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Biometric and Mobile Gait Analysis for Early Diagnosis and Therapy Monitoring in Parkinson`s Disease

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Abstract-**Parkinson`s disease (PD) is the most frequent neurodegenerative movement disorder. Early diagnosis and effective therapy monitoring is an important prerequisite to treat patients and reduce health care costs. Objective and non-invasive assessment strategies are an urgent need in order to achieve this goal.**

In this study we apply a mobile, lightweight and easy applicable sensor based gait analysis system to measure gait patterns in PD and to distinguish mild and severe impairment of gait. Examinations of 16 healthy controls, 14 PD patients in an early stage, and 13 PD patients in an intermediate stage were included. Subjects performed standardized gait tests while wearing sport shoes equipped with inertial sensors (gyroscopes and accelerometers). Signals were recorded wirelessly, features were extracted, and distinct subpopulations classified using different classification algorithms. The presented system is able to classify patients and controls (for early diagnosis) with a sensitivity of 88% and a specificity of 86%. In addition it is possible to distinguish mild from severe gait impairment (for therapy monitoring) with 100% sensitivity and 100% specificity. This system may be able to objectively classify PD gait patterns providing important and complementary information for patients, caregivers and therapists.

I. Introduction

The most frequent neurodegenerative movement disorder today is Parkinson disease (PD). While the prevalence is 12.5 in 100,000 people in the age group of 40-44 years, it increases to 2,205 in the age group over 85 years [2]. Due to an aging society, increasing industrialization, and environmental factors, the number of patients will grow rapidly in the forthcoming decades [3].

Primary symptoms of PD are bradykinesia (a slowness of movements), rigidity (stiffness of muscles during passive movement), tremor (abnormal, repetitive contractions of agonist and antagonists) and postural instability (an impaired balance) [5]. Due to these symptoms characteristic gait impairments occur. Examples are shuffling gait (decreased foot roll-over movement), reduced step length, impaired gait initiation, and reduced gait speed [6].

The Unified Parkinson`s Disease Rating Scale (UPDRS) - Part III is the most commonly used scale to rate motor symptoms in PD [7]. The UPDRS is standardized, but remains subjective and depends on the patient`s momentary status. Nevertheless, the UPDRS is an internationally accepted rating scale to assess efficacy in clinical studies [5, 8, 9]. Additionally it is widely used in outpatient centers for movement disorders.

Several studies focus on gait symptoms like "freezing of gait" in PD. Moore et al. [10] and Baechlin et al. [4] used accelerometers attached to the leg, detecting gait changes to avoid falls and prevent injuries. Patel et al. published a system to monitor motor fluctuations using eight accelerometers attached to the upper and lower limbs [11] including a web-based application to provide information to a clinical center [12]. Pansera et al. measured gait changes with accelerometers attached to arms, calves, and trunk in a small number of PD patients [13]. Automated movement analysis of the upper extremity has also been introduced to PD patients [8, 14, 15] without assessing gait impairment. General bradykinesia was also detected using accelerometer based systems [9].

Systems already presented in the literature have a number of disadvantages for objective clinical assessment of PD, e.g. they use a complicated sensor setup, are non-mobile or do not provide an objective rating of the gait impairment. Therefore, the purpose of the presented research is to overcome existing disadvantages and to develop a sensor based mobile measurement system based on inertial sensors for objective assessment of gait disorders in Parkinson`s disease. We aim to establish an instrument to objectively measure and rate PD gait symptoms, using a mobile, non-invasive and easy applicable sensor based system.

II. Methodology

A. Sensor platform and setup

We used inertial sensors (gyroscopes, accelerometers) integrated in the SHIMMER (Sensing Health with Intelligence, Modularity, Mobility, and Experimental Reusability) sensor platform (Shimmer Research Ltd., Dublin, Ireland). They provided an extensible platform for real-time motion sensing [16]. Data were directly transmitted via Bluetooth® to a receiver unit [16]. The

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complete sensor had a small form factor (50 x 25 x 12.5 mm) and was lightweight (15 g).

The sensor platform contains a MSP430F1611 microprocessor running TinyOS and a three axis low-g accelerometer (MMA7260Q, Freescale Semiconductors, Austin, TX, USA) with an adjustable range of ± 1.5g to 6g and a sensitivity of 0.0025g at 4g. The built-in MEMS gyroscope was an InvenSense (Sunnyvale, CA, USA) 500 series, with a range of ± 500 degree/sec and a sensitivity of 2mV per degree/sec.

The sensor unit was attached to the lateral heel of a sport shoe (Fig. 1). To provide comparable conditions, identical shoe models were used for each subject. Data was captured synchronously from both feet via Bluetooth® with the software BioMOBIUS - Eyes Web (InfoMus Lab, University of Genoa, Italy) using an accelerometer range of ± 4g and a sampling rate of 100 Hz.

