Parkinson's Disease Detection by Using Machine Learning Algorithms and Hand Movement Signal from LeapMotion Sensor

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Abstract—**This work is devoted to the detection of Parkinson's disease (PD) by the kinematic parameters of hand movements using machine learning methods. Hand movements of PD patients (N16) and control group (N16) were recorded using a Leap Motion sensor. Three motor tasks were chosen based on MDS-UPDRS part 3: finger tapping (FT), pronation - supination of the hand (PS), opening-closing hand movements (OC). For the signal received from the sensor, 25 kinematic parameters were calculated by key points. The key point determination was carried out with maximums and minimums finder algorithm, as well as manual marking, using a specially designed user application. For the binary classification (PD or non-PD), for each motor task separately and for three combined, various feature extraction options were used. Four classifiers: kNN, SVM, Decision Tree (DT), Random Forest (RF) were trained. Testing was carried out in the 8-fold cross-validation mode. The best results were obtained using the combination of the most significant features of both hands. The results for each task were the following: for FT 95.3%, for OC 90.6%, for PS 93.8%. The combined features result of all motor tasks was 98.4%.**

I. Introduction

Nowadays, a large number of people suffer from Parkinson Disease (PD). The prevalence of the disease is estimated to be about 1.0% of the general population aged $\geq$ 60 years and 3.0 % aged $\geq$ 80 years [1]. The annual incidence of PD ranges from 8 to 18 per 100,000. According to the data presented by Dorsey et al. the number of cases will increase two times in the next decade [2]. Therefore, monitoring and detection of the disease are actual tasks. Currently, the assessment of PD is performed by a neurologist according to Unified Parkinson's Disease Rating Scale UPDRS and Hoehn-Yahr scale during a visual examination of the patient. The most significant PD motor symptoms are: muscle stiffness, hypokinesia, rest tremor, postural instability. Hypokinesia is the most important symptom for diagnosis of the disease. Its assessment is mainly based on special motor tasks presented in Part 3 of the MSD UPDRS. While a patient performs the motor task a neurologist evaluates such important parameters of movement as rhythm, speed, amplitude. However, visual assessment cannot give an accurate and quantitative characterization of movements so a neurologist can face difficulties in diagnosing hypokinesia especially if not being trained in movement disorders. For the quantitative assessment of various symptoms of the disease different devices are used such as: accelerometer [3], gyroscope [4], electromagnetic sensor [5]. For automatic recording of hands movements various sensors and systems can be used [6], [7], [8].

The results of works [6], [7], [9], [10], [11] based on calculation of kinematic parameters of hand movements from MDS-UPDRS are presented in Table I. The authors obtained classification results using machine learning algorithms, both for each motor task separately, and with combination of three tasks. To record hand movements data, various sensors were used in the works: LM sensor, Microsoft Kinect sensor, developed by the authors Human Computer Interface (HCI), Polhemus Patriot Electromagnetic (EM) tracking sensors. The ratio of a PD patient and healthy patients group (HG) was different in each works.

TABLE I. Results review

Source	Algorithm	FT (%)	OC (%)	PS (%)	FT+OC+PS (%)	Device	PD/HG
[6]	NB	91.70	86.16	98.97		HCI	57/25
	LDA	93.71	88.57	91.75			
	MNR	95.60	91.44	98.7			
	SVM	98.44	90.06	98.97			
	KNN	94.10	90.34	97.94			
[7]	SVM	100	80	100		Kinect	8/5
[9]	LR				82.14	LM	16/12
	NN				71.4		
	SVM				85.71		
[10]	LR				70.37	LM	16/12
	NB				81.4		
	SVM				74.07		
[11]	Cartesian Genetic Programming (CGP)	82.66	75.22	80.54		EM sensors	22/20

The best results were presented in work [6], however, the authors use their own developed system that requires to use additional tools for hand movements recording - gloves. The results are obtained in [7] work are quite high, however, datasets of HG and PD groups are not wide enough. The results of studies, which use the LM sensor and the EM sensors, do not differ significantly. The LM is widely available sensor with low cost and with high accuracy assessment of fine motor skills of the hands. The LM software allows to record the coordinates of hand key points and rotation angles in three-dimensional space. It has a high frame rate per second, an average of 100 frames per second.

