NEW METHODOLOGY OF PARKINSONIC DYSGRAPHIA ANALYSIS BY ONLINE HANDWRITING USING FRACTIONAL DERIVATIVES

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Abstract: Parkinson's disease (PD) is the second most frequent neurodegenerative disorder. One typical hallmark of PD is disruption in execution of practised skills such as handwriting. This paper introduces a new methodology of kinematic features calculation based on fractional derivatives applied on PD handwriting. Discrimination power of basic kinematic features (velocity, acceleration, jerk) was evaluated by classification analysis (using support vector machines and random forests). For this purpose, 37 PD patients and 38 healthy controls were enrolled. In comparison to results reported in other works, we proved that FDE in online handwriting analysis brings promising improvements. The best result of multivariate analysis was achieved with 83.89 % classification accuracy in combination with 5 features using only one handwriting task (overlapped circles). This study reveals an impact of fractional derivatives based features in analysis of Parkinsonic dysgraphia.

Keywords: Binary classification; fractal calculus; fractional derivative; online handwriting; overlapped circles; Parkinson's disease

1 INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder with prevalence rate estimated to approximately 1.5 % for people aged over 65 years [1]. The most significant biological finding associated with the disease is a rapid degeneration of dopaminergic cells in *substancia nigra pars compacta* [2], however the exact pathophysiological cause of PD has not yet been discovered. The cardinal motor symptoms incorporate tremor in rest, rigidity, bradykinesia, and loss of postural reflexes. Also, PD accompanies several non-motor symptoms such as sleep disorders, cognitive deficits, depression, dementia, etc. [3].

Handwriting is a highly skilled and complex coordinated motor activity [4]. Considering motor dysfunctions in people suffering from PD some recent studies have suggested that handwriting can be used as a significant biomarker for PD diagnosing [5]. PD patients tend to perform sequential movements in a more segmented fashion. Continuous handwriting and similar motor tasks are performed more slowly than in a healthy case and hesitations and pauses are more often observed [6]. Because the disorders are not limited to micrographia only, Letanneux et al. (2014) introduced a more general term: PD dysgraphia [7].

Several tasks were proposed for analysis of PD handwriting such as the Archimedean spiral, overlapped circles, characters, words or sentences [3, 4, 8]. Discrimination power of handwriting features in previous related papers (2014–now) were evaluated by correlation analysis (Spearman) [8, 9], classification analysis (SVM, ANN, K-NN) [3, 4, 10, 11] or analysis of variance (ANOVA) [12, 9]. For the purpose of this work, overlapped circles task was selected.

The aim of this paper is to introduce advanced kinematic features that replace the conventional ones by utilizing fractional derivative (FDE) and to confirm our previous results. The potential of FDE in PD dysgraphia quantification is demonstrated by classification analysis and a discrimination power of the newly designed features is compared with a baseline [3, 4, 10, 11].

2 MATERIALS AND METHODS

2.1 DATASET

The dataset consisted of 75 participants: 38 healthy controls (HC) with (mean $\pm$ std) age: 62.42 $\pm$ 11.24 years, and 37 PD patients with (mean $\pm$ std) age: 69.32 $\pm$ 10.82 years, PD duration: 8.38 $\pm$ 4.73 years, UPDRS V (Unified Parkinson's disease rating scale, part V: Modified Hoehn & Yahr staging score): 2.27 $\pm$ 0.83 and LED (L-dopa equivalent daily dose): 1432.19 $\pm$ 695.19 mg. The participants were enrolled at the First Department of Neurology, St. Anne's University Hospital in Brno, Czech Republic. All participants reported Czech language as their native language and all participants were right-handed. The PD patients completed the tasks approximately 1 hour after their regular L-dopa medication. All participants signed an informed consent form approved by the local ethics committee.

2.2 DATA ACQUISITION

The overlapped circles task is a part of the PaHaW database [3]. Participants had several attempts for drawing the overlapped circles where the last attempt was taken for analysis. Online handwriting signals were recorded using the Intuos 4M (Wacom technology) digitizing tablet, with sampling rate 100 Hz. The tablet was overlaid with an empty paper template. The following features were acquired (time sequences): x and y coordinates – $x[t]$, $y[t]$; time-stamp – t; in-air/on-surface status – $b[t]$; pressure – $p[t]$; azimuth $az[t]$; and tilt $al[t]$.

