]:

- spiral is a simple drawing task typically used for tremor evaluation;
- "lll" is a simple writing task able to minimize the linguistic comprehension processes, moreover it involves execution abilities in sequentially reproducing the same pattern;
- "lektora" (female teacher in Czech) is a very popular word and it is familiar to all people regardless of their age or level of schooling.

These three tasks and the use of the proposed features can be able to reveal slowness, reduction in amplitude of repeated actions (bradykinesia on the "lll" pattern), micrografia, tremor and rigidity typically observed in PD patients. At the same time, it must be underlined that not all these characteristics (micrographia, slowness, etc.) have been simultaneously observed (in literature) during any task, so that the selection of an ensemble of the most profitable tasks is a non-trivial problem [2]. According to very recent studies, these simple tasks are easy to be correctly performed at home without an examiner present [20], [21]. Moreover, from a pattern recognition perspective, the similarity index of the three classifiers can be considered as a measure of their mutual behaviour [22]. More specifically, if the similarity index is 1, then the three different classifiers always provide the same output (HC or PD) for each given input, so that their combination is un-useful. In this case the similarity index of the three task-based classifiers is 0.72 thus suggesting the possibility of a suitable combination [20]. Here the combination has been performed at features level by lumping features related to the three tasks within a single vector. Under these conditions, the overall final accuracy of 98.44% has been gained. Results are reported in Table III. This result confirms the idea proposed in this letter and outperforms the current state of the art in HC/PD classification on the PAHAW dataset [19]. It is also of interest to consider that results obtained in [19] are related to the use of fractional derivatives of the handwriting evaluated on velocity, acceleration, jerk and their horizontal and vertical variants so that number of features and their computational complexity are comparable.

Although the idea here proposed has a solid background in terms of signal processing as well as in terms of relevance of the velocity signal for HC/PD classification, the main limitation of this letter relies in the possibility to generalize results since dataset is small. Another limitation is related to the fact that the dataset does not offer the possibility of a multiclass evaluation (e.g., HC vs. PD patients at different disease stages) due to very few examples for some classes and, more in general, un-balanced data.

## V. CONCLUSION

In this letter, different velocity-based features have been employed for discriminating handwriting of people affected by PD from HC. More specifically, the sigma log-normal model, the Maxwell-Boltzmann distribution, the Fourier and the Cepstrum transforms have been considered. The sigma-lognormal model feature set describes handwriting in terms of velocity signals, the other three features sets have been computed on the velocity standard signals. It has been showed that combining the new set features with more classic measures improves performance, in fact, a simple features selection schema placed the new sets within the list of the most relevant features for classification aims. The final accuracy of 98.44% in the HC/PD classification on the freely available PaHaW dataset has been gained. This result outperforms the current state of the art. Finally, it has been also showed that these features are able to exploit potentialities of different tasks and of the Archimedes spiral task which, in other cases, has been considered of limited impact for the classification aim.

## REFERENCES


[1] C. De Stefano, F. Fontanella, D. Impedovo, G. Pirlo, and A. S. di Freca, “Handwriting analysis to support neurodegenerative diseases diagnosis: A review,” *Pattern Recognit. Lett.*, vol. 121, pp. 37–45, 2019.

[2] D. Impedovo and G. Pirlo, “Dynamic handwriting analysis for the assessment of neurodegenerative diseases: A pattern recognition perspective,” *IEEE Rev. Biomed. Eng.*, vol. 12, pp. 209–220, 2019.

[3] F. Astrom and R. Koker, “A parallel neural network approach to prediction of Parkinson’s disease,” *Expert Syst. Appl.*, vol. 38, no. 10, pp. 12470–12474, 2011.

[4] S. Rosenblum, M. Samuel, S. Zlotnik, I. Erikh, and I. Schlesinger, “Handwriting as an objective tool for Parkinson’s disease diagnosis,” *J. Neurology*, vol. 260, no. 9, pp. 2357–2361, 2013.

[5] C. R. Pereira *et al.*, “A step towards the automated diagnosis of Parkinson’s disease: Analyzing handwriting movements,” in *Proc. IEEE 28th Int. Symp. Comput. Based Med. Syst.*, 2015, pp. 171–176.

[6] C. O’Reilly and R. Plamondon, “Development of a sigma–lognormal representation for on-line signatures,” *Pattern Recognit.*, vol. 42, no. 12, pp. 3324–3337, 2009.