III. EXPERIMENTS

A. Database

The study involved 16 patients with PD (6 women, 10 men), an average age of 58.3 ± 13.5 and 16 patients (13 women, 3 men) in the control group, without any neurological disorders, average age of 49.2 ± 10.1. Patients with PD were selected at the Federal State Budget Scientific Institution "Scientific Center of Neurology", the control group were selected at the Scientific and Educational Medical and Technological Center (SEMTCN) of BMSTU. All patients signed a voluntary consent to participate in the experiment and permission to process personal data. PD patients' data are presented in Table II.

TABLE II. PD PATIENT INFORMATION

№	Sex	Age, years	Disease duration, years	Hoehn and Yahr stage
1	m	63	11	2
2	f	63	10	3
3	m	72	7	3
4	m	61	19	3
5	f	55	7	3
6	m	58	5	2
7	m	33	5	2
8	f	59	9	3
9	m	68	1,5	1
10	f	76	15	3
11	m	82	7	3
12	f	58	2	3
13	m	50	7	2
14	m	37	6	2
15	m	39	5	2.5
16	f	57	15	2

B. Data recording

Data recording was carried out using the Leap Motion sensor (Fig. 1), which was located at the arm's length from the patient. The patient's hand was located in the sensor's working area, at a distance of 15-30 cm. Before starting, the participant was instructed to perform the following motor tasks from UPDRS: finger tapping, pronation-supination of the hands, opening-closing hand movements with the maximum possible amplitude and speed. Each task was recorded for 16 seconds. The movement signal of each hand was recorded separately, twice for each patient, with breaks for rest. The total number of records was 128. During processing of the records, data separation of right and left hands was not carried out.

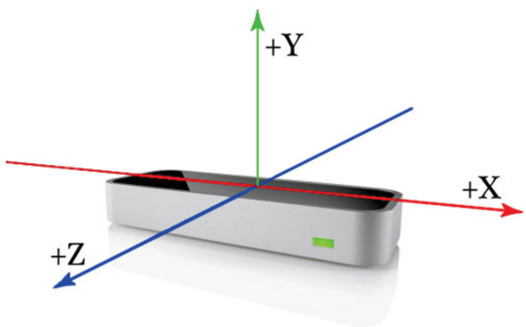

Fig. 1. Leap Motion's coordinate system [12]

C. Processing

LM allows to obtain the rotation angles and key points coordinates in 3D space. To plot signals for each motor task, key points of the hand were selected and are presented in Fig. 2. For each motor task, the plot of the dependence amplitude's movements on the frame number was plotted by calculation:

• for FT: Euclidean distance between the index finger tip and the thumb finger tip, amplitude expressed in mm.

• for OC: Euclidean distance between middle finger tip and palm centre, amplitude expressed in mm.

• for PS: angle of rotation of the palm center, expressed in degrees.

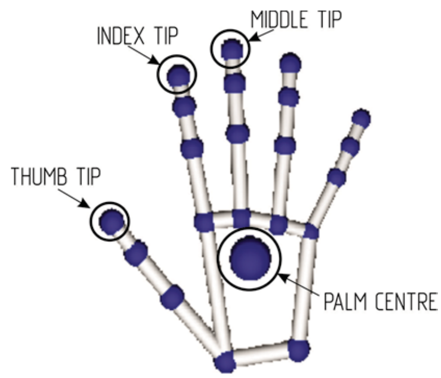

Fig. 2. Leap Motion's hand model [13] with key points

With python libraries for peak finder the maximum and minimum points on the movement plots were determined. Additionally, the manual correction of point location was used. A custom application for marking up records was developed with C# language. The records of each motor task with peaks, as example, are presented in Fig. 3.

