Assessment of Parkinson’s Disease Severity based on Automatic Analysis of Facial Expressions and Motor Activity of the Hands

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Abstract: Assessment of the severity of the disease is an important task in the study of Parkinson's disease. Using non-contact methods for assessing the motor activity of patients, quantitative assessments of motor parameters were obtained, including the assessment of facial expressions and the motor activity of the hands of patients with PD. The study involved 18 patients with PD, whose facial expressions and the motor activity of the hands assessed using the MDS-UPDRS scale by neurologist. In this paper, a regression model was developed that allows to predict the total MDS-UPDRS scores for 3 hand movement exercises with R2 0.781 and RMSE 0.893 based on 5 features of motor activity. To predict the MDS-UPDRS scores, the classification problem is also solved. The patient group was divided into 2 groups according to the severity of the disease based on the fitting of a cut-off value, which is the median value of the MDS-UPDRS scores. The feature space was reduced to 4 using PCA. The best classification result 95% was obtained using logistic regression and support vector machine in a 5-fold cross-validation mode.

1 INTRODUCTION

Parkinson's disease is an incurable disease characterized by progressive impairment of human motor functions (Pal et al., 2013). In clinical practice, the Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) Part III (Goetz et al., 2008) is used to assess the severity of movement disorders in Parkinson's disease. The MDS-UPDRS provides a specific set of exercises to enable the neurologist to assess the degree of movement impairment on a discrete scale of 0 to 4 for each exercise.

The disadvantage of using the rating scale is its subjectivity, since ratings vary between experts (Espay et al., 2016), and the use of MDS-UPDRS does not allow recording minor changes in movement disorders (Ferraris et al., 2018), trained medical personnel are required for examination the patient and his presence in the clinic, which takes a long time (Boka et al., 1994).

Thus, there is a need to objectify the assessment of the disease. At the same time, the automation of the assessment of the severity of the disease will allow the use of an assessment tool without the participation of a specialist, which will open up additional possibilities of its application in the tasks of telemedicine control, home use, and as a second expert opinion. Currently, there are works devoted to assessing the severity of PD, which are based on the use of regression models on various human motor activity data (Kaur et al., 2020; Nilashi et al., 2018; Lin et al., 2017; Lee et al. al., 2019). Assesment of the severity of the disease can also be presented as a classification problem (Kaur et al., 2020, Mehta et al., 2021; Maachi et al., 2021; Lu M. et al., 2021; Ferraris C. et al., 2018), where the number of classes corresponds to the number of discrete MDS-UPDRS scores or the sample is divided into several classes according to a threshold set by the author based on MDS-UPDRS scores.

The data obtained in the analysis of facial expressions and the motor activity of the hands (MAH) are the one of the data more available and reliably suitable for PD assessment. In previous works (Moshkova et al., 2021; Moshkova et al., 2020; Moshkova et al., 2021), devoted to the

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recognition of PD, high classification accuracy was shown using MAH and facial expressions features obtained by a contactless method. The problem of the severity prediction of the disease is no less important than the recognition of PD; therefore, the purpose of this work is to study the possibility of predicting MDS-UPDRS scores based on features extracted during analysis of MAH and facial expressions of patients with PD.

2 MATERIALS AND METHODS

2.1 Feature Space Formalization

In previous works devoted to the study of PD (Moshkova et al., 2021; Moshkova et al., 2020; Moshkova et al., 2021) the features of MAH and facial expressions were formed. Facial expressions features, in turn, is subdivided into parameters of dynamic facial activity and static emotional expressions assessing.

The features of MAH were obtained based on the analysis of hand movement signals recorded using the LeapMotion sensor when performing 3 movement exercises: finger tapping (FT), open/close of the hand (OC), pronation/supination of the hand (PS).

Facial activity features were obtained based on the analysis of signals from action units (AU), recorded during participants performed a series of repeated mimic movements («Raise eyebrows», «Smile with effort»). Each of the mimic exercises is characterized by AUs, which are activated during exercise: AU04 when performing the «Raise eyebrows» exercise, AU12 and AU14 when performing the «Smile with effort» exercise. Emotional expressions features characterize the degree of expressiveness of facial expressions when participants shows 6 basic emotions by imitating. Facial activity and emotional expressions features were obtained by processing 2D video images of a face.

All in all, 11 kinematic parameters were calculated for each signal of hands movement and facial activity based on the significant parameters of movement: frequency, speed in the opening phase (beginning of movement), speed in the closing phase (end of the movement), and amplitude.

The general vector of features of the patient includes 72 features (33 features of MAH, 33 features of facial activity, and 6 features of emotional expressions).

2.2 Database Collecting

The database of participants includes 18 PD patients with stages 2 and 3 according to Hoehn & Yahr. Information about participants is presented in Table 1. Patients data were collected at the Scientific Center of Neurology. All participants signed voluntary informed consent to participate in the study. Each of the participants was assessed according to the III part of the MDS-UPDRS scale, namely, expert assessments were obtained on the following points: 3.2 Facial Expression (FE), 3.4 Finger Tapping (FT), 3.5 Hand movements (OC), 3.6 Pronation-supination of the hand (PS).

