Classification of parkinsonism based on foot tapping test

Vladislava Bobić, Milica Djurić-Jovičić, Milica Ječmenica-Lukić, Igor Petrović, Nataša Dragašević, Vladimir Kostić, and Mirjana Popović

***Abstract*— Foot tapping represents a standard clinical test used for the assessment of motor abilities of patients with Parkinson's disease (PD). In this paper, we analyzed the data recorded by gyroscope mounted on a foot bridge during the foot tapping test (FTT). The data was collected from 17 healthy controls, 17 patients with PD and 17 patients with Multiple System Atrophy (MSA). By using the several signal processing techniques, we extracted the features, and organized these into three datasets based on their type and clinical usability. One dataset comprised basic spatio-temporal features: tapping angle, duration and speed, whereas the second feature set included two more spatio-temporal features: maximum lifting and maximum foot drop velocities. Frequency-based parameters describing tap-to-tap variability and rhythm regularity were further added forming the third feature set. The feature sets were fed to the Support Vector Machine, and the accuracy was assessed with 10-fold cross validation. Obtained results showed that frequency-based parameters contribute to better differentiation between the evaluated groups with accuracy of 83.94±1.17%.**

***Index Terms*—Foot tapping; Classification; Parkinson's disease; Multiple System Atrophy; Frequency analysis.**

I. Introduction

Foot (or toe) tapping represents clinical test that is commonly used for the assessment of motor abilities and estimation of rigidity and tremor in patients with Parkinson's disease (PD) [1], [2]. It is evaluated as a part of the Unified Parkinson Disease Rating Scale (UPDRS) [3]. Within the test, the patients are asked to tap their toes as fast as possible for 10-15 s, while holding the heel on the ground. The assessment is performed visually by the physicians. Such subjective quantification may result with rough resolution and imprecise evaluation [4]. There is a great need for new systems and methodologies that could contribute to precise and objective quantification of tapping performance, and potentially lead to development of new automatic diagnostic systems.

By using small and lightweight wearable sensors, tapping performance can be objectively described and quantified. Inertial measurement units (IMU), comprising 3-axis accelerometers and/or 3-axis gyroscopes, were already applied in several studies for objective quantification of toe and finger tapping tests. The evaluation was performed with variety of different spatio-temporal features (such as rhythm, amplitude, tapping angle, opening velocity, etc.) [5]-[7].

Some studies suggested that frequency-based parameters can provide better quantification of tapping performance [8], [9]. Both time and frequency domain features were extracted from finger and toe tapping inertial data. Support Vector Machine was used for classification between PD patients and healthy controls, with error rate over 30% for both datasets [10]. The results showed that, by using several measures of motor performances, patients with PD and healthy subjects can be differentiated with accuracy, sensitivity, and specificity of above 88% [11]. Others reported that PD patients can be discriminated from healthy controls with accuracy over 90%, using the features extracted from accelerations and angular velocities describing finger tapping [12], [13].

In a case of differential diagnostics where other diseases or atypical PD forms are included in analysis, objective quantification and automatic prediction becomes more demanding. Multiple System Atrophy (MSA) represents atypical form of Parkinson's disease that has very low response to standard treatment of PD [14]. The symptoms may be confused with those in PD, especially in early stages of disease.

Different approaches were used for distinction between PD patients, and those with some atypical form of Parkinsonian syndrome. It was shown that MRI images of PD patients can be distinguished of those obtained from MSA patients with accuracy of 97% [15]. PET scans were also used for discrimination between healthy controls and PD, as well as healthy controls and MSA patients [16]. However, to our knowledge, there is no system based on wearable inertial technology providing classification between parkinsonisms.

In this paper, we present a methodology for discrimination between three groups of subjects: patients with Parkinson disease, patients with Multiple System Atrophy and healthy controls. The classification is based on the use of Support Vector Machine model, trained on three feature sets, extracted from the inertial data describing foot tapping movements.