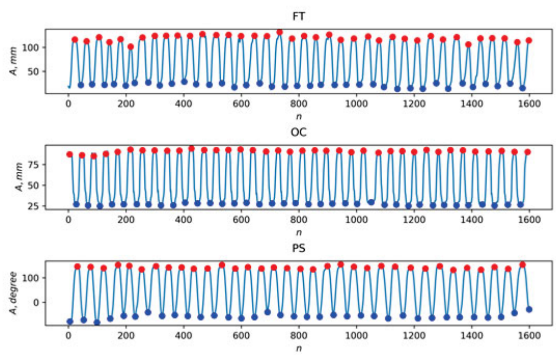

Fig. 3. The amplitude of movements (A) dependence on the frame number (n)

IV. FEATURE EXTRACTION

The feature calculation is based on the motion estimation parameters from UPDRS: speed, frequency, and amplitude estimates. The formulas for calculating the motion parameters are given in Table III. The notation in the formulas is given in accordance with Fig. 4.

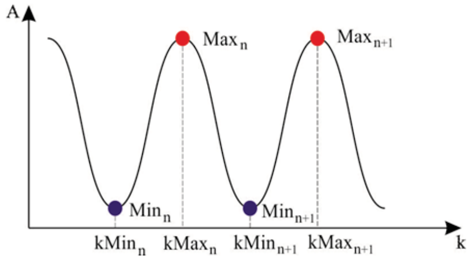

Fig. 4. Schematic designation of the amplitude of movements (A) dependence on the frame number (k)

TABLE III. BASIC MOVEMENT PARAMETERS

Parameter	Definition	Formula
Frequency	A unit divided by the time span of one movement.	$\frac{1}{kMax_{n+1} - kMax_n}$
Opening speed	The difference between the maximum and minimum peaks of the opening phase of the movement, divided by the corresponding time interval.	$\frac{Max_n - Min_n}{kMax_n - kMin_n}$
Closing speed	The difference between the maximum and minimum peaks of the closing phase of the movement, divided by the corresponding time interval.	$\frac{Max_n - Min_{n+1}}{kMax_n - kMin_{n+1}}$
Opening amplitude	The difference between the maximum point and the minimum point of opening phase of movement.	$Max_n - Min_n$
Closing amplitude	The difference between the maximum point and the minimum point of closing phase of movement.	$Max_n - Min_{n+1}$

For each patient's hand movement records of the control group and PD group, 25 kinematic features were calculated for each exercise using the maximum and minimum points marked on the signal. The kinematic parameters are presented in Table IV.

TABLE IV. MOVEMENT PARAMETERS

№	Definition
1	The number of movements counting by maximum points
2	The maximum point among the maximum points
3	The maximum point among the minimum points
4	The minimum point among the maximum points
5	The minimum point among the minimum points
6	Average maximum counting by maximum points
7	Standard deviation of maximum points
8	Average minimum counting by minimum points
9	Standard deviation of minimum points
10	Average frequency
11	Standard deviation of frequency
12	Average opening speed
13	Average closing speed
14	Maximal opening speed
15	Minimal opening speed
16	Maximal closing speed
17	Minimal closing speed
18	The average amplitude of the opening
19	Standard deviation of opening amplitude
20	Maximal opening amplitude
21	Minimal opening amplitude
22	Average closing amplitude
23	Standard deviation of closing amplitude
24	Maximal closing amplitude
25	Minimal closing amplitude

VI. RESULTS AND DISCUSSION

A. The results of the different feature vectors formation

The training was carried out using 4 classifiers: kNN, SVM, Decision Tree (DT), Random Forest (RF). Testing was conducted in the 8-folds cross-validation mode. To construct a model of the difference between the two groups HG and PD, the following variations of the feature vector were used.