Fig. 1. Sensor setup for data capturing: sports shoe with attached SHIMMER sensor unit

B. Data collection

Data was captured from 14 patients with mild motor impairment (UPDRS < 15, defined as *group 1*) and 13 patients with intermediate motor impairment (UPDRS > 20, defined as *group 2*), respectively. The control population consisted of 16 healthy subjects (patient and control characteristics in table 1). UPDRS rating was obtained by a movement disorder specialist prior to the biometric gait analysis. PD was staged according to Hoehn and Yahr (H&Y) [17]. Exclusion criteria consisted of non-PD related gait impairments (e.g. arthrosis). Patients also had to be able to walk independently (H&Y<4). Study was done after positive ethics votum (Ethics committee, FAU Erlangen-Nuremberg Re.-No. 4208) and informed consent of participants.

Subjects underwent standardized gait tests:

1) 10-meter walk: The subjects were asked to walk for 10 meters at a comfortable walking speed, corresponding to the item "gait" of the UPDRS – Part III [7, 18]. Subjects passed 10 meter distance 4 times.

2) Heel-toe tapping: While sitting, heel and toes had to be tapped alternately on the floor for 20 seconds. The test required a flexion mainly within the ankle, comparable to the item "leg agility" of the UPDRS [7].

TABLE 1
CHARACTERISTICS OF PATIENTS AND CONTROLS

Characteristics	**IPS patients** (n=27)		**Controls**
	Group 1 UPDRS <15 (n=14)	Group 2 UPDRS >20 (n=13)	(n=16)
Sex (m:f)	12:2	9:4	7:9
Age (y)	63.4 ±9.3	66.6 ±10.5	64.9 ±6,9
Age on disease begin (y)	58.1 ±9.3	60.2±13.0	/
Disease duration (y)	5.3 ±5.5	6.3 ±3.9	/
UPDRS Motorscore	9.0 ±3.6	32.5 ±11.2	/
L-Dopa Equivalent dose (mg)	408 ±415	563 ±359	/

Characteristics and clinical parameters of Parkinson`s patients and healthy controls (Mean ± standard deviation).

3) Circling: While sitting, subjects had to perform a circling foot movement 5 - 10 cm above the floor for 20 seconds. The diameter of the circles was required to be about 30 cm. This test was designed in order to assess the ability to constantly move the feet without the influence of the body weight.

C. Feature extraction

Biometric features were extracted from the recorded gyroscope and accelerometer signals. Features were obtained from single steps and complete gait sequences. Additional features were computed from the Fourier-Transform of gait sequences to incorporate a frequency based analysis [19].

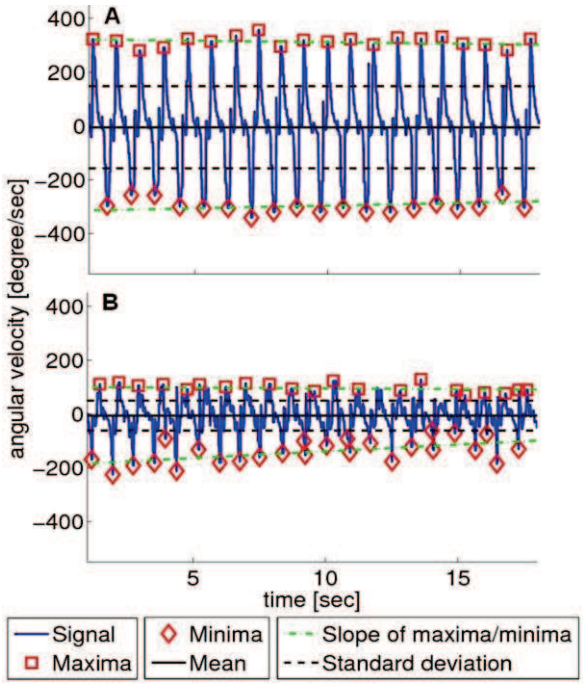

Fig. 2. Signals of the gyroscope (z-axis, sagittal plane) during heel-toe tapping of a control (A) and a patient (B, UPDRS=8). Sensor signal is superposed with typical features.

As features were computed for each shoe, axis and sensor, this procedure resulted in 290 features for the walking test. For the other tests no step dependent features were calculated, resulting in only 174 features per test.