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II. METHOD

A. Instrumentation

The measurement system includes one miniature inertial measurement unit (IMU), and one force plate [17]. IMU comprises a 3D gyroscope L3G4200 (STMicroelectronics, USA). During testing, the IMU is attached directly to the foot bridge and, with light and tiny cable, connected to sensor control unit (SCU), positioned on the leg. The inertial unit is small and lightweight, allowing subjects to naturally perform the task.

The force platform is a mechanical construction with combination of active and passive areas corresponding to metatarsal and heel, respectively. The passive plate is connected to the fixed part of the platform, while active plate allows measurement of force range up to 50N. The platform is connected to the SCU, and all system components are fully synchronized.

B. Experiment

Seventeen patients with Parkinson disease - PD (Age: 61.9±8.4 years), seventeen patients with Multiple System Atrophy – MSA (Age: 58.1±4.5 years), and seventeen age and gender matched healthy controls – CTRL (Age: 59.0±8.9 years) were enrolled in this study. During the experiment, the subjects were sitting comfortably in the chair with their feet lowered to the ground.

The participants were asked to perform foot tapping test: to tap their toes and metatarsals (while holding the heel on the ground), as fast and as high as possible, during the 15 s of test. Three recordings were made for each leg separately, with one minute of rest period in between.

The study was performed at the Neurology Clinic, Clinical Centre of Serbia. The subjects gave their written consent prior to the participation in the study. The experiment was performed in accordance with the ethical standards of the Declaration of Helsinki.

C. Signal processing

The signals were recorded with the sampling frequency of f_s=200 Hz. Acquired signals were processed by custom-made software (scripts written in Matlab 7.6.0., R2008a). In the analysis, we have used the gyro axis ω that describes foot rotations in a sagittal plane. The examples of recorded gyro signals for the three groups are presented in Fig. 1.

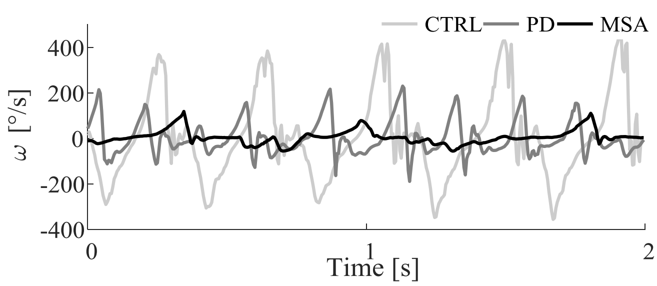

Fig. 1. The examples of 2 s of recorded gyro signals for one CTRL subject, one PD patient and one MSA patient.

1) Feature extraction

In order to quantify tapping performance, we have extracted a set of parameters that can be used for objective quantification of the foot tapping test. The parameters were organized in three datasets: 1) basic spatio-temporal parameters expressing tap angle, duration and speed; 2) all spatio-temporal parameters expressing tap angle, duration, speed, maximum foot lifting and maximum foot drop velocity; 3) all spatio-temporal parameters and frequency-based parameters describing tap-to-tap variability and rhythm regularity.

a) Spatio-temporal parameters

The parameters were designed to match the criteria that are relevant within the UPDRS scale for assessment of patients' motor abilities. Therefore, the first feature set comprised: maximum tap angle and duration and tapping speed.

In order to obtain tapping angle, the gyro signal was integrated. The normalized ground reaction force (GRF_N) signal obtained from the force platform was used for drift removal (Fig. 2): high peaks in GRF_N signal represent the instants when toes and metatarsals strike the ground, i.e. when the angle between the foot and the ground equals to zero. We have fitted the cubic spline polynomial in between those samples and subtracted it from the drifted angle sequence [18].

