Data-Driven Analysis of Parkinson's Disease and its Detection at an Early Stage

Aleksandr Talitckii*
Anna Anikina
Ekaterina Kovalenko
Skolkovo Institute of Science and Technology
Moscow, Russia

Oscar Mayora
Venet Osmani
Fondazione Bruno Kessler
Trento, Italy

Olga Zimniakova
Maxim Semenov
Ekaterina Bril
A.I.Burnazyan Federal Medical and Biophysical Center
Moscow, Russia

Dmitry Dylov
Andrey Somov
Skolkovo Institute of Science and Technology
Moscow, Russia
a.somov@skoltech.ru

ABSTRACT

Parkinson's Disease (PD) is the neurological condition caused by the destruction and death of neurons. Nowadays, PD can not be cured and the number of the patients with the PD is continuously growing. In this work, we report a feasibility study involving 74 subjects to whom we proposed 15 exercises helping reveal the risk of PD at an early stage. In this study, we collected the data using wireless wearable sensors and perform the data analysis relying on machine learning techniques. Experimental results demonstrated that the proposed solution tested in real conditions is promising for more complex diagnostic workflow including the assessment of quality of PD therapy.

CCS CONCEPTS

• **Information systems → Data analytics**.

KEYWORDS

Parkinson's disease, wearable sensors, machine learning

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*Authors contributed equally to this research.

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1 INTRODUCTION

Parkinson's disease (PD) is a neurodegenerative disorder characterized by motor symptoms like tremor, rigidity and bradykinesia, which can fluctuate during the day. Today these symptoms are measured using Movement Disorder Society - Unified Parkinson's Disease Rating Scale (MDS-UPDRS). However, the most convenient exercises and tools for identification of specific PD symptoms still require research and pilot studies.

At the moment there are three key state-of-the-art directions for sensor-based PD detection.

Analysis of sleep. The developed methods make it possible to detect the characteristic signs of PD by the movement of the eyes in sleep [5]. However, this approach uses visual identification of Rapid-Eye Movements in dream, being a time consuming process [1].

Analysis of speech. Changes in speech ability are one of the signs of PD [4]. In this approach, machine learning is used to identify the variations on speech through signal analysis. The complexity of the method consists in filtering and removing noise in the collected data. Moreover, scientists agree that this approach should be used, as an addition to other methods to improve the accuracy of diagnosis of the disease.

Behaviour analysis based on wearable sensors [6] or video [3]. The advantage of this approach is the convenience for the user: the sensors can be used 24 hours a day and evaluate the received data in real time without interfering with the daily activity of the user. However, existing methods tend to rely on the accelerometer data for detecting tremor [2] without using sensors of a different type. This leads to false diagnosis since tremor can be a sign of another disease, for example, associated with the thyroid disorders. An attempt to automatically detect the PD using the Leap Motion video controller is described in [3].

In this work, we present a preliminary trial study on clinical PD detection at an early stage. Our testbed includes a low-power wearable sensing system supported by 15 newly targeted designed exercises for the patients in a hospital. Upon collecting the data we apply machine learning techniques for solving classification related tasks. The long-term goal of this work is the evaluation of the quality of therapy and contribution of the wearable sensors

analysis to assess the potential help that they may bring to doctors in choosing the right therapy for each patient.

2 DATA COLLECTION

We designed 15 exercises aimed at revealing the specific PD symptoms. Due to the space limitation we list them without providing details. The exercises are divided into the 4 following groups and are summarized in Table 1:

- Gross Motor (GM): general movements. (3 exercises : 1, 3, 6)
- Fine Motor (FM): movements that require fine coordination.(4 exercises : 4, 5, 7, 9)
- Tremor at Rest (TR): tremor during the absence of any body movement. (1 exercise : 8)
- Clinical Evaluation (CE): activities that are used by clinicians to evaluate tremor. (7 exercises : 2, 10, 11, 12, 13, 14, 15)

