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Gait and balance patterns related to Free-Walking and TUG tests in Parkinson's Disease based on plantar pressure data

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Abstract **- Continuous monitoring of patients with Parkinson's Disease (PD) is critical for their effective management, as early detection of improvement or degradation signs play an important role on pharmaceutical and/or interventional plans. Within this work, a group of seven PD patients and a group of ten controls performed a set of exercises related to the evaluation of PD gait. Plantar pressure signals were collected and used to derive a set of analytics. Statistical tests and feature selection approaches revealed that the spatial distribution of the Center of Pressure during a static balance exercise is the most discriminative analytic and may be used for every-day monitoring of the patients. Results have revealed that out of the 28 features extracted from the collected signals, 10 were statistically significant (p < 0.05) and can be used to machine learning algorithms and/or similar approaches.**

Keywords: Gait analysis, plantar pressure data, Parkinson's disease, gait patterns

I. Introduction

Normal gait is an activity related to the proper functioning of different organs and systems such as the central peripheral nervous system, spine and spinal system [1]. The main characteristics of the bipedal are: a) the periodic movement of each foot from the support position to the next, which forms a circle and, b) the ground reaction forces (GRF), which are applied to the legs to support the body (vertical Ground Force Reaction - vGRF) [1]. The study of GRF and plantar pressure analysis are efficient evaluation methods for gait biomechanics. GRF and body weight are the only external forces applied on the human body during normal walking. vGRF seems to be a representative indicator for mechanical stress on the plantar surface of the foot, which is related to the overall forces developed by the joints and muscles during walking [2] while, the center of pressure (CoP) is the point where the instantaneous resultant vGRF acts on the foot.

The individual gait pattern is influenced by age, personality, mood, and sociocultural factors. Preferred walking speed in older adults is a sensitive indicator of overall health while safe walking requires excellent cognitive function and executive control [3]. The onset of a gait disorder may indicate cerebrovascular or other acute damage to the nervous system, as well as systemic disease or adverse effects of a medication, especially in the case of poly-pharmaceuticals. The prevalence of gait disorders increases from 10% in people aged 60-69 years to more than 60% in people over 80 years [4]. Dysesthesia disorder due to polyneuropathy, Parkinson disease, and frontal gait disorders due to subcortical vascular encephalopathy or dementia-related disorders are some of the most common neurological causes [5]. With advanced age, the percentage of patients with multiple causes or combinations of neurological and non-neurological disorders, gait disorders increase [6]. The various pathological conditions lead to gait patterns with specific characteristics.

Many gait phase detection algorithms have been developed and presented in the literature [7]. Simple systems based on foot pressure [7], inertia and gyroscope data [8] distinguish gait phases but they appeared to be weak in correcting the resulting errors. More advanced and complex artificial intelligence algorithms (machine learning, fuzzy logic, support vector machine, artificial neural network) have been introduced [9] for more accurate and error resistance gait phase recognition based on both foot pressure and inertial measurement units (IMU) data. However, what is of most concern to many researchers today is the detection of those features that could be considered indicators of Parkinson's disease progression. According to the literature, the most obvious symptom in the locomotor system is the difficulty of walking, which is associated with stiffness, rigidity, and bradykinesia. In addition, both PD patients and aged people are found to have difficulty controlling their balance during gait and posture, which can lead to falls, injuries, and reduced quality of life. In particular, the pre-existing literature provides information on the fact that people with Parkinson's perform smaller steps, have reduced step height and an extended support phase compared to healthy people [10].

The aim of this work is to compare the patterns of free-walking at a slow, natural and high pace and the Time Up and Go (TUG) test between mild PD patients, throughout ON status, and the control group which includes healthy age-matched subjects with the use of smart insole (in-shoe pressure sensors array along with a 6-axis IMU sensor). In addition, we evaluate the extracted features by means of innovative algorithmic pipelines to classify individuals.

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The research novelty of this work includes (a) the identification of patterns related to the presence of PD, (b) a novel approach for quantification of the patterns related to PD which can lead to the classification of patients according to PD symptoms severity and (c) a statistically significant ranking of features related to standing and walking exercises, as analyzed by plantar pressure data, which can facilitate the design of both machine learning approaches and PD rehabilitation exercises.