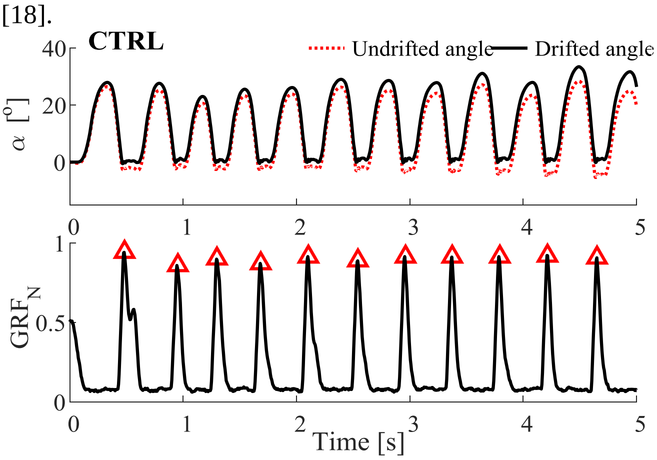

Fig. 2. The representation of: top) undrifted (red dashed line) and drifted (solid black line) angle sequence, bottom) normalized ground reaction force (GRF_N) signal. Red triangles mark detected peaks that correspond to toes and metatarsals ground impact moments. The example is given for CTRL subject.

The segmentation of the tapping sequence is performed based on the positive peaks in the force data (red triangles in the bottom panel, Fig. 2). The tap duration is expressed as temporal distance between the two consecutive peaks. The mean value of lifting and foot drop velocities for each individual tap represents the tapping speed.

The abovementioned features were calculated for each individual tap, and final parameters were expressed with the following: mean value (averaged over all taps), standard deviation (over all taps), coefficient of variation – CV (calculated as the ratio of standard deviation and mean value, expressed in percentage) and slope of the linear regression, fitted through values obtained for individual taps. Therefore, the first feature set included twelve parameters for quantification of tapping performance.

In addition to these basic parameters, we have introduced features describing the maximum foot lifting rate (positive peaks in Fig. 1.), and the maximum rate of the foot drop (negative peaks in Fig. 1). Both velocities were calculated for each individual tap and expressed with parameters that were introduced earlier: mean value, standard deviation, CV [%] and slope. Finally, the second feature set comprised 20 parameters.

b) Frequency domain analysis

In addition to spatio-temporal parameters, we have implemented frequency domain methods that can contribute to better evaluation and description of tapping performance [9].

By using the Continuous Wavelet Transform (CWT) it is possible to quantify tapping performance in terms of rhythm regularity [9]. By using the algorithm that is based on the Fast Fourier Transform, CWT coefficients of gyro signal were calculated (Fig. 3) using the complex Morlet mother wavelet (center frequency f_0=1 Hz). Time resolution of the resulting coefficient matrix was 5 ms, whereas frequency resolution was set to 0.1 Hz. By summing the absolute values of CWT coefficients, we obtained additional characteristic: cross-sectional area perpendicular to the t-axis (CSA-T_{tot}). Final CSA-T_{tot} values were expressed as percent of its maximum energy (Fig. 3) [9]. The regions with energy loss below the threshold of TH=50% correspond to modified rhythmic behavior, and these regions were described in terms of energy-loss duration (parameter CWT<50 expressed in seconds).

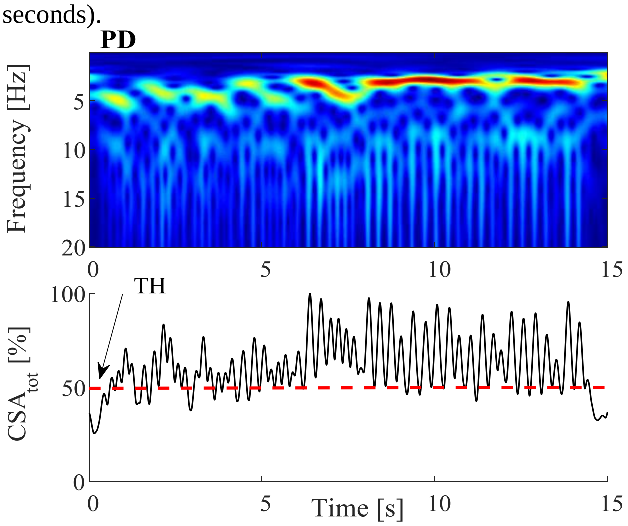

Fig. 3. The representation of: top) CWT coefficients, and bottom) calculated CSA$_{tot}$ characteristic. Red dashed line marks introduced threshold TH at 50%. The example is given for PD patient.

