2016 15th IEEE International Conference on Machine Learning and Applications

Recognition and Analysis of the Contours Drawn During the Poppelreuter's Test

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***Abstract*—This study aims to digitalize the Poppelreuter's overlapping figures test. The Poppelreuter's test used in psychology and neurology to assess visual perceptual function. Its recent modification performed with pencil and paper. Replacing the pencil and paper by the tablet computer equipped with the stylus, allows recording and analyzing fine motor motions observed during the test. On the one hand, this provides an opportunity to compute the measures describing condition of the participant. On the other hand, this possess two major problems to be tackled. The first one is to recognize the contours of the overlapping objects drawn by the participant. In the case of severe neurologic disorder, dissimilarity between the etalon shape and drawn contour may be very high. The second problem is to identify errors made during the drawing. The both problems are addressed within this study. Traditional machine learning techniques K-means, k-nearest neighbors and random forest used in this study to identify drawn contours and drawing mistakes. Finally, to demonstrate applicability of the proposed approach, kinematic parameters analyzed for the pilot groups of Parkinson Disease patients and healthy individuals.**

I. INTRODUCTION

The present paper is devoted to the recognition of the overlapping contours, drawn during Poppelreuter's figure visual perceptual function test (here and after Poppelreuter's test). The test was initially developed by Walther Poppelreuter to assess the brain injury. Later it become widely used to assess disorders caused by different neurologic and psychiatric diseases [1]. During the test, the picture is placed in front of the participant (testee or patient). The picture contains contours of the overlapping objects, for example see Fig 2. Different modifications of the test has appeared in the literature, the participant is asked to name or to point the object [2]. We used the modified version of the test [3], [4], where participant asked to find the shapes of the objects and trace (draw) their contours, one by one, with the pen. Observing practitioner should note all the mistakes done by the participant and make an assessment about condition of the participant. Such classical setting have two noticeable drawbacks. The first one is that assessment contains subjective component. The second one is that human eye could not observe and record all the kinematics of the drawing process. The modified Poppelreuter's test follows the same procedure as many other fine motor tests. The only difference is that fine motor tests require the participant to trace copy or continue certain periodic line or pattern [5], [6] and the Poppelreuter's test relies on tracing more complex, meaningful shapes. While the problem of digitalizing fine motor tests has been extensively treated for more than twenty years [7], [6], in the best knowledge of the authors the same problem for the Poppelreuter's test did not got the same attention. This is surprising, because more complicated clock drawing test got quite a lot of attention from the digitalization point of view [8]. Digitalization of the Poppelreuter's test would allow reducing subjectiveness of the assessment and providing a possibility to study kinematics of the drawing process with respect to neurologic disorders.

Recognition of the hand drawn contours belong to the area of sketch analysis and shape extraction from the sketch. This area have been extensively studied in light of different problems. For example [9] devoted to the analysis of hand drawn maps. Recognition of the hand drawn electronic circuits has been studied by [10], diagram recognition in [11] and matching face sketches to the face photographic images in [12]. Each of these cases has its own particularities to be taken into account. The nature of the drawings studied in this paper is the closest to the one reported in [13]. In many cases, participants tend to trace the shapes in a multi stroke fashion [14]. One of the major obstacles to apply existing "out of the box" solutions directly is, that in addition to the object recognition it is required to detect the errors during the drawing process. Also unlike [14] it is required to identify partially traced shapes.

Results reported in the present paper, based on the pilot research, conducted with the group of fourteen Parkinson's disease (PD) patients and ten healthy individuals (controls). K-means, k-nearest neighbors and random forest algorithms used to identify the drawn shape, or part of the shape and

978-1-5090-6167-9/16 $31.00 © 2016 IEEE
DOI 10.1109/ICMLA.2016.145

detect drawing errors. For each identified shape the values of kinematic parameters are computed. It is demonstrated, that for the case studied in this paper, it is possible to select a subset of kinematic parameters, which values differ significantly between the groups of PD patients and controls. In addition we demonstrate that some kinematic parameters linearly correlate to the unified Parkinson's Disease Rating Scale (UPDRS) Part: III (clinician-scored monitored motor evaluation) values [15] and minimental state examination scores (MMSE) [16]. The first one is the most commonly used scale in the clinical study of Parkinson's disease.