Table 1: Common Tasks

Task	Purpose	Type
1. Walking, sitting down on chair, standing up	RT, BR	GM
2. Pronation/Supination of forearms	KT	CE
3. Fold a towel	KT, BR	GM
4. Tighten nut on bolt	KT, BR	FM
5. Tighten the kronstein	KT, BR	FM
6. Reorder books from one organizer into another	KT, BR	GM
7. Fill glass with water	KT, BR	FM
8. Rest with arms relaxed	RT	TR
9. Read sentence, write it down, and trace spiral	AT, BR	FM
10. Finger tapping on table	KT, BR	CE
11. Finger tapping (only index and thumb) with elbows bent	KT, BR	CE
12. Touching nose with index finger	AT, BR	CE
13. Outstretched arms	PT	CE
14. Arms folded in front of chest, hands pointed inward	PT	CE
15. Arms folded in front of chest, hands pointed outward	PT	CE

RT - Tremor at Rest
KT - Kinetic Tremor
AT - Action Tremor
PT - Postural Tremor
BR - Bradykinesia

For collecting the data while the subjects perform the exercises we used the wearable sensing platform SensorTile. It is a tiny 13.5 x 13.5 mm square-shaped sensor node with a number of sensors on board and powered by 100 mAh battery. The core element of SensorTile is a 32-bit low-power Microcontroller Unit (MCU) ensuring the data collection from sensors and their submission to a smartphone via Bluetooth low energy. In this work, we collect the data from an accelerometer, gyroscope and magnetometer with 100 Hz sampling rate. All measurements were synchronized and collected separately for each exercise.

The scale MDS-UPDRS was used to determinate the diagnosis. Totally we collected the data from 72 subjects. Among them there are 36 individuals with the PD and 13 individuals having other types of tremor. The control group consists of 23 subjects.

3 PROBLEM DEFINITION AND METHODOLOGY

Type of tremor is an important part of our research. It is divided into 2 main categories [1]: resting tremor and action tremor where the latter one can be divided into postural tremor, kinetic tremor, intention tremor, and task-specific tremor.

3.1 Problem definition

Parkinson's disease is a complex disease with various symptoms, such as tremor, bradykinesia and others. Its analysis becomes complicated if the goal is to investigate conditions and symptoms. Our goal was to create a complex model that can provide feedback on the signs and attributes of the PD based on sensory information (accelerometer, magnetometer and gyroscope). For this task, we decided to prepare a step-by-step model for detecting PD:

1. **Choosing the best subset for predefined task.** Here we select what exactly we want to predict. And according to the chosen task we determined what exercise to do.
2. **Detecting exercises what person does.** Sometimes the subjects may do a mistake during the exercise. We tried to extract the quality of the training process and check the inaccuracy made by the subjects, e.g. incorrect exercise, runtime error, incorrect understanding of the exercise.
3. **Early stage diagnostic of the PD.** Identifying early stages of PD is important for the course of treatment. We tried to separate stage 1 PD and healthy patients.

3.2 Methodology

We used different ML techniques for the prediction and analysis outcomes. The workflow consisted of 3 stages:

(1) Features Extraction
(2) Dimensionality Reduction (DR) and Features selection (FS)
(3) Classification by ML algorithms

Features Extraction will be discussed in detail in the next section. We used the following DR algorithms:

- Principal Component Analysis (PCA) with linear, Radial basis function, sigmoid and polynomial kernel
- Multidimensional scaling
- Factor Analysis
- Independent Component Analysis (ICA)

Features' Selection Methods:

[1] https://www.ninds.nih.gov/Disorders/Patient-Caregiver-Education/Fact-Sheets/Tremor-Fact-Sheet

- Feature importance based on mean impurity decrease for random forest.
- Chi2 selection
- Removing features with low variance

ML models for each task were the same:

- RandomForest with different number of estimators and maximal depth
- SVM (One vs All approach in multiclass classification)
- Logistic Regression (One vs All approach in multiclass classification)
- Decision Tree
- Naive Bayesian algorithm
- k-nearest neighbors classifier (with different k)

One of the problems in our dataset was an unbalanced classification. We solved this using weights in proportion to the number of class samples. All classifier parameters, DR algorithm, and FS methods were selected using the Grid Search method.