It was suggested that parameters describing the main peak within the Welch's estimation of power spectral density function can provide adequate quantification of signal intra-variability [19]. The method was evaluated for two sets of data: gait [19] and finger tapping [9] for PD patients and healthy subjects. The parameters include (Fig. 4): the peak frequency PSD_f, the peak amplitude or height PSD_h, the peak width PSD_w (at half of the peak's amplitude) and the peak slope PSD_s (from the peak maximum to the point of half of the peak's amplitude). Higher values of width and smaller values of slope indicate higher intra-variability [19].

The third feature set included frequency-based parameters: CWT<50, PSD_f, PSD_h, PSD_s, and PSD_w, in addition to previously introduced spatio-temporal parameters, comprising 25 parameters in total.

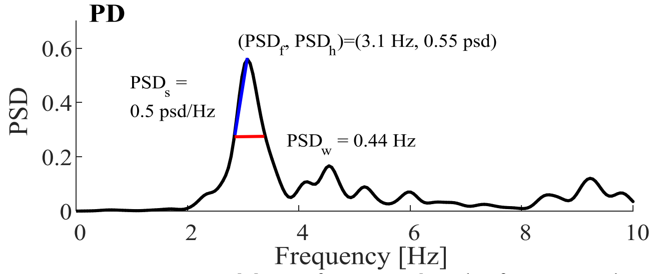

Fig. 4. Power spectral density function with peak's frequency and amplitude (PSD_f, PSD_h), slope (PSD_s) and width at half of peak's amplitude (PSD_w). The example is given for PD patient.

2) *Classification*

The obtained parameters were used for classification among 3 groups of subjects: CTRL, PD, and MSA. For classification we have used Support Vector Machine (SVM). SVM represents a supervised learning algorithm that forms a decision boundary separating different classes in the feature space. It is given in a form of hyperplane, and while training, classifier aims to maximizes margin, i.e. the distance between the support vectors (closest data points) and hyperplane [20]. SVM performs binary classification, but for purposes of multi-class classification "one-vs-all" method is used. SVM uses kernels, i.e. similarity functions for achieving complex non-linear classification. In our implementation, we applied one of the most commonly used kernel functions – radial basis function (RBF).

At first, the input parameters were centered and normalized with their standard deviation. Afterwards, the classifier was separately trained for each of the introduced feature sets. The classifier was evaluated with 10-fold cross validation. Due to different initial conditions, the procedure was repeated 10 times for each feature set and the final result was averaged over all repetitions.

3) *Data visualization*

For the purpose of data visualization, we have implemented Principal Component Analysis (PCA). PCA allows transformation of data into new feature space, where axes correspond to principal components (PCs). The components are obtained as linear combinations of original feature vectors. As PCs are orthogonal to each other, there is no information redundancy. We have calculated the percentage of data variance described by each of the components. The first three components explain more than 95% of variance (Fig. 5), and therefore the original data can be presented in 3D PC space, without losing significant amount of information.

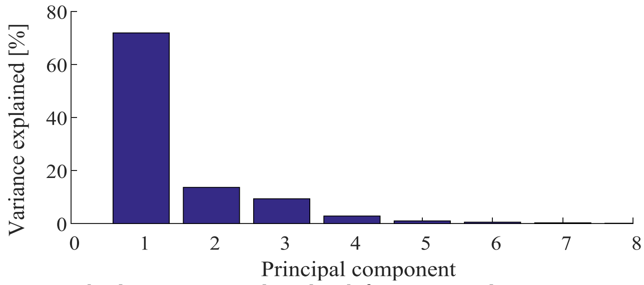

Fig. 5. The data variance explained with first 8 principal components.