1) Each patient was described by 25 features (Table IV) of one (any) hand. Since for each patient there were 4 records (2 records for each hand), the equivalent number of patients and controls were 64. The results for each exercise are shown in Table V. The classification results for merged vectors of features of 3 exercises are shown in Table IX.

2) Each patient was described by 50 features: 25 features of the right hand and 25 features of the left hand. Since for each patient there were 4 records (2 records for each hand), the equivalent number of patients and controls were 64. The results for each exercise are shown in Table VI. The classification results for merged vectors of features of 3 exercises are shown in Table X.

3) Each patient was described by 25 differences in the features of the right and left hands. Since for each patient there were 4 records (2 records for each hand), the equivalent number of patients and controls were 32. The results for each exercise are shown in Table VII. The classification results for merged vectors of features of 3 exercises are shown in Table XI.

4) Each patient was described by 25 average values of features of the right and left hands. Since for each patient there were 4 records (2 records for each hand), the equivalent number of patients and controls were 32. The results for each exercise are shown in Table VIII. The classification results for merged vectors of features of 3 exercises are shown in Table XII.

For the each variations of the feature vector, the best combinations of features were selected with logistic regression by ranking the features by significance.

The best results for each motor task and the best result for 3 merged exercises are highlighted in the tables. Column N in the tables indicates the number of selected features.

TABLE V. CLASSIFICATION RESULTS USING FEATURES OF EACH HAND SEPARATELY

Classifier	Exercises					
	FT		OC		PS	
	Accuracy (%)	N	Accuracy (%)	N	Accuracy (%)	N
KNN	79. 7 (k=4)	22	80.5 (k=16)	10	72.7 (k=11)	18
SVM	83.6	15	85.9	7	79.7	7
DT	81.3	8	80.5	25	71.9	18
RF	90.4	12	85.9	15	85.9	24

TABLE VI. CLASSIFICATION RESULTS USING COMBINED RIGHT AND LEFT HANDS FEATURES

Classifier	Exercises					
	FT		OC		PS	
	Accuracy (%)	N	Accuracy (%)	N	Accuracy (%)	N
KNN	84.4 (k=18)	1	78.1 (k=7)	6	82.8 (k=22)	2
SVM	**95.3**	15	**90.6**	8	**93.8**	19
DT	82.3	13	76.6	11	78.1	25
RF	91	22	83.6	47	88.7	13

TABLE VII. CLASSIFICATION RESULTS USING DIFFERENCE BETWEEN THE RIGHT AND LEFT HANDS FEATURES

Classifier	Exercises					
	FT		OC		PS	
	Accuracy (%)	N	Accuracy (%)	N	Accuracy (%)	N
KNN	71.9 (k=14)	6	70.3 (k=7)	10	75 (k=4)	11
SVM	76.6	12	60.9	8	59.4	11
DT	60.9	7	73.4	6	65.6	2
RF	71.5	10	69.9	23	64.1	13

TABLE VIII. CLASSIFICATION RESULTS USING MEAN VALUE OF THE RIGHT AND LEFT HANDS FEATURES

Classifier	Exercises					
	FT		OC		PS	
	Accuracy (%)	N	Accuracy (%)	N	Accuracy (%)	N
KNN	84.4 (k=7)	5	73.4 (k=8)	19	84.4 (k=16)	2
SVM	90.6	10	85.9	11	82.8	2
DT	81.3	2	78.1	12	76.6	4
RF	87.5	14	82	24	84.8	24

The best classification accuracy for single exercises was obtained using 50 features: 25 features of the right hand and 25 features of the left hand, combined into one vector. The result for FT task was: 95.3 %, for OC: 90.6 %, for PS: 93.8 %.