The present paper is organized as follows. Necessary background about the Poppelreuter's test and formal problem statement is provided in section II. Section III discusses recognition of the contours drawn by the participant. One of the goals of these studies is to analyze kinematics of the drawing process. Analysis of the kinematic parameters, observed during the test presented in section IV. Concluding remarks are drawn in the last section.

II. Background and Problem Statement

In the modified tracing form used before, only the time parameter may be measured precisely. Usually practitioner assesses visually overall similarity to the etalon and identifies tracing errors. During the Poppelreuter's test, mistake is the choice of a "wrong" contour on the intersection. Whereas three types of errors are distinguished

1) Error was fixed by returning to the contour of initial object without lifting stylus from the screen. See Fig.1 first shape on the left.
2) Error was fixed by starting new stroke. See Fig. 1 shape in the center.
3) Error was not fixed at all (participant continued to follow contour of another shape). See Fig. 1 last right shape.

The third type of error may be quite common for PD patients which increases complexity of the drawn (traced) contour recognition. In Fig. 2 gray color represent etalon shapes and black color represent contours traced by the participant. While controls tend to trace shapes one by one see Fig 3, PD patients switch between tracing different contours see Fig. 4. While drawings are flat, in Fig. 3 and 4 time is added as the vertical axis to demonstrate that tracing order is not followed by PD patient.

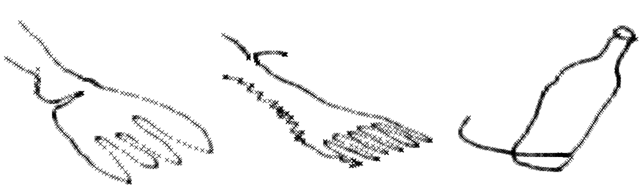

Fig. 1. Drawing mistakes observed during shape contour tracing

Proper digitalization of the Poppelreuter's test requires one to identify drawn shapes (even partially) and identify all the mistakes made by the participant.

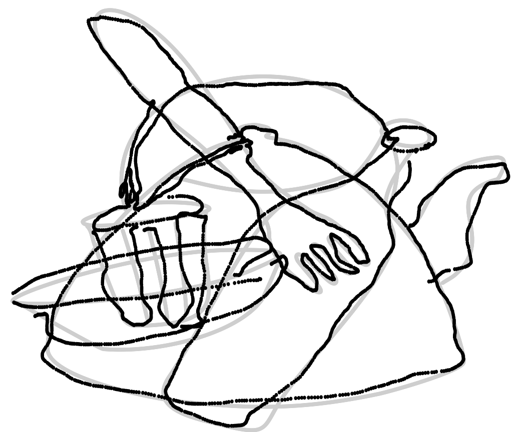

Fig. 2. Etalon shapes (gray) and traced contours (black)

The work flow for digitalized fine motor testing was outlined by [7]. In order to follow the protocol of the modified Poppelreuter's test, traced contours should be identified and drawing errors counted. Then it is possible to extend the test and analyze kinematic parameters, similarly to other digitalized fine motor tests. Etalon picture, in this case contours of the overlapping objects, is stored in the tablet memory and shown to the participant in the beginning of the test. Participant instructed to find the shapes (objects) on the screen and trace their contours with the stylus. Tablet computer records the coordinates of the stylus tip, accompanied by pressure information and time-stamps. Once recording is completed, traced contours, and drawing errors should be identified. Followed by the analysis of the parameters describing kinematics and pressure observed during drawing process.