III. Results

The three feature sets were used for classification among CTRL, PD and MSA groups. The database included 17 subjects per group, 3 recordings per subject, in total: 153 examples for classification. The descriptive statistics (average ± standard deviation) of introduced spatio-temporal and frequency-based parameters are shown in Table I and Table II, respectively. The results are presented for all three subject groups.

TABLE I
Descriptive statistics (av±std) of all spatio-temporal parameters

Feat.	Par.	CTRL	PD	MSA
Duration [s]	Mean	0.39±0.09	0.46±0.14	0.75±0.44
	Std	0.07±0.03	0.09±0.04	0.18±0.16
	CV	17.51±7.08	20.51±9.76	23.36±16.57
	Slope	0.01±0.03	0.02±0.05	-0.03±0.03
Angle [°]	Mean	18.04±7.37	9.53±3.98	8.56±5.27
	Std	2.79±1.14	1.87±0.89	1.42±0.58
	CV	16.32±6.08	21.83±10.44	20.68±11.03
	Slope	0.01±0.19	-0.04±0.12	-0.02±0.13
Average velocity [°/s]	Mean	96.5±27.3	46.2±13.2	28.6±13.5
	Std	15.54±5.52	9.66±4.71	6.35±2.56
	CV	16.53±5.29	22.11±10.61	25.27±12.13
	Slope	-0.17±0.63	0.34±0.48	-0.13±0.38
Max. lifting rate [°/s]	Mean	207.2±73.0	105.8±46.6	71.0±34.4
	Std	38.46±20.36	26.78±15.94	16.49±6.88
	CV	18.26±6.31	25.67±10.61	25.27±8.55
	Slope	-0.24±1.86	-0.49±1.23	-0.21±1.21
Max. rate of foot drop [°/s]	Mean	-258.7±68.6	-174.1±57.9	-114.6±58.8
	Std	42.49±22.85	37.62±17.37	25.75±10.02
	CV	16.74±9.07	23.98±11.99	26.88±13.58
	Slope	0.52±1.81	1.47±2.04	0.48±2.09

TABLE II
Descriptive statistics (av±std) of Frequency-based parameters

Parameter	CTRL	PD	MSA
CWT<50 [s]	2.43±1.91	5.65±2.89	8.31±3.41
Peak height, PSD_h [psd]	2.85±0.75	2.58±0.91	1.98±1.09
Peak frequency, PSD_f [Hz]	1.43±0.43	1.01±0.37	1.09±0.42
Peak slope, PSD_s [psd/Hz]	3.35±1.62	2.34±1.28	2.67±1.39
Peak width, PSD_w [Hz]	0.48±0.12	0.49±0.15	0.48±0.15

The classification was performed for three datasets separately and evaluated using the 10-fold cross validation. The results are presented in Table III, as descriptive statistics (av.± st. dev.), obtained for 10 repetitions.

As shown, the best result was obtained for the third feature set (grey shaded row in Table III), that contains 25 parameters, including all spatio-temporal features and frequency-based parameters. For that case, we have graphically presented results in 3D principal component space (Fig. 6).

TABLE III
Descriptive statistics (av±std) of classification accuracy, for all three feature sets

Feature set	Accuracy [%]
I	74.70±1.72
II	79.87±1.11
III	83.94±1.17

IV. Conclusion

In this paper, we presented the results of the classification among three groups of subjects: healthy controls and two groups of parkinsonisms: one typical (PD) and one atypical (MSA). The analysis is based on the inertial data describing foot tapping movements.