[7] C. Kahindo, M. A. El-Yacoubi, S. Garcia-Salicetti, A. Rigaud, and V. Cristancho-Lacroix, “Characterizing early-stage Alzheimer through spatiotemporal dynamics of handwriting,” *IEEE Signal Process. Lett.*, vol. 25, no. 8, pp. 1136–1140, Aug. 2018.

[8] P. Drotár, J. Mekyska, I. Rektorová, L. Masarová, Z. Smékal, and M. Faundez-Zanuy, “Decision support framework for Parkinson’s disease based on novel handwriting markers,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 3, pp. 508–516, May 2015.

[9] M. P. Caligiuri, H. L. Teulings, J. V. Filoteo, D. Song, and J. B. Lohr, “Quantitative measurement of handwriting in the assessment of drug-induced Parkinsonism,” *Human Movement Sci.*, vol. 25, no. 4, pp. 510–522, 2006.

[10] M. M. Ponsen, A. Daffertshofer, E. C. Wolters, P. J. Beek, and H. W. Berendse, “Impairment of complex upper limb motor function in de novo Parkinson’s disease,” *Parkinsonism Related Disorders*, vol. 14, no. 3, pp. 199–204, 2008.

[11] M. P. Broderick, A. W. Van Gemmert, and H. A. Shill, “Hypometria and bradykinesia during drawing movements in individuals with Parkinson disease,” *Exp. Brain Res.*, vol. 197, no. 3, pp. 223–233, 2009.

[12] E. J. Smits *et al.*, “Standardized handwriting to assess bradykinesia, micrographia and tremor in Parkinson’s disease,” *PLOS One*, vol. 9, no. 5, 2014, Art. no. e97614.

[13] C. Kotsavasiloglou, N. Kostikis, D. Hristu-Varsakelis, and M. Arnaoutoglou, “Machine learning-based classification of simple drawing movements in Parkinson’s disease,” *Biomed. Signal Process. Control*, vol. 31, pp. 174–180, 2017.

[14] H. L. Chen *et al.*, “An efficient diagnosis system for detection of Parkinson’s disease using fuzzy k-nearest neighbor approach,” *Expert Syst. Appl.*, vol. 40, no. 1, pp. 263–271, 2013.

[15] T. Duval, C. Remi, R. Plamondon, J. Vaillant, and C. O’Reilly, “Combining sigma-lognormal modeling and classical features for analyzing graphomotor performances in kindergarten children,” *Human Movement Sci.*, vol. 43, pp. 183–200, 2015.

[16] D. Impedovo *et al.*, “Writing generation model for health care neuromuscular system investigation,” in *International Meeting on Computational Intelligence Methods for Bioinformatics and Biostatistics*. Berlin, Germany: Springer, 2013, pp. 137–148.

[17] W. A. Van Gemmert, R. Plamondon, and C. O’Reilly, “Using the sigma-lognormal model to investigate handwriting of individuals with Parkinson’s disease,” in *Proc. 16th Biennal Conf. Int. Graphonomics Soc.*, 2013, pp. 119–122.

[18] G. Li *et al.*, “Temperature based restricted Boltzmann machines,” *Sci. Rep.*, vol. 6, 2016, Art. no. 19133.

[19] J. Mucha *et al.*, “Identification and monitoring of Parkinson’s disease dysgraphia based on fractional-order derivatives of online handwriting,” *Appl. Sci.*, vol. 8, no. 12, 2018, Art. no. 2566.

[20] E. J. Smits *et al.*, “Graphical tasks to measure upper limb function in patients with Parkinson’s disease: Validity and response to dopaminergic medication,” *IEEE J. Biomed. Health Inform.*, vol. 21, no. 1, pp. 283–289, Jan. 2017.

[21] P. Zham, S. P. Arjunan, S. Raghav, and D. K. Kumar, “Efficacy of guided spiral drawing in the classification of Parkinson’s disease,” *IEEE J. Biomed. Health Inform.*, vol. 22, no. 5, pp. 1648–1652, Sep. 2018.

[22] G. Pirlo, D. Impedovo, and D. Barbuzzi, “The similarity index lower and upper bounds: Theoretical considerations and experimental verification,” *Int. J. Math. Models Methods Appl. Sci.*, vol. 7, no. 7, pp. 682–691, 2013.