TABLE IX. CLASSIFICATION RESULTS USING MEAN VALUE OF THE RIGHT AND LEFT HANDS FEATURES FOR 3 EXERCISES

Classifier	Exercises	
	FT+OC+PS	
	Accuracy (%)	N
KNN (k=7)	85.9	5
SVM	95.3	32
DT	85.2	6
RF	94.1	22

TABLE X. CLASSIFICATION RESULTS USING MEAN VALUE OF THE RIGHT AND LEFT HANDS FEATURES FOR 3 EXERCISES

Classifier	Exercises	
	FT+OC+PS	
	Accuracy (%)	N
KNN (k=11)	81.3	9
SVM	**98.4**	28
DT	82.8	15
RF	94.1	94

TABLE XI. CLASSIFICATION RESULTS USING MEAN VALUE OF THE RIGHT AND LEFT HANDS FEATURES FOR 3 EXERCISES

Classifier	Exercises	
	FT+OC+PS	
	Accuracy (%)	N
KNN (k=10)	73.4	7
SVM	76.6	29
DT	65.6	4
RF	73.8	41

TABLE XII. CLASSIFICATION RESULTS USING MEAN VALUE OF THE RIGHT AND LEFT HANDS FEATURES FOR 3 EXERCISES

Classifier	Exercises	
	FT+OC+PS	
	Accuracy (%)	N
KNN (k=4)	89	6
SVM	90.6	12
DT	85.9	29
RF	95.3	27

The classification accuracy using combined features of all motor tasks was 98.4 %, which is higher than each result separately. It indicates the importance of using the features of each motor task for PD determination. All of the above results were obtained with SVM classificatory.

The results of this work are superior to the results obtained in [9], [10], using the Leap Motion sensor with the features combination of three UPDRS motor tasks. However, in these works, the dataset consisted mainly of PD patients with 1-st Hoehn-Yahr stage, when ours contains patients with 2-3 stages. It shows more violent movement differences in patients with a greater stage of the disease. The results [6] obtained by using various classifiers are slightly higher, but the authors use their own developed system with additional tools for recording - gloves. The OC task result obtained in our work are exceeded the result in [7] obtained by using Microsoft Kinect Sensor.

Additionally, while analyzing the results of our work, we noticed that the FT task is the most informative motor task, with the highest classification result.

B. The results of the different feature selection ways

For a more stable result to different datasets, pairs of identical features for the right and left hands were selected. The features were ranked by significant with logistic regression in different ways.

1) The features of the right and left hands were in the same dataset. No matter what set of features belongs to the left or right hand, all features were ranked. For single task, 25 features were ranked, for three combined tasks, 75 features were ranked. The results for each exercise are shown in Table XIII. The classification results for merged vectors of features of 3 exercises are shown in Table XVI.

2) The features of the right and left hands were ranked separately. For single task, 25 features of each hand were ranked, for three combined tasks, 75 features of each hand were ranked. Mean values of the identical pairs of features were ranked by significant. The results for each exercise are

shown in Table XIV. The classification results for merged vectors of features of 3 exercises are shown in Table XVII.

3) The features of the right and left hands were concatenated and ranked together. For single task, 50 features of both hands were ranked, for three combined tasks, 150 features of both hands were ranked. Then mean values of the identical pairs of features were ranked by significant. The results for each exercise are shown in Table XV. The classification results for merged vectors of features of 3 exercises are shown in Table XVIII.

4 classifiers were trained with all of this ways of features selection methods. According to the above results, the highest result was obtained with using merged features of 3 tasks and concatenated features for both hands. Further results were obtained using this approach for feature vector formation for binary classification. Column N in the tables indicates the number of selected identical pairs of features.