Support Vector Machine model with RBF kernel was applied for classification. The features were extracted and organized into three datasets based on their type and clinical usability. The first set comprises only basic spatio-temporal features: tapping angle, duration and speed. These features are commonly evaluated in clinical practice. As shown in Table III, this feature set performed poorly, with error rate higher than 25%. We added two extra spatio-temporal features to initial dataset and examined the performance of all included parameters. However, although slightly higher, the classification accuracy didn't improve significantly, with error rate above 20%. The complete and final set included 5 more features that were extracted with Continuous Wavelet Transform (CWT) and Welch's estimation of power spectral density (PSD) function. It was already shown in the literature that these features can be used for objective quantification and evaluation of finger tapping patterns [9]. CWT may be used for estimation of duration of rhythm interruptions/hesitations. Peak from PSD function can be a good indicator of signal intra-variability (tap-to-tap variability). In a case with all parameters included, the classification outperformed the previous two cases with accuracy of 83.94%. This result suggests that frequency-based features contribute to better differentiation among the three groups (Fig. 6).

In the literature, majority of the methodologies use finger tapping data for classification between PD patients and healthy controls. It was reported that using the finger tapping inertial data, healthy controls and PD patients can be discriminated with high accuracy above 90% [12], [13]. However, no similar result was published for the analysis that includes atypical PD forms or foot tapping data. Classification between typical and atypical PD forms was usually based on the use of medical images, obtained from MRI and PET scanners. Such analysis can provide classification with high accuracy; however, it is time consuming and expensive. The methodology presented in this paper requires simple and fast setup, and provides automated analysis, that can be applied with little or no technical skills of medical staff. In addition, the methodology provides classification of three groups with acceptable accuracy.

Our future work will include enhancement of features and examination of their potential for differential diagnostics (testing on other atypical PD forms).

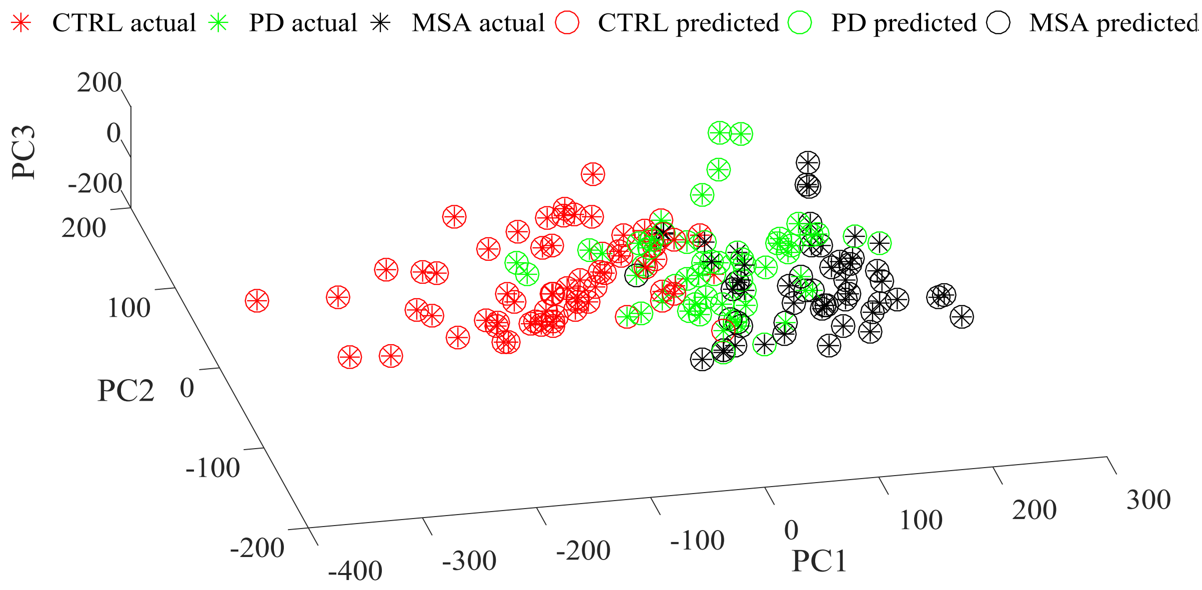

Fig. 6. The presentation of obtained results for the third feature set in 3D principal component space.

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