II. Materials And Methods

Various clinical measurement protocols have been proposed and used in both normal and pathological walkers to evaluate gait parameters, balance in posture and in motion, and for the risk of falling. Most of them include a number of straight-paced steps, usually at different speeds (slow, normal and fast), as well as walking on an inclined plane and stairs. For pathological walkers, and especially for patients with Parkinson disease (PD), many researchers recommend TUG test (time for uprising and start walking from a sitting position without assistance from the upper extremities), walking on a treadmill with obstacles, and dual task walking (walking while the patient also performs. an arithmetic operation, conversation, transfer of an object, etc.) [11]. The design of the clinical measurement protocol for our study was carried out with simplicity, security, and completeness following the guidelines to avoid falls in elderly and Parkinson's patients (patients at high risk of falls).

The patients who were recruited were informed for the study (and join it after signing the volunteer consent form) during their visit to the rehabilitation center. Specifically, the study was conducted at Palladion which is a medical rehabilitation and follow-up care centre in Tripoli, Greece. The study inclusion criteria for PD patients were: Hoehn and Yahr scale classification between 1 and 3 regardless age, with the ability to perform the protocol's exercises and for the elder group: age over sixty years old without any musculoskeletal and neurological problem that affect the subject's gait and balance. The data collection included 10 elder people and 7 PD patients who met the inclusion criteria as described in the clinical research protocol. Table I shows the averages of the anthropometric data and demographic characteristics of the patients.

TABLE I: DEMOGRAPHIC PARAMETERS (IN THE FORM OF MEDIAN ± STANDARD DEVIATION VALUES).

	CG	PD
Age [years]	73,3±11,79	72,3±7,54
Weight [kg]	79,9±7,62	81,1±9,75
Foot Size	42,3±1,06	42,4±1,13
Height [cm]	172,5±5,74	171,7±6,57
Gender [male ratio]	1	1
BMI	26,9±3,19	27,5±3,19

CG = Control Group subjects, PD = Parkinson's disease patients.

A. *Experimental Procedure*

1) *10m Free Walking in various gait velocities (Exercise 1)*

In this exercise, the subject was asked to walk in a straight line for 10m starting from an upright position. At the end of the 10m the subject makes a 180° turn and returns to his original position. The exercise is repeated twice. This exercise was performed for three different walking speeds (slow, natural and fast) as perceived by the walker.

2) *Timed Up and Go (TUG) test (Exercise 2)*

In this exercise, participants were requested to start the exercise from a sitting position. Then, the subjects were asked to get up from the sitting position on the chair (without the help of their arms) and start walking in a straight line for 10m. At the end of the 10m mark the subject made a 180° turn and returned to their original position sitting on the chair. The exercise was repeated twice for every subject.

3) *Static exercise for postural analysis (Exercise 3)*

The subjects stand upright with their feet at about 30cm distance while the feet facing forward. Subjects stand still for 10sec with their eyes open. Then it was requested from the participants to continue the exercise with their eyes closed for another 10sec time period.

B. *Sensing devices*

For the recording of plantar pressure and IMU data from the CG and PD participants, Moticon's® insoles solution was chosen, for their construction simplicity (no additional cables and external module), for the satisfactory integrated number of pressure sensors and for the fact that they have built-in accelerometer and gyroscope sensors [12]. Specifically, each insole incorporates 16 pressure sensors with a measuring pressure range from 0-50 N / cm^2, a resolution of 0.25 N / cm^2 and a sampling frequency which can reach 100Hz. At the central area of each insole, the 6-axis IMU along with Bluetooth communication dongle and the battery are placed. The built-in accelerometer records the acceleration of the insole on the three axes with a range of ± 16g while the gyroscope records the rotation rate of each insole with respect to its axes with a range in ± 2000dps.

C. *Data Acquisition*

The collected data of each experimental trial consists of, synchronization timestamp, pressure data from all sensors and 3-axial accelerometer and 3-axial gyroscope data of both insoles with a sampling frequency of 100 Hz. Each task was video recorded. A video camera was placed in such a way that only the lower part of the patient's legs was visible. Prior to registration, insoles were calibrated and adapted individually to the shoes of each participant.

D. *Gait and balance metrics and analytics*

The collected signals from the insoles were analysed, aiming to calculate and extract the gait metrics. The gait metrics are related to the important gait events, as presented in Table II. More specifically, as presented in Algorithm 1, the proposed methodology calculates for each gait cycle the time periods between the consecutive gait events. The algorithm includes a pre-processing step, which handles the normalization and the denoising of the data.

TABLE II: TIMING ON THE GAIT EVENTS.