TABLE XIII. CLASSIFICATION RESULTS USING BEST SET OF FEATURE PAIRS

Classifier	Exercises					
	FT		OC		PS	
	Accuracy (%)	N	Accuracy (%)	N	Accuracy (%)	N
KNN	84.4 (k=18)	1	81.3 (k=11)	1	82.8 (k=19)	1
SVM	84.4	14	85.9	12	78.1	1
DT	79.7	1	82.8	3	82.8	4
RF	91.8	13	83.2	2	89.5	25

TABLE XIV. CLASSIFICATION RESULTS USING BEST SET OF FEATURE PAIRS

Classifier	Exercises					
	FT		OC		PS	
	Accuracy (%)	N	Accuracy (%)	N	Accuracy (%)	N
KNN	82.3 (k=13)	2	81.3 (k=11)	1	82.8 (k=16)	2
SVM	85.9	7	84.4	3	79.7	1
DT	79.7	18	76.6	1	82.8	12
RF	90.2	10	82.4	1	89.5	25

TABLE XV. CLASSIFICATION RESULTS USING BEST SET OF FEATURE PAIRS

Classifier	Exercises					
	FT		OC		PS	
	Accuracy (%)	N	Accuracy (%)	N	Accuracy (%)	N
KNN	84.4 (k=18)	1	81.3 (k=18)	2	79.7 (k=7)	1
SVM	89.1	10	84.4	3	82.8	20
DT	82.8	3	76.6	3	81.3	14
RF	91.8	9	85.2	19	88.3	7

TABLE XVI. CLASSIFICATION RESULTS USING BEST SET OF FEATURE PAIRS FOR 3 EXERCISES

Classifier	Exercises	
	FT+OC+PS	
	Accuracy (%)	N
KNN (k=16)	87.5	2
SVM	89.1	6
DT	82.8	2
RF	94.5	37

TABLE XVII. CLASSIFICATION RESULTS USING BEST SET OF FEATURE PAIRS FOR 3 EXERCISES

Classifier	Exercises	
	FT+OC+PS	
	Accuracy (%)	N
KNN (k=3)	84.4	6
SVM	85.9	11
DT	82.8	30
RF	95.3	65

TABLE XVIII. CLASSIFICATION RESULTS USING BEST SET OF FEATURE PAIRS FOR 3 EXERCISES

Classifier	Exercises	
	FT+OC+PS	
	Accuracy (%)	N
KNN (k=15)	81.3	2
SVM	89.1	9
DT	82.8	53
RF	94.5	26

Analyzing the results in Tables XIII - XVIII, we noticed that there are no significant differences in the classification results, depending on the method of feature ranking, but these results are lower than the results obtained, without selecting identical features. Most likely, by adding less significant features, data is noisy. Thus, it is not the best combination of features selected.

The best classification results for any ways of ranking features were obtained with the RF classifier, with features combination of three exercises. But for RF classifier the largest number pairs of features were used, in contrast to others.

The best result of 95.3% was obtained with the following way of ranking features: mean values of the identical pairs of features for both hands, where the right and left hands were ranked separately. The best set of feature pairs for classification was 56 out of 75 feature pairs for 3 combined tasks.

The ranked features by this way: 5_OC, 1_OC, 17_FT, 3_FT, 6_FT, 19_FT, 24_PS, 5_FT, 2_OC, 5_PS, 8_FT, 1_PS, 23_FT, 25_FT, 20_FT, 19_PS, 13_FT, 14_FT, 3_PS, 20_PS, 4_FT, 16_FT, 8_PS, 18_OC, 1_FT, 8_OC, 22_OC, 16_PS, 18_FT, 22_FT, 2_FT, 17_OC, 23_PS, 14_OC, 2_PS, 24_FT, 20_OC, 25_OC, 4_OC, 7_OC, 25_PS, 21_OC, 12_PS, 7_FT, 9_OC, 12_FT, 19_OC, 23_OC, 13_PS, 6_PS, 21_PS, 24_OC, 9_PS, 6_OC, 13_OC, 7_PS, 18_PS, 21_FT, 4_PS, 9_FT, 12_OC, 14_PS, 17_PS, 15_FT, 3_OC, 15_PS, 16_OC, 15_OC, 22_PS, 10_OC, 11_OC, 10_PS, 10_FT, 11_PS, 11_FT.

The first digit is the feature number, according to Table 4. The prefix FT, OC, PS denotes the exercise for which this feature was selected.