This leads the following problem statement:

- On the basis of recorded stylus tip coordinates and pressure identify traced objects.
- For each identified object detect and classify tracing mistakes.
- For each object find the set of kinematics and pressure parameters, which values differ significantly between the PD patients and controls.
- For each object find the set of kinematic and pressure parameters, which values correlate to the parameters commonly used to describe mental or physical state of the patient.

III. Proposed Approach

Most of the shape recognition solutions operate with complete contours of the objects to perform classification. In majority of cases the goal is to detect the presence of a particular object on the image and evaluate the confidence of this claim. What makes digitalization of the Poppelreuter's test different is that even partial presence of the object should be analyzed. Also drawing (tracing) mistakes should be evaluated. Taking in to account that majority of participants tracing the

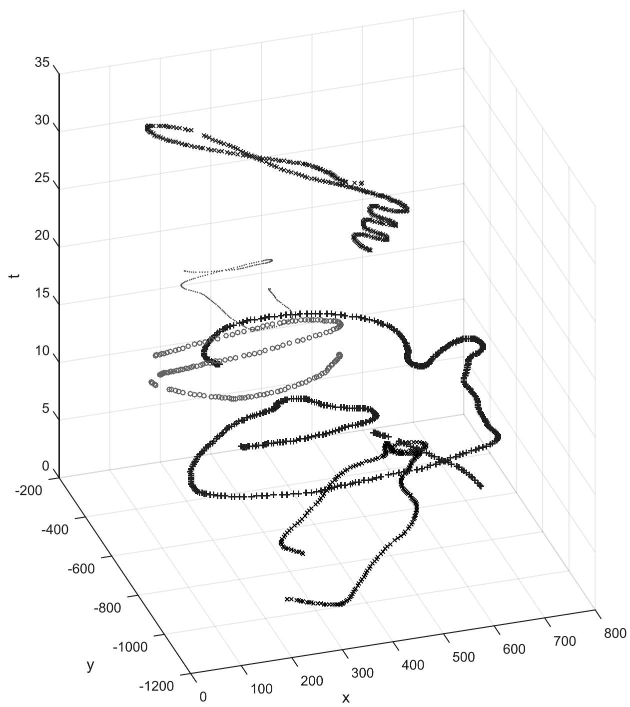

Fig. 3. Tracing performed by the control

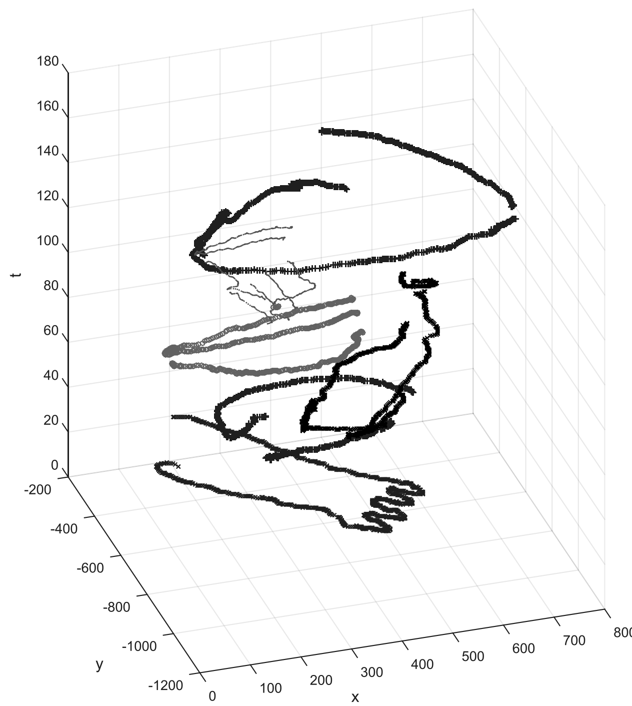

Fig. 4. Tracing performed by the PD patient

shapes (objects) with the number of strokes, leads the idea to classify each pen stroke. During the process of stroke classification, the parameters that would be significant for PD classification should be identified and computed.