In each task we used **Leave-one-out Cross Validation** (LOO CV) to assess our results. Several metrics were used to understand the performance and to compare the classification models:

- Accuracy and Balanced Accuracy
- ROC AUC value (one vs all approach) micro and macro averaging
- F1-score, Precision and Recall

4 RESULTS

4.1 Pre-processing

To pre-process the data the signals were split up into the clips of 5 seconds (or 500 points) with 50% overlap. The length of the window and overlapping parameters were chosen according to the research reported in [6]. In total, we generated 8922 windows or an average 600 windows per exercise. All signals were filtered with a high-pass filter (0.5 Hz) making the results not dependent on the effect of a limb orientation. Examples of the data are shown in Fig. 1.

4.2 Feature Extraction

However, using the data we have to detect not only the tremor symptoms, but also bradykinesia which can be detected using a lower frequency. A combination of these signs gives us the opportunity to detect the PD and other types of tremor. Based on this knowledge we extracted the features from 5 s clips.

For each part of the cut signal we calculated standard statistical features, such as mean, standard deviation (STD), skew, kurtosis, minimum and maximum values. Afterwards, we defined the main trend using the rolling window and the signal without the trend (noise signal). Next, we applied Fast Fourier Transform (FFT) to find the dominant frequency and amplitude. FFT Features were divided into two classes: Tremor and Bradykinesia detection. The Tremor features were extracted in the frequency range from 3 to 10 Hz, and the localization of signs of Bradykinesia is limited by 3 Hz. For the trend and noise signal we searched for peaks in the Frequency domain. For each symptom (Tremor and Bradykinesia) we considered only peaks where the amplitude was more than the mean plus the standard deviation of Fourier transformed data. Finally, we calculated the mean and STD for frequencies of peaks,

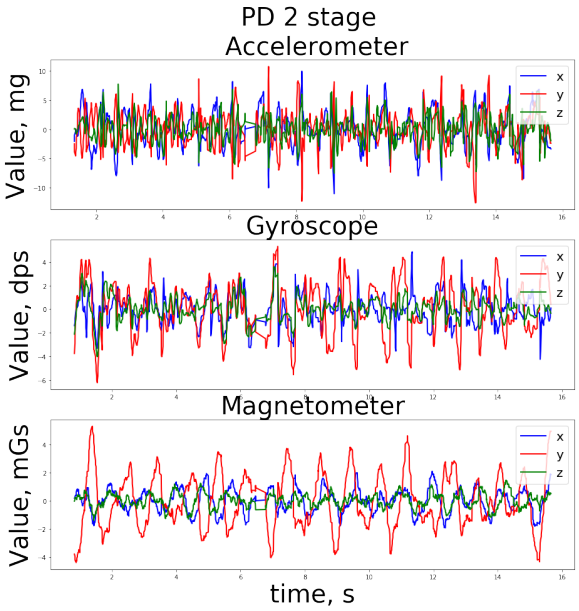

Figure 1: Example of pre-processed data.

the mean and STD for amplitudes, min and max values, dominant frequency as well as the power of spectrum.

4.3 Exercise Analysis

Table 2: Exercise Classification.

Exercise	precision	recall	f1-score
exercise 1	0.82	0.82	0.82
exercise 2	0.98	0.96	0.97
exercise 3	0.84	0.71	0.77
exercise 4, 5	0.70	0.89	0.78
exercise 6	0.86	0.81	0.83
exercise 7	0.85	0.73	0.79
exercise 8	0.98	0.91	0.94
exercise 9	0.94	0.95	0.95
exercise 10	0.96	0.90	0.93
exercise 11	0.93	0.85	0.89
exercise 12	0.95	0.88	0.91
exercise 13, 14, 15	0.89	0.94	0.92
macro avg	0.89	0.86	0.87
weighted avg	0.88	0.87	0.87

In this section we demonstrate how to determine the exercise based on sensor signals. Here we did not divide our signal into 5 s clips because different parts of an exercise can have different representation in the feature domain. It can lead to the misclassification. Moreover, the features describing the trend were very important since these characteristics represent the general behavior of signal.

To achieve better results we unite exercise 4 and exercise 5 due to their similarity. Also, exercises 13-15 were united because of the same reason.