FE was assessed on a scale from 0 to 4, which characterizes the severity of the impairment of facial expressions. FT, OC, PS were assessed for the right and left hands separately from 0 to 4. As a result, the average score for the right and left hands was taken for each patient.

For the study, different scores combinations were used, which can be predicted based on the prepared vector of features:

- points assessment of facial expressions - MDS-UPDRS FE;
- total scores of 3 hand movement exercises - MDS-UPDRS FT+OC+PS;
- total scores of 3 hand movement exercises and facial expressions - MDS-UPDRS FE+FT+OC+PS.

Mean values and standard deviations in PD patients group of the MDS-UPDRS scores are presented in Table 1.

Table 1: PD participant's information.

Number of participants	18
Average age of participants	65.3±10.0
MDS-UPDRS FE	1.61±0.99
MDS-UPDRS FT+OC+PS	4.11±2.11
MDS-UPDRS FE+FT+OC+PS	5.73±2.38

2.3 Predicting MDS-UPDRS Scores

2.3.1 Regression Model

The target or output variable in the dataset is one of the MDS-UPDRS scores (FE, FT+OC+PS, or FE+FT+OC+PS). The following regression models were used to predict MDS-UPDRS scores: k-nearest neighbors (k-NN), support vector machine (SVM), random forest (RF), and linear regression.

The prediction of the regression model is evaluated by the following metrics:

- R-squared (R2): coefficient of determination;
- root mean square error (RMSE).

The evaluation of the regression models was carried out in a 5-fold cross-validation mode. A greedy algorithm was used to select the best combination of features.

2.3.2 Classification

To solve the classification problem, the sample of 18 patients was divided according to the disease severity based on the threshold value (median value) (Table 2) into 2 groups (PD1 and PD2), where the PD1 group includes patients with MDS-UPDRS scores less than the median value, and the group PD2 includes patients with MDS-UPDRS scores greater than the median. The ratio of patients in the PD1/PD2 groups is balanced. Groups PD1 and PD2 were formed for each MDS-UPDRS scores set: FE, FT+OC+PS, and FE+FT+OC+PS.

Table 2: Thresholds and group's ratio.

	MDS-UPDRS		
	FE+FT+OC+PS	FT+OC+PS	FE
Median	6.5	4.75	2
PD1/PD2	9/9	9/9	11/7

To solve the binary classification problem, 4 classifiers were trained: k-NN, SVM, RF, logistic regression (LR) in the 5-fold cross-validation mode. Classification was performed with 3 subsets of MDS-UPDRS scores (FE, FT+OC+PS, or FE+FT+OC+PS).

Patient data were standardized using the *StandartScaler* method. Principal component analysis (PCA) is applied to a dataset of 72 features to solve multicollinearity problems in the dataset and to reduce the dimension of the input feature space. Then the reduced input features space was introduced into the proposed classification model. The hyperparameters were tuned using the *GridSearchCV* method. Data processing, implementation of classification and regression models were carried out in the Python using built-in machine learning libraries.

3 RESULTS

3.1 Predicting MDS-UPDRS Scores based on Regression Model

The best result was obtained when predicting MDS-UPDRS FT+OC+PS scores (Table 3).

Table 3: The best regression model.

Model	RandomForestRegressor(n_estimators=100, max_features ='sqrt')
R2	0.781
RMSE	0.893
Features number	5

The selected 5 features are presented in Table 4.

Table 4: Selected 5 features for assessment disease severity based on a regression model.

№	Title	Signification
1	AvgVclose_AU12	Average closing speed when performing the «Smile with effort» exercise
2	VarVopen_AU12	Closing speed variation when performing the «Smile with effort» exercise
3	AvgVclose_AU04	Average closing speed when doing the «Raise eyebrows» exercise
4	DecV_PS	Speed decrement during exercise PS
5	VarFrq_FT	Frequency variation during FT exercise

Table 5 shows the Spearman correlation coefficient (r) between values of the the selected 5 features and different sets of MDS-UPDRS scores.

Table 5: Spearman correlation coefficients of 5 features with MDS-UPDRS scores.

	MDS-UPDRS		
№	FE+FT+OC+PS	FT+OC+PS	FE
1	-0.65	-0.72	0.26
2	0.28	0.32	-0.23
3	-0.61	-0.68	0.06
4	-0.14	0.13	-0.3
5	0.38	0.48	-0.29

The highest correlation coefficient r=-0.72 was found between the AvgVclose_AU12 parameter and the MDS-UPDRS FT + OC + PS score.

3.2 Binary Classification of PD Severity

The best classifications accuracy were obtained using the 4 principal components of the PCA. The results of training classifiers in the 5-fold cross-validation mode are presented in Table 6.

Table 6: Results of the binary classification of PD severity.

	PD1 vs. PD2		
	FE+FT+OC+PS	FT+OC+PS	FE
RF	88 %	83 %	53 %
k-NN	78 %	85 %	72 %
SVM	95 %	90 %	58 %
LR	95 %	83 %	62 %

The highest result 95% was obtained using the SVM classifier with a linear kernel and LR with default hyperparameters.