The recording is a sequence of points, that represent the complete picture drawn by the patient. The drawing can be described as a trajectory of the stylus tip movements. Each stroke may be seen as a trajectory, segment of the recording and therefore may be described by a $n \times 4$ matrix, where n is the number of time instances, constituting the stroke. Each point (*row*) has Descartes coordinates x, y of the tip of the stylus, pressure applied to the screen and the time-stamp. Overall digitalization of the test consist of three main components. On the first stage contours drawn during shape tracing are identified. On the second stage kinematic parameters are computed and analyzed for each identified contour. On the third stage drawing mistakes are detected. The following algorithm is used to identify drawn contours.

- Each point of the etalon drawing is assigned a label corresponding to the shape it belongs to.
- On the phase of preparation individual strokes are extracted on the basis of the time and coordinates.
- Stroke analysis is performed in two steps:
  1) Each point represented by its x and y coordinates is assigned class label by k-nearest neighbors algorithm. Whereas points of the etalon drawing are used as the reference set.
  2) Mode label of the stroke is assigned to entire stroke. (The best results were obtained with k = 5).
  3) If the purity of the stroke is lower than certain threshold (best results were achieved with the value of 65%) - the stroke is considered to be an outlier.

In the case of controls implementation of this algorithm is one hundred percent accurate. In the case of PD patients the algorithm was not able to identify shape correctly in less that ten percent.

Kinematic and pressure parameters computed for each identified shape were analyzed in two steps:

1) With respect the diagnosis distinguish between the PD patients and controls (Ability to diagnose PD)
2) Correlations between the kinematic parameters and UPDRS. Correlations between the kinematic parameters and MMSE. Correlations between the kinematic parameters and duration of disease.

Section IV explains the analysis results in detail.

Unlike the first step, detection of the drawing mistakes is a more complicated process. For each shape it requires the database with reference drawings (correctly and incorrectly drawn shapes). Flow chart of this part is depicted in Fig.6.

- Etalon shape is clustered into m clusters with k-means algorithm (Euclidean distance is used). These clusters may be seen as artificially defined strokes.
- Each reference drawing of the database is segmented into the m segments. Each point is classified with k-nearest neighbors algorithm, whereas centroid found during the previous step are used as the reference set.

- For each segment kinematic parameters listed in Section IV are computed and complemented by the coordinates of corresponding centroid and label.
- Then random forest model is trained on this set.

Detection of the drawing mistakes is performed in the following way, see Fig. 7 for flow chart of this procedure.

- Each shape to analyze is segmented into m segments.
- For each segment kinematic parameters are computed and complemented by the coordinates of the corresponding centroid.
- Random forest algorithm is used to answer the question if the stroke is done correctly or not.
- Then miss detections (wrongly detected errors) are filtered out.

During the current studies the value $m = 30$ was defined experimentally. The error rate observed on the training data set is about 18%.