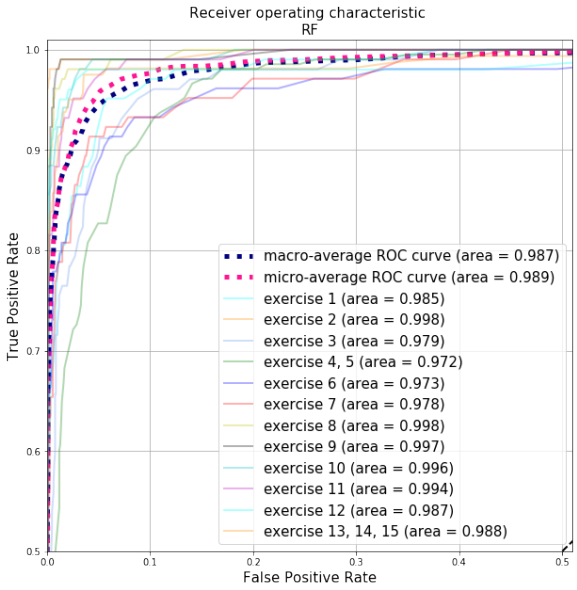

Figure 2: Exercise importance based on the ROC-AUC value.

We calculated precision, recall and f1-score for each class and also plot ROC curve in the one-vs-all classifier approach. Finally, we showed the micro and macro averaging of ROC curve and AUC value.

For choosing the best model we used the ROC curve and micro-averaging Area Under Curve value.

4.4 PD analysis

Our task was defining the best set of exercises to predict an early stage of PD. For this purpose we used features not only from one exercise. Instead we did classification using the features from a number of exercises. Since the subjects made dissimilar movements during different exercises this led to different exercises that may show different symptoms. That is why we decided to just iterate through all possible subsets of less than 3 exercises. In this way, we selected a subset of the exercises and finally tried to diagnose the early stage of PD.

The detection of early stages is necessary to start treatment as fast as possible. Early PD diagnosis is important since the therapy involving the medicines, e.g. levodopa/carbidopa, is more effective when administered early on the disease. Non-pharmacologic therapy such as the increased exercise activity, is easier to perform at the early stage of PD and may help slow down the disease progression.

The General Workflow was described in Section 3.2.

Choosing the best set of exercises for the classification purposes can help doctors and researchers to diagnose faster and further study of the PD.

Figure 3 shows the best subset of exercises only.

Our results demonstrate that exercise 11 and exercise 2 are the best for this task. According to ROC AUC value we defined the best 5 subsets and chose the best exercises. Obviously, one of the exercises used in the clinical evaluation should be in the best subset. In fact, exercise 11 is truly used for the clinical assessment and corresponds to the subjects asked to do finger tapping (only index and thumb) with elbows bent.

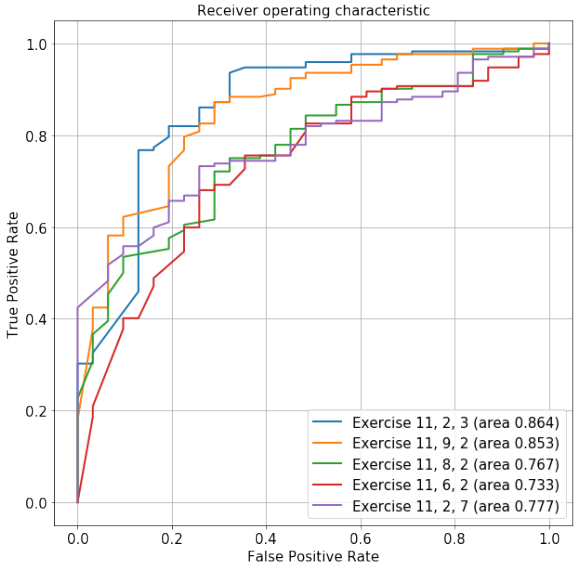

Figure 3: ROC curve for early detection.

Exercise 2 consisted in a Pronation / Supination of forearms. This task is more informative and demonstrated better achievements for early detection.

5 CONCLUSION

In this paper, we performed the analysis of an early stage of PD diagnosis based on the collected data from wearable sensors. Our approach helped identify a better subset of exercises for the PD detection at an early stage which is useful for future research and medical staff. In addition, we have shown that the exercises classification can be performed effectively using ML methods. In general, the most informative exercises are pronation / supination exercises and tasks used in clinical evaluation.

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