4 DISCUSSION

The assessment of the disease severity was carried out by many authors based on data of various PD manifestations obtained using both wearable sensors and non-contact methods. The results of these works shows the prospects for the further use of the developed methods for predicting MDS-UPDRS scores. The authors use different patient's data sources to correlate with MDS-UPDRS scores: voice, gait, hand movement, and other exercises. In (Kaur et al., 2020), an ensemble of models is presented that makes it possible to predict the MDS-UPDRS score with an accuracy of 99.6% based on the features extracted from the voice recording of 42 PD patients. The regression model proposed by the authors (Lin et al., 2017) predicts the MDS-UPDRS scores of 15 patients with a high $R2 = 0.99$ score based on FT exercise features. The authors (Lee et al., 2019) report that the cumulative MDS-UPDRS score for bradykinesia for 8 patients, predicted by linear regression, coincides ($r=0.86$) with the clinical scores in the cross-validation mode. In the work (Maachi et al., 2020), the authors achieved an accuracy of 85.3% in predicting the severity of Parkinson's disease (5 classes) by analyzing the gait of 93 patients using a 1D convolutional neural network.

The use of one or another method for assessing the PD severity can often be limited by the conditions in which it will be applied. Therefore, one of the important components of the method used is its applicability at home, for telemedicine control using affordable and inexpensive equipment (Rimskaya et al., 2021; Anishchenko et al., 2019).
In our work, we showed the possibility of using a non-contact method for assessing the features of facial expressions and MAH in the prediction task of MDS-UPDRS scores by developed a regression model and in the binary classification task of the PD severity. In the works (Maachi et al., 2020; Ferraris et al., 2018), the authors present the results of PD patients classification into 3 or 4 classes, divided according to MDS-UPDRS scores. However, in our work, we used the division into 2 classes due to small size of dataset.

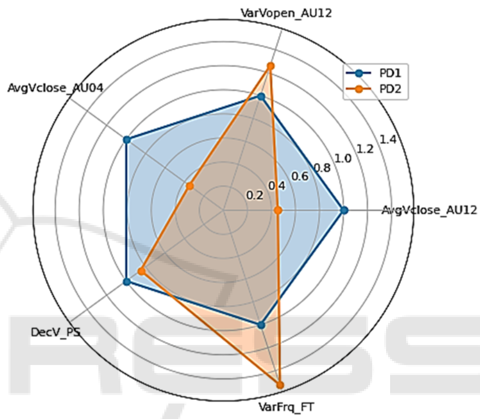

Figure 1: Diagram of the ratio of features of MAH and facial expressions for 2 groups of patients (PD1 and PD2) divided by the median value of MDS-UPDRS FE+FT+OC+PS scores.

In Figure 1, we plot a diagram of the ratio of 5 features that are most significant for predicting scores with regression model. It can be noted, that there are visible differences in the dynamics of disease progression with increasing MDS-UPDRS scores. The parameters are presented in the diagram for 2 groups, which were divided by the threshold value of the MDS-UPDRS FE+FT+OC+PS scores.

Using the Mann-Whitney test for each of the 5 features the p-value was calculated. The parameters AvgVclose_AU04 ($p=0.001$) and AvgVclose_AU12 ($p=0.004$), characterizing the speed of the exercises «Raise eyebrows» and «Smile with effort», respectively, in the PD2 group have a lower value than in the PD1 group of patients with lower MDS-UPDRS scores. The value of the parameters VarFrq_FT ($p=0.047$), VarVopen_AU12 ($p=0.189$), on the contrary, is lower in the PD1 group than in the PD2 group, which indicates a greater rhythm disturbance in the group of patients with high MDS-

UPDRS scores. There is a slight difference in the DecV rate decrement value between groups (p=0.213).

5 CONCLUSIONS

The method of automated assessment of the PD severity is based on the use of features calculated based on analysis of special motor exersice aimed at assessing facial expressions and the motor activity of the hands. With machine learning methods, a regression model based on random forest was developed. Using a greedy algorithm, a set of 5 features was determined, including features of both the motor activity of the hands and facial expressions, to achieve the best regression result. The best result was obtained for the assessment of the total score of the motor activity of the hands according to MDS-UPDRS in the 5-fold cross-validation mode; the coefficient of determination R2 of the regression model 0.781, RMSE error 0.893. Dividing the PD group of patients into 2 classes according to the median value of the total MDS-UPDRS scores of the motor activity of the hands and facial expressions for binary classification (PD1 vs. PD2) made it possible to achieve a classification accuracy of 95% using SVM or LR by using 4 principle components of the entire feature space. The obtained result shows the applicability of the developed method for assessing the PD severity, both with regression and classification methods.

Using the classification method, high results were obtained, but there are limitations in prediction of scores, which are determined by the number of classes. To improve the results, it is necessary to expand the existing patient database, which will make it possible to carry out a multi-class classification. Moreover, we plan to supplement the feature space by analysing other manifestations of Parkinson's disease.

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