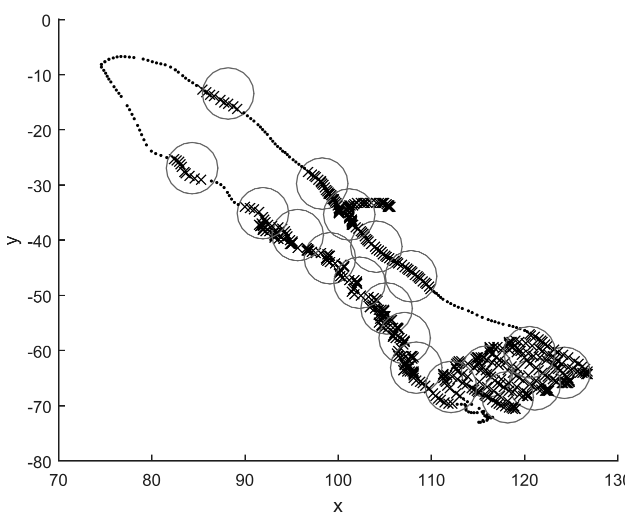

Fig. 5. Detection of drawing mistakes on the traced contour

IV. Analysis of the Kinematic Parameters

One of the goals of identifying the shapes drawn by the participant is to compute kinematic parameters. Shape wise analysis of the kinematic parameters intends to serve two goals. The first goal is to diagnose the disease. The second goal is to describe the state of the patient as the function of kinematic parameters. The both goals assist the idea to support diagnostics and disease monitoring with computable numeric characteristics. To achieve the first goal statistical hypothesis testing is used. For each shape and for each kinematic parameter the values observed for the PD patients are compared to the values observed for controls. To achieve the second goal present of the linear correlation is checked for each figure and each parameter on the one side and UPDRSIII MMSE and duration of the disease on the other side.

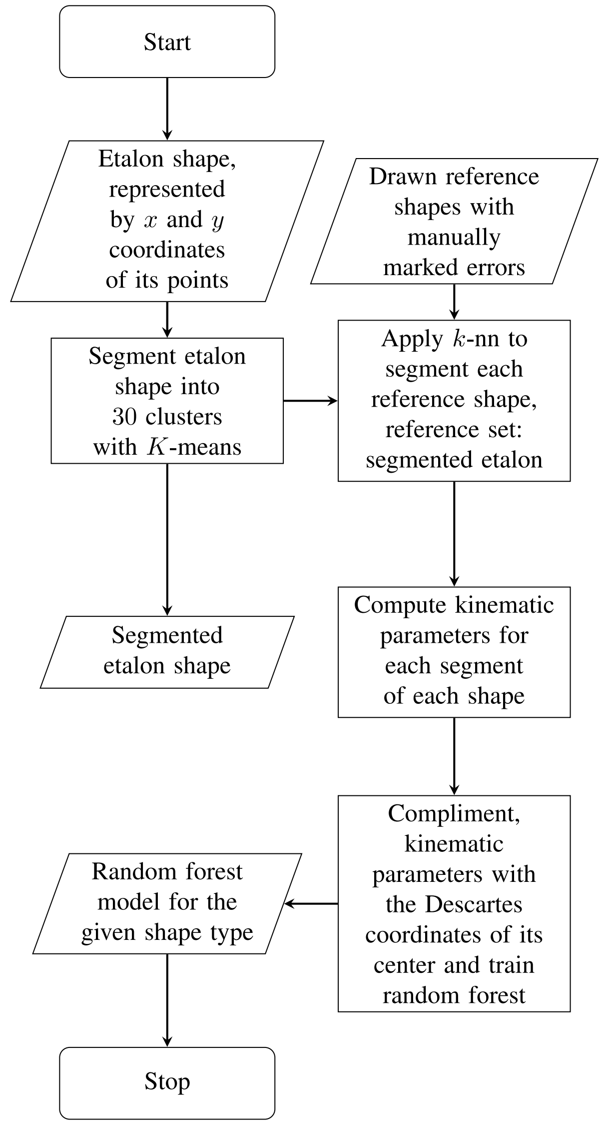

Fig. 6. Model training for drawing mistakes detection

A. Distinguishable Kinematic Parameters

Digitalized versions of many fine motor tests employ different kinematic parameters to diagnose neurologic diseases. The number and set of parameters depend on the type of test. Originally [7] five parameters based on velocities, lengths and accelerations were used. Nowadays [6] lists twenty different parameters. Usual set of kinematic parameters includes average values for the velocities, accelerations, jerks, directional changes and pressure changes. This set is complemented by motion mass parameters proposed in [17], [18] and later applied for gross motor analysis of PD patients [19]. Contour tracing is frequently performed in strokes. Many kinematic and pressure parameters are computed stroke wise and in some case later averaged for entire test. In order to make this paper self-sufficient, kinematic parameters necessary to