2.3 FRACTIONAL DERIVATIVE

There are several approaches of calculation FDE [13, 14]. In this paper, the implementation of FDE by Jonathan Hadida, which follows the Grünwald-Letnikov approximation was used. The Grünwald-Letnikov approximation reads [14]:

$$D^{\alpha}y(t) = \lim_{h\to 0}\frac{1}{h^{\alpha}}\Delta_h^{\alpha}y(t), \tag{1}$$

where $D^{\alpha}y(t)$ means a derivative with order α of function $y(t)$, and h represents sampling lattice. In our case, the FDE substitutes the conventional differential derivative during calculation of the kinematic features. A detailed description of the FDE can be found at [13, 14].

2.4 HANDWRITING FEATURES

To demonstrate the impact of FDE in analysis of PD dysgraphia only basic on-surface kinematic features were extracted [3, 4]: velocity, acceleration, jerk and their horizontal and vertical variants. These features were calculated for different orders α of the FDE in range from 0.1 to 1.0 with 0.1 steps. Consequently, statistical properties of the features were described using following statistics: mean, median, standard deviation (std), and maximum (max) [3, 4, 11]. In total 360 features were extracted.

2.5 STATISTICAL ANALYSIS

To evaluate a discrimination power of the features, univariate binary classification (PD/HC) models (stratified 7-fold cross-validation with 50 repetitions) based on random forests (RF) and support vector machines (SVM) with radial basis function (RBF) were employed. Next, some improvements in classification accuracy were done by multivariate approach with the same classifiers and the same cross-validation settings. In this case, the sequential floating forward selection (SFFS) algorithm was used in order to select the most appropriate combination of the features. Classification performance was evaluated by the Matthew's correlation coefficient (MCC), classification accuracy (ACC), sensitivity (SEN) and specificity (SPE).

3 RESULTS

Results of the univariate and multivariate analysis are summarized in Table 1. Regarding the univariate classification, only the best features (in terms of the MCC values) are reported. The best feature of the univariate classification is mean of horizontal acceleration with $\alpha = 0.6$, where ACC $= 75.79\,\%$ (classified by SVM). Behaviour of ACC depending on order α of FDE for mean of horizontal acceleration is visualized on Figure 1. Regarding the multivariate classification analysis, ACC of 83.89 % (MCC = 0.69) was achieved using combination of 5 features classified by RF. The set of these features as gradually selected by SFFS and their α is: horizontal acceleration (mean) $\alpha = 0.6$; velocity (std) $\alpha = 0.9$; vertical acceleration (median) $\alpha = 1.0$; horizontal acceleration (mean) $\alpha = 0.7$; horizontal acceleration (mean) $\alpha = 0.2$.

Table 1: Results of the univariate and multivariate classification analysis

Univariate analysis						
Classifier	Feature	α	MCC	ACC [%]	SEN [%]	SPE [%]
SVM	horizontal acceleration (mean)	0.6	0.52	75.79	69.57	81.84
SVM	vertical velocity (mean)	0.9	0.50	75.17	73.78	76.52
SVM	horizontal acceleration (mean)	0.2	0.49	74.03	62.20	85.47
SVM	horizontal acceleration (mean)	0.1	0.47	72.75	66.38	80.26
SVM	horizontal acceleration (mean)	0.3	0.46	72.59	60.59	84.58
SVM	vertical velocity (mean)	1.0	0.45	72.51	69.01	76.00
SVM	vertical velocity (mean)	0.3	0.45	72.45	63.73	81.05
SVM	horizontal velocity (mean)	1.0	0.45	72.34	66.27	78.47
RF	horizontal acceleration (mean)	0.6	0.44	72.05	70.27	74.36
Multivariate analysis						
Classifier	Number of features		MCC	ACC [%]	SEN [%]	SPE [%]
RF	5		0.69	83.89	83.05	85.56
SVM	17		0.52	76.68	63.54	88.21

α – order of fractional derivative; RF – random forests; SVM – support vector machine;
MCC – Matthew's correlation coefficient; ACC – accuracy; SEN – sensitivity; SPE – specificity.