Event	time point
right heel strike	t_1
left toe off	t_2
right toe strike	t_3
right heel off	t_4
left heel strike	t_5
right toe off	t_6
left toe strike	t_7
left heel off	t_8

Algorithm 1: Gait metrics calculation algorithm

```
Input: stream of [p_{1-16}, a_{xyz}, g_{xyz}] from both insoles
Output: gait metrics t1, t2, t3, t4, t5, t6, t7, t8 per gait cycle
device-initialization();
while device streams data do
    data = get-batch();
    [data_left, data_right] = data-preprocessing(data);
    [left - pressure_hl] = get_heel([data_left]) ;
    [left - pressure_toe] = get_toe([data_left]) ;
    [right - pressure_hl] = get_heel([data_right]) ;
    [right - pressure_toe] = get_toe([data_right]) ;
    [binary - left - pressure_hl = binarize([left - pressure_hl]);
    [binary - left - pressure_toe = binarize([left - pressure_toe]);
    [binary - right - pressure_hl = binarize([right - pressure_hl]);
    [binary - right - pressure_toe = binarize([right - pressure_toe]);
    t_i = getNextEvent([binary - left - pressure_hl, [binary - left -
      pressure_toe], [binary - right - pressure_hl], [binary - right -
      pressure_toe];
end
```

Based on the metrics calculated for each gait cycle, the following gait analytics are calculated using the formulas presented below (Table III).

TABLE III: GAIT ANALYTICS CALCULATION BASED ON GAIT METRICS.

Gait analytic	Calculation
Right single support time	$a_1 = t_2\|_{nextcycle} - t_5$
Left single support time	$a_2 = t_1\|_{nextcycle} - t_6$
Double support time	$a_3 = (t_2 - t_1) + (t_6 - t_5)$
Right stance phase duration	$a_4 = t_6 - t_1$
Left stance phase duration	$a_5 = t_2\|_{nextcycle} - t_5$
Right load response time	$a_6 = t_2 - t_1$
Right terminal stance time	$a_7 = t_4 - t_2$
Right pre-swing time	$a_8 = t_5 - t_4$
Right gait cycle time	$a_9 = t_1\|_{nextcycle} - t_1$
Left loading response time	$a_{10} = t_6 - t_5$
Left terminal stance time	$a_{11} = t_7 - t_6$
Left pre-swing phase time	$a_{12} = t_1\|_{nextcycle} - t_7$
Left gait cycle	$a_{13} = t_2\|_{nextcycle} - t_2$
Cadence	$a_{14} = \frac{1}{t_2\|_{nextcycle} - t_1}$
Right single support time percentage over gait cycle	$a_{15} = \frac{a_1}{a_9}$
Left single support time percentage over gait cycle	$a_{16} = \frac{a_2}{a_9}$
Double support time percentage over gait cycle	$a_{17} = \frac{a_3}{a_9}$
Right stance phase time percentage over gait cycle	$a_{18} = \frac{a_4}{a_9}$
Right stance phase time percentage over gait cycle	$a_{19} = \frac{a_5}{a_9}$
Right loading response percentage time over gait cycle	$a_{20} = \frac{a_6}{a_9}$
Right stance phase time percentage over gait cycle	$a_{21} = \frac{a_7}{a_9}$
Right pre-swing phase time percentage over gait cycle	$a_{22} = \frac{a_8}{a_9}$
Left loading response percentage phase time over gait cycle.	$a_{23} = \frac{a_{10}}{a_9}$
Left terminal stance time percentage over gait cycle.	$a_{24} = \frac{a_{11}}{a_9}$
Left pre-swing phase time percentage over gait cycle	$a_{25} = \frac{a_{12}}{a_9}$

All the aforementioned analytics have been calculated for each gait cycle for the walking part of Exercise 1 and 2. For the whole exercise, the mean values and the standard deviations of the derived analytics were also calculated. Additionally, the stand-up time (sut) and time-to-go (gt) time were also computed based on the input pressure data from the insoles. From Exercise 3, the spatial distribution of the CoP of both feet (bcopl & bcopr) have been calculated and quantified as the average Euclidean distance from the center of the insole. All calculated values have been normalized over the maximum value of each analytic.

III. RESULTS

A. Statistical analysis

In order to identify the statistical relevance of each calculated analytic, specific statistical measures, like information gain and chi-squared test have been determined. The results for the 10 most relevant analytics are presented in Table IV.

TABLE IV: STATISTICAL ANALYSIS ON THE GAIT ANALYTICS.

analytic	Information Gain	Chi-square test
bcorp	0.269	8.417
bcopl	0.303	8.417
sut	0.316	8.337
a9(mean)	0.163	5.307
a13(std)	0.2	5.307
a19(mean)	0.309	5.307
a2(std)	0.343	5.307
a8(mean)	0.461	5.307
a4(mean)	0.126	4.019
a3(mean)	0.126	4.019

For the analytics presented in Table IV, a box plot diagram is presented in Fig. 2, where the analytics are compared for the two groups. For all of the analytics it is clear that mean values and the variance for the PD patients are substantially higher than the ones for the elder subjects.