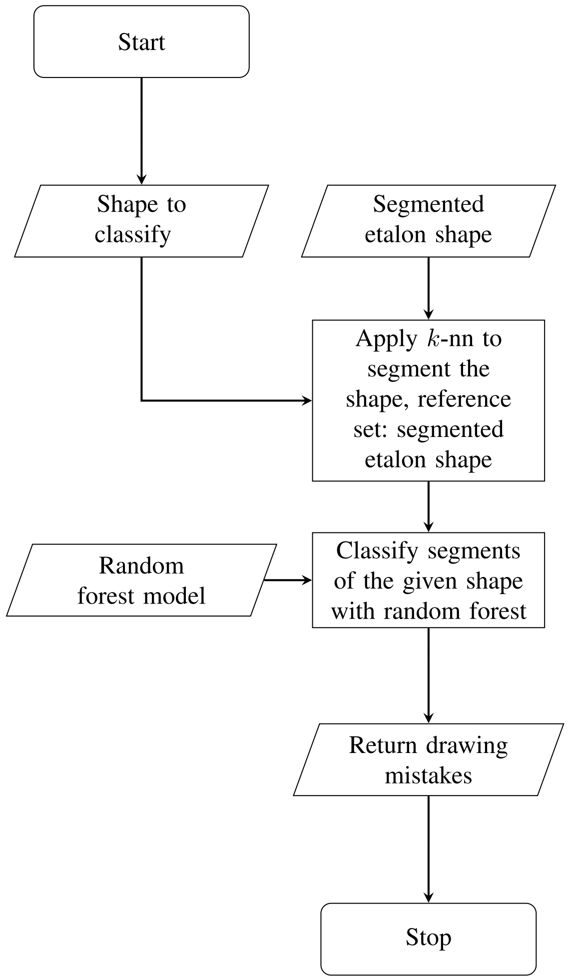

Fig. 7. Drawing mistakes detection

present results of the research are listed below.

- **Stroke** - the line produced during physical contact between the stylus tip and screen of the tablet. Lengths and duration are the immediate parameters to associate with the stroke.
- **Pause** - time interval between two consequent strokes.
- **Velocity mass** - computed as the sum of the absolute values of velocity at each observation point.
- **Acceleration mass** - computed as the sum of the absolute values of accelerations at each observation point.
- **Completeness** - Ratio of the length of the drawn contour to original one.
- **Purity** - Ratio between the number of majority of points within a stroke classified with the figure label and the number of points classified to be parts of another figure.

For each shape kinematic parameters recorded for the PD patients were compared to those of controls. The null hypothesis is that the samples representing controls and PD patients belong to the independent populations with equal means, and the alternative hypothesis is that the samples representing controls and PD patients comes from the populations with unequal means. Results of the two-sample t-test, performed for entire tests are presented in Tab. I. Results of the two-sample t-test, performed for each shape are presented in II. In the both cases t-test was performed at $\alpha = 0.05$ significance level.

TABLE I
DISTINGUISHABLE KINEMATIC AND PRESSURE PARAMETERS FOR COMPUTED FOR THE ENTIRE TEST.

Parameter	p-value	t-statistic
Number of Strokes	0.0084	2.8840
Pause Time	0.0174	2.5627
Ratio of Draw time to Pause time	3.4029e-04	-4.2021

TABLE II
DISTINGUISHABLE KINEMATIC AND PRESSURE PARAMETERS SHAPE WISE.

Parameter	Object ID	p-value	t-statistic
Number of strokes	Fork	0.0460	2.1093
	Plate	0.0133	2.6928
	Teapot	0.0165	2.5960
	Bottle	0.0479	2.0892
	Glass	0.0336	2.2666
Average stroke length	Fork	0.0150	-2.6281
	Plate	0.0080	-2.9169
	Teapot	0.0035	-3.2679
	Glass	0.0093	-2.8504
Average velocity mass of the stroke	Fork	0.0153	-2.6201
	Plate	0.0072	-2.9648
	Teapot	0.0054	-3.0841
	Glass	0.0027	-3.3781
Total pause time	Fork	0.0382	2.1994
	Plate	0.0328	2.2781
	Teapot	0.0308	2.3071
Average acceleration mass of the stroke	Fork	0.0196	-2.5086
	Plate	0.0213	-2.4785
	Glass	0.0027	-3.3781
Number of strokes per minute	Fork	0.0400	-2.1771
	Teapot	0.0176	-2.5673
Ratio of the drawing time to pause time	Plate	0.0223	-2.4586
	Teapot	0.0052	-3.0991
Completeness	Fork	0.0112	-2.7590
	Glass	0.0124	-2.7232