4 DISCUSSION

According to the reported results, previous hypothesis that application of the FDE in calculation of kinematic features brings promising potential in automatic diagnosis of PD dysgraphia can be confirmed. Considering, that only the basic kinematic features such as velocity, acceleration, and jerk were extracted, the results of discrimination analysis are promising, in comparison with previous related papers (baseline) [3, 4, 15, 11]. The top results of univariate analysis are mostly achieved by SVM classifier (see Table 1). The best result of multivariate analysis (ACC $= 83.89\,\%$, MCC = 0.69) was achieved by the RF classifier in combination with 5 features selected by SFFS. Considering, that results in this paper were achieved based on quantification of one handwriting task only, it can be argued that FDE in handwriting analysis brings promising improvement. Especially in comparison to the baseline where the accuracy of classification is 82–89 % [3, 4, 15, 11] for combination of features

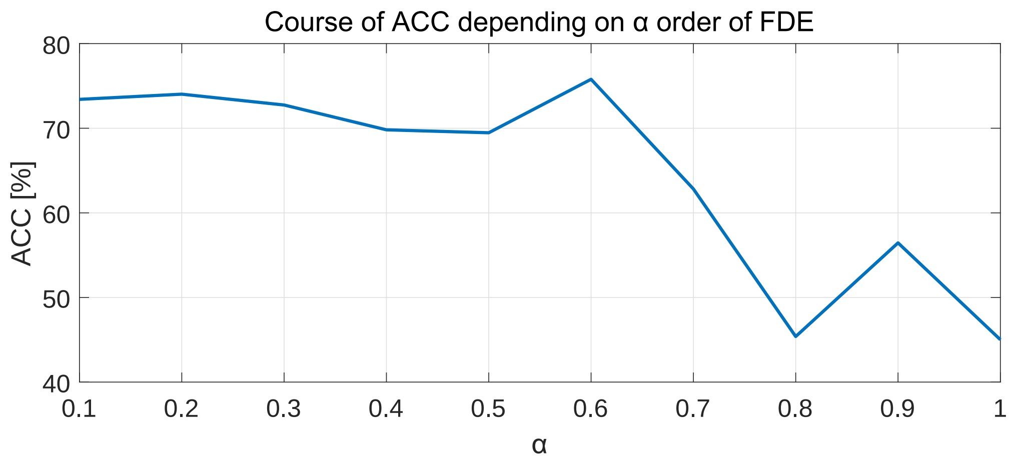

Figure 1: Behaviour of ACC according to α order of FDE for mean of horizontal acceleration.

extracted from different handwriting tasks. Moreover, from the feature description of univariate and multivariate analysis, it is evident that most of the parameters were based on $\alpha \neq 1$, which confirms full utilization of the FDE. Also, it's appropriate to note that mean of horizontal acceleration in different α variations is the most frequent feature in our results. From the results summarized in Figure 1 we can also confirm utilization of the FDE in the case of mean of horizontal acceleration where the highest ACC is achieved around $\alpha = 0.6$. Considering, that this feature describes rate at which the velocity of pen changes with time we can confirm reduced movement abilities in PD cohort, which is caused mainly by rigidity and bradykinesia [16].

5 CONCLUSION

With respect to the results we can conclude, that using the FDE in kinematic analysis brings new improvements in quantitative PD dysgraphia processing and add-on to the existing conventional techniques. This study is considered as a pilot one and its conclusions should be confirmed and extended by further research. For instance, it would be interesting to combine the newly developed parameters with other features such as temporal, spatial or dynamic ones. Moreover, the other tasks (e.g. Archimedean spiral, words, drawings) could be quantified. Another implementation of the FDE should be evaluated as well. Finally, a bigger dataset must be used to be able to generalize the conclusions.

REFERENCES

[1] S. Sapir, L. Ramig, and C. Fox, "Speech and swallowing disorders in Parkinson disease," *Curr. Opin. Otolaryngol. Head Neck Surg.*, vol. 16, no. 3, pp. 205–10, 2008.

[2] O. Hornykiewicz, "Biochemical aspects of Parkinson's disease," *Neurology*, vol. 51, no. 2 Suppl 2, pp. S2–S9, 1998.