Fig. 3 presents the spatial distribution of the CoP during the static balance exercise for PD and elder subjects. The variance of the CoP justifies the high statistical importance of bcopl and bcopr analytics, as it is obvious that PD subjects present considerably higher values compared with the elder subjects.

B. Gait Patterns

Aiming to identify specific patterns between the two groups of subjects, two visualizations are proposed. Fig. 1 presents the separability of the two classes using a RadViz Visualizer [13]. RadViz is a multivariate data visualization algorithm that plots each feature dimension uniformly around the circumference of a circle and then plots points on the interior of the circle such that the point normalizes its values on the axes from the center to each arc.

Finally, Fig. 4 presents for each participant the heatmap of the analytics presented in Table 4. This visualization provides a clear conceptual insight of the analytics patterns for the PD patients compared with the elder subjects. The higher values for almost all selected analytics provide a “lighter” pattern which can be easily distinguished.

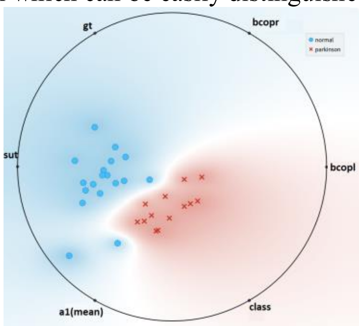

Figure 1: RadViz visualization on the 5 most relevant analytics.

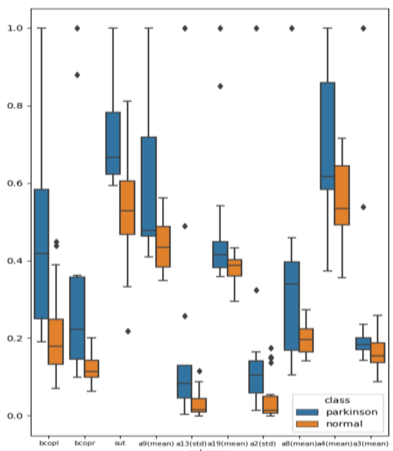

Figure 2: Box plots for the 10 most relevant analytics.

I. Conclusions

Continuous monitoring of the status of PD patients and/or high-risk elder individuals is crucial for either assessing the improvement or degradation of the condition in the first case of early diagnosis in the latter. Focusing on the quality of life of the patients, quick and targeted assessment methods, which can be performed in home environment, are of great importance.

The results of the study provide a clear proposal of the most important gait analytics based on plantar pressures that a system / method should collect in order to assess the condition of an individual related to PD. Most important, the fact that the three most important analytics derives from the static balance exercise and the stand-up time during exercise and not from the gait analytics.

Consequently, based on plantar pressures, a simple static balance exercise can provide important information about the status of the patient, without having to involve necessarily complex gait analysis. Thus, these analytics have the capacity to act as screening or first-level tests on PD patients.

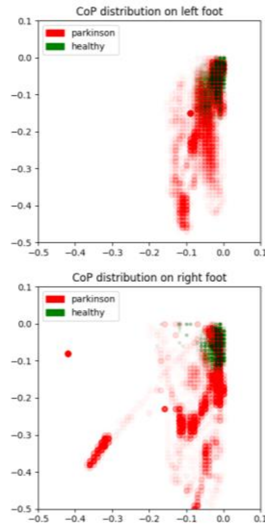

Figure 3: Spatial distribution of 7 PD and 10 elder subjects. The values have been normalized around the center of the axes.

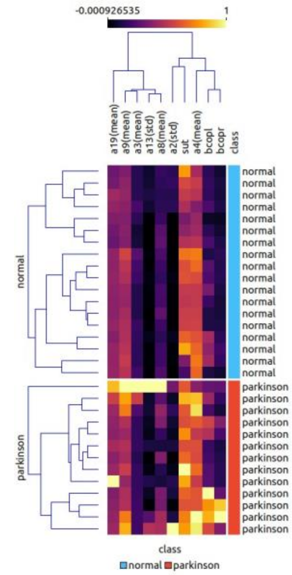

Figure 4: Heatmap of the most relevant analytics.

Future work will focus on enlarging the plantar pressures dataset and on applying artificial intelligence models on the proposed analytics aiming to produce inference models related to the progression of PD.

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