B. Relations Between the Kinematic Parameters and PD Patient Condition

Among the parameters usually presented in the medical record of a PD patient, unified Parkinson's Disease Rating Scale (UPDRS) Part: III (clinician-scored monitored motor evaluation), minimental state examination (MMSE) and duration of the disease change in time. Therefore these parameters are of an interest to relate their values to kinematic parameters. UPDRS III describes the state of the motor functions and MMSE state of the mental condition of the patient.

MMSE values demonstrated negative correlation $\rho = -0.6192$, $p = 0.0182$ only with total pausing time between the strokes.

While the strength of the correlations may seem weak from the engendering point of view, for the medical and behavioral studies these are relatively strong indicators. Strong significant

TABLE III
CORRELATIONS BETWEEN THE KINEMATIC PARAMETERS AND UPDRS VALUES

Shape ID	Kinematic param.	ρ	p-value
Fork	Strokes per min	-0.63212	0.0153
	Average stroke length	-0.6284	0.0161
	Average velocity mass	-0.6271	0.0163
	Average acceleration mass	-0.6286	0.0160
Plate	Nr. of strokes	0.6770	0.0110
Teapot	Average stroke length	-0.5502	0.0415

TABLE IV
CORRELATIONS BETWEEN THE KINEMATIC PARAMETERS AND DURATION OF THE DISEASE

Shape ID	Kinematic param.	ρ	p-value
Fork	Average acceleration mass	-0.5706	0.0331
Plate	Average stroke length	-0.5664	-0.0436
	Average velocity mass	-0.5578	0.0476

correlations indicate possibility to model UPDRS and MMSE parameters on the basis kinematic parameters.

V. CONCLUSIONS

The process of digitalization of the Poppelreuter's test is described in the present paper. Traditional machine learning techniques K-means, k-nearest neighbors and random forest are used to identify drawn contours and detect drawing mistakes observed during the Poppelreuter's test. For each identified shape kinematic parameters describing the process of drawing are computed. For each shape there exists a set of parameters which differ significantly between the groups of PD patients and controls. This indicates that digitalized test may be used diagnose PD. Some kinematic parameters linearly correlate to those commonly used by neurologists to describe severity of the disease. the presence of linear correlations supports the idea to model formally progresses of the disease. The future research will be directed towards adaptation of the proposed approach to the cases of other neurologic diseases.

ACKNOWLEDGMENT

The work of Sven Nõmm was supported by Tallinn University of Technology through the direct base funding project B37. The work of Aaro Toomela was partially supported by the Estonian Research Council through the Grant IUT3-3.

REFERENCES

[1] S. D. Sala, M. Laiacona, C. Trivelli, and H. Spinnler, "Poppelreuter-ghent's overlapping figures test: Its sensitivity to age, and its clinical use," *Archives of Clinical Neuropsychology*, vol. 10, no. 6, pp. 511 – 534, 1995. [Online]. Available: http://www.sciencedirect.com/science/article/pii/088761779400049V

[2] R. Sells and A. J. Larner, "The poppelreuter figure visual perceptual function test for dementia diagnosis," *Progress in Neurology and Psychiatry*, vol. 15, no. 2, pp. 17–21, 2011. [Online]. Available: http://dx.doi.org/10.1002/pnp.193

[3] A. Toomela, "Konkreetsete ja abstraktsete kontuuride jlgimise lesanne [concrete and abstract contour tracing task]," in *Eesti laste arengu longituuduuringute testikogu*, A. Toomela and E. Kikas, Eds. Tallinn: Institute of Psychology, Tallinn University, 2007, p. C5A.