[3] P. Drotar, J. Mekyska, I. Rektorova, L. Masarova, Z. Smekal, and M. Faundez-Zanuy, "Evaluation of handwriting kinematics and pressure for differential diagnosis of Parkinson's disease," *Artificial Intelligence in Medicine*, vol. 67, pp. 39 – 46, 2016.

[4] P. Drotar, J. Mekyska, Z. Smekal, I. Rektorova, L. Masarova, and M. Faundez-Zanuy, "Contribution of different handwriting modalities to differential diagnosis of Parkinson's disease," in *Medical Measurements and Applications (MeMeA), 2015 IEEE International Symposium*, 2015, pp. 1–5.

[5] S. Rosenblum, M. Samuel, S. Zlotnik, I. Erikh, and I. Schlesinger, "Handwriting as an objective tool for Parkinson's disease diagnosis," *Journal of neurology*, vol. 260, no. 9, pp. 2357–2361, 2013.

[6] J. L. Contreras-Vidal, P. Poluha, H.-L. Teulings, and G. E. Stelmach, "Neural dynamics of short and medium-term motor control effects of levodopa therapy in Parkinson's disease1supported in part by ninds grant ro1 ns33173, the flinn foundation and the bryng bryngelson fund.1," *Artificial Intelligence in Medicine*, vol. 13, no. 1, pp. 57 – 79, 1998.

[7] A. Letanneux, J. Danna, J.-L. Velay, F. Viallet, and S. Pinto, "From micrographia to Parkinson's disease dysgraphia," *Movement Disorders*, vol. 29, no. 12, pp. 1467–1475, 2014.

[8] S. Broeder, E. Nackaerts, A. Nieuwboer, B. Smits-Engelsman, S. Swinnen, and E. Heremans, "The effects of dual tasking on handwriting in patients with Parkinson's disease," *Neuroscience*, vol. 263, pp. 193–202, mar 2014.

[9] E. Heremans, E. Nackaerts, S. Broeder, G. Vervoort, S. P. Swinnen, and A. Nieuwboer, "Handwriting impairments in people with Parkinson's disease and freezing of gait," *Neurorehabilitation and Neural Repair*, vol. 30, no. 10, pp. 911–919, jul 2016.

[10] P. Drotar, J. Mekyska, I. Rektorova, L. Masarova, Z. Smekal, and M. F. Zanuy, "Decision support framework for Parkinson's disease based on novel handwriting markers," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, pp. 1–1, 2015.

[11] P. Drotar, J. Mekyska, I. Rektorova, L. Masarova, Z. Smekal, and M. Faundez-Zanuy, "Analysis of in-air movement in handwriting: A novel marker for Parkinson's disease," *Computer Methods and Programs in Biomedicine*, vol. 117, no. 3, pp. 405–411, 2014.

[12] E. Heremans, E. Nackaerts, G. Vervoort, S. Vercruysse, S. Broeder, C. Strouwen, S. P. Swinnen, and A. Nieuwboer, "Amplitude manipulation evokes upper limb freezing during handwriting in patients with Parkinson's disease with freezing of gait," *PLOS ONE*, vol. 10, no. 11, p. e0142874, nov 2015.

[13] S. G. Samko, A. A. Kilbas, O. I. Marichev *et al.*, "Fractional integrals and derivatives," *Theory and Applications, Gordon and Breach, Yverdon*, vol. 1993, p. 44, 1993.

[14] I. Podlubny, *Fractional differential equations an introduction to fractional derivatives, fractional differential equations, to methods of their solution and some of their applications*. San Diego: Academic Press, 1999.

[15] P. Drotar, J. Mekyska, I. Rektorova, L. Masarova, Z. Smekal, and M. Faundez-Zanuy, "A new modality for quantitative evaluation of Parkinson's disease: In-air movement," in *13th IEEE International Conference on BioInformatics and BioEngineering, BIBE 2013, Chania, Greece, November 10-13, 2013*. IEEE Computer Society, 2013, pp. 1–4.

[16] M. Thomas, A. Lenka, and P. K. Pal, "Handwriting analysis in Parkinson's disease: Current status and future directions," *Movement Disorders Clinical Practice*, vol. 4, no. 6, pp. 806–818, 2017.