For example, we can notice that the features number 1 and 5 have the most significant value among the all features of 3 exercises, when ranking features by significance. Features with number 10, 11, are equally not significant for 3 exercises.

C. The results of patient's classification

By the method of features selecting: mean values of the identical pairs of features were ranked by significant, where the features of each hand were previously ranked separately. Class labels were assigned to each combined feature vector of the right and left hands in 8-folds cross-validation mode. Since each patient has 2 records, then if label of one of the two records indicated the presence of a disease, we assign the patient to the PD class, the confusion matrices with each classifier are given below in Tables XIX, XX, XXI, XXII.

TABLE XIX. CONFUSION MATRIX WITH KNN CLASSIFIER USING 3 FEATURES

	FT+OC+PS	
	HG	PD
HG	13	3
PD	3	13

TABLE XX. CONFUSION MATRIX WITH SVM CLASSIFIER USING 15 FEATURES

	FT+OC+PS	
	HG	PD
HG	10	6
PD	0	16

TABLE XXI. CONFUSION MATRIX WITH DT CLASSIFIER USING 34 FEATURES

	FT+OC+PS	
	HG	PD
HG	12	4
PD	1	15

TABLE XXII. CONFUSION MATRIX WITH RF CLASSIFIER USING 33 FEATURES

	FT+OC+PS	
	HG	PD
HG	13	3
PD	0	16

The classification results for KNN, SVM, DT, and RF classifiers according to confusion matrices presented are 81.3 %, 81.3 %, 84.4 %, and 90.6 % respectively.

The result of the patient's classification is not much different from the results of classification by records with the selection of feature pairs. The best classification result for patients is 90.6 %, with RF classifier and using 33 feature pairs.

A review of modern sources shows that the results obtained with any way of the binary classification, are comparable with the results published by other authors.

VII. CONCLUSION

In this study, the hands movement activity of PD group and control group were recorded. Signals were obtained with 3D Leap Motion sensor. Plots of amplitude of movements dependence frame number were plotted. For each movement signal, 25 kinematic parameters were calculated based on 3 important motion parameters: speed, amplitude, frequency. Various feature vectors combination was used for the training of 4 classifiers. The results of PD detection were obtained for each motor task separately and with combination the features of all tasks.

The result of combining the kinematic features of the three tasks was the best and amounted to 98.4 %. The result for motor task FT: 95.3 %, OC: 90.6 %, PS: 93.8 %. The presented results were obtained with SVM classifier trained with feature vector, which consists of the right and left hands features. Thus, the most informative approach for PD detection is based on the features combination of three MDS UPDRS motor tasks performed by two hands.

Also, for a more stable result in different datasets, we conducted a selection of identical feature pairs from right and left hand, by using various ways for ranking the signs of right and left hand. The results obtained did not have fundamental differences between the ranking ways, so we concluded that the method of ranking features is not significant.

However, the results obtained for the selection of identical feature pairs were lower than the results excluding identical feature pairs. Nevertheless, the best classification result for the selection of identical feature pairs was 95.3 % for RF classifier. It was obtained with the following feature ranking way: the features of the right and left hands were ranked separately. Mean values of the identical pairs of features were ranked by significant. The results were obtained using the RF classifier for the combined feature vector for 3 tasks. Ranked 75 feature pairs are listed in descending order of significance.

For the same method of feature space forming we calculated the accuracy of the classification, not by individual records, but by subjects, since there were 2 records for each patient. The best classification result was 90.6 %, with an RF classifier and 33 feature pairs.

RF classifier demonstrated significantly better results than other classifiers in the feature space, formed by identical features pairs for both hands. Despite the fact that the use of these features does not give best classification result, we believe that these features can provide stable results for different datasets, which should be verified in future.

All results were obtained for our PD dataset that consists primarily of patients with stage 2 and 3. In the future, we are planning to study considered features and to adopt PD detection method for patients with PD at early stage.

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