[4] V. Tammik and A. Toomela, "Relationships between visual figure discrimination, verbal abilities, and gender," *Perception*, vol. 42, no. 9, pp. 971–984, 2013.

[5] S. Nomm, A. Toomela, J. Kozhenkina, and T. Toomsoo, "Quantitative analysis in the digital luria's alternating series tests," in *The 14th International Conference on Control, Automation, Roboics and Vision*, Nov 2016, p. Accepted.

[6] 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.

[7] C. Marquardt and N. Mai, "A computational procedure for movement analysis in handwriting," *Journal of Neuroscience Methods*, vol. 52, no. 1, pp. 39 – 45, 1994. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0165027094900531

[8] W. Souillard-Mandar, R. Davis, C. Rudin, R. Au, D. J. Libon, R. Swenson, C. C. Price, M. Lamar, and D. L. Penney, "Learning classification models of cognitive conditions from subtle behaviors in the digital clock drawing test," *Machine learning*, vol. 102, no. 3, pp. 393–441, 2016.

[9] J. deKnecht and K. Schutte, "Finding map correspondence using geometric models," in *Pattern Recognition, 1996., Proceedings of the 13th International Conference on*, vol. 2, Aug 1996, pp. 755–759 vol.2.

[10] B. Edwards and V. Chandran, "Machine recognition of hand-drawn circuit diagrams," in *Acoustics, Speech, and Signal Processing, 2000. ICASSP '00. Proceedings. 2000 IEEE International Conference on*, vol. 6, 2000, pp. 3618–3621 vol.6.

[11] Y. Qi, M. Szummer, and T. P. Minka, "Diagram structure recognition by bayesian conditional random fields," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, vol. 2, June 2005, pp. 191–196 vol. 2.

[12] H. Han, B. F. Klare, K. Bonnen, and A. K. Jain, "Matching composite sketches to face photos: A component-based approach," *IEEE Transactions on Information Forensics and Security*, vol. 8, no. 1, pp. 191–204, Jan 2013.

[13] A. Sadovnik and T. Chen, "Pictorial structures for object recognition and part labeling in drawings," in *2011 18th IEEE International Conference on Image Processing*, Sept 2011, pp. 3613–3616.

[14] T. Hammond and B. Paulson, "Recognizing sketched multistroke primitives," *ACM Trans. Interact. Intell. Syst.*, vol. 1, no. 1, pp. 4:1–4:34, Oct. 2011. [Online]. Available: http://doi.acm.org/10.1145/2030365.2030369

[15] L. V. Metman, B. Myre, N. Verwey, S. Hassin-Baer, J. Arzbaecher, D. Sierens, and R. Bakay, "Testretest reliability of updrs-iii, dyskinesia scales, and timed motor tests in patients with advanced parkinson's disease: An argument against multiple baseline assessments," *Movement Disorders*, vol. 19, no. 9, pp. 1079–1084, 2004. [Online]. Available: http://dx.doi.org/10.1002/mds.20101

[16] J. Dick, R. Guiloff, A. Stewart, J. Blackstock, C. Bielawska, E. Paul, and C. Marsden, "Mini-mental state examination in neurological patients." *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 47, no. 5, pp. 496–499, 1984.

[17] S. Nõmm and A. Toomela, "An alternative approach to measure quantity and smoothness of the human limb motions," *Estonian Journal of Engineering*, vol. 19, no. 4, p. 298308, 2013.

[18] S. Nomm, A. Toomela, and J. Borushko, "Alternative approach to model changes of human motor functions," in *Modelling Symposium (EMS), 2013 European*, Nov 2013, pp. 169–174.

[19] S. Nõmm, A. Toomela, M. Vaske, D. Uvarov, and P.Taba, "An alternative approach to distinguish movements of parkinson disease patients," in *The 13th IFAC/IFIP/IFORS/IEA Symposium on Analysis, Design, and Evaluation of Human-Machine Systems*, August 2016, p. Accepted.