TABLE 2
BIOMETRIC SIGNAL FEATURES

Feature	Name	Category	Description
1	Step duration	Step feature	Duration from the beginning of swing phase to end of stance phase
2	Rise gradient of swing phase	Step feature	Gradient from begin to max. positive rotation of swing phase in sagittal plane,
3	Fall gradient of swing phase	Step feature	Gradient from max. positive rotation of swing phase to heel-on in sagittal plane
4	Standard deviation of minima	Step feature	Standard deviation of the max. negative foot rotation in sagittal plane during heel strike and toe-off in the stance phase of steps
5	Maxima minima difference	Step feature	Difference between max. positive foot rotation and heel-on in sagittal plane
6	Variance	Signal sequence	Measure for signal spreading, defined as the square of standard deviation
7	Integral	Signal sequence	Expresses the area of the region in xy-plane bounded by the signal
8	Entropy	Signal sequence	Derived from information theory, a measure of the uncertainty of a signal [1]
9	Dominant frequency	Frequency analysis	Characterizes the main speed of an exercise
10	Energy ratio	Frequency analysis	Complete signal sequence energy divided by energy value of dominant frequency
11	Energy in band 0.5 to 3 Hertz	Frequency analysis	Energy in a frequency band describes parts of distinct frequencies in the signal, typical frequency bands for specific movements can be defined [4]
12	Energy in band 3 to 8 Hertz	Frequency analysis	

List of classification relevant features: step features extracted from gyroscope z-axis, signal sequence and frequency features usable for all axes of accelerometer and gyroscope signals

An exemplary gait signal of a patient and a control with typical features is shown in Fig. 2. Table 2 shows a selected set of features which is used for final classification results.

D. Feature selection and classification

Pattern recognition approaches were used for classification and feature selection. Due to the *"No-Free-Lunch-Theorem"*, there is no optimal classifier for every given classification tasks [20]. Hence three different classifiers were evaluated in this study, Boosting with Decision Stump as a weak learner [21], Linear Discriminant Analysis (LDA) [22] and Support Vector Machines (SVM) with linear and RBF Kernel [22]. The classifiers were trained using the features to define decision boundaries for separation of the subgroups.

TABLE 3
CLASSIFICATION RESULTS - INDIVIDUAL TEST

Experiment	Exercise	Classifier	Features	Sensitivity / Specificity
Control vs. group 1	10-meter walk	LDA	1,2,3,4,5, 6,7,9,10,	88 / 86 %
Control vs. group 2	Heel-toe	LDA	7,8,9,11	94 / 100 %
Group 1 vs. group 2	Circling	Boosting	8,12	88 / 100 %

For each test, classifiers, sensors and features were selected according to best sensitivity and specificity. Features used are listed in Table 2.

In a next step, the number of features was reduced to the most relevant using *Sequential Backward Selection* [22]. This algorithm omitted one feature after another by using the classification accuracy as a criterion. The result was a subset of features that allowed an optimal distinction between the tested subgroups. Finally the specificity and sensitivity of this optimal feature set was calculated.

The classification accuracy was assessed in all experiments with a *leave-one-subject-out-cross-validation* [20].

III. EXPERIMENTS AND RESULTS

The current study aimed to develop an objective sensor based gait analysis system to identify gait patterns in PD and to distinguish between mild and severe impairment of gait. Therefore, three classification experiments were performed using the present subpopulations: *control versus group 1* (early diagnosis), *control versus group 2* and *group 1 versus group 2* (therapy monitoring).

In a first step, each gait test was assessed separately. Best classifiers and features for each test were identified to reach optimal classification accuracy (Tab. 3).

TABLE 4
CLASSIFICATION RESULTS - COMBINED TESTS

Experiment	Classifier	Features	Sensitivity / Specificity
Control vs. group 1	*No improvement*		
Control vs. group 2	LDA	1,5,6,8,10,11	100 / 100 %
Group 1 vs. group 2	LDA	1,3,4,5,6,7,8,9,10,11	100 / 100 %

Classifiers, sensors and features were selected according to best sensitivity and specificity. Features used are listed in Table 2.

In a second step, the most accurate features of the individual tests were combined into a multi-test-classifier to further improve the classification of the subgroups (Tab. 4). Improvement was expected because significant features and new combinations of them are usable for one classification task with data from all tests.

Best classification of *control versus group 1* resulted in a sensitivity of 88% and specificity of 86% using only the 10-meter walk test. Distinction of both *control versus group 2* and *group 1 versus group 2* reached a sensitivity and specificity of 100% using a combination of all tests. The best overall accuracy was reached in each case using the LDA classifier. No classification improvement was reached with SVM classifier.

IV. DISCUSSION

Two different aims were investigated in the presented study:

(1) Detection of gait symptoms correlating with mild motor impairment in PD compared to controls to support early diagnosis of PD. This was represented by the experiment *control versus group 1*.

(2) Differentiation between mild and intermediate gait impairment in PD to support therapy monitoring in PD. This was represented by the experiment *group 1 versus group 2*.

For both of these tasks a high sensitivity and specificity could be reached using the proposed sensor based system. The presented classification results on data from 43 subjects promise a high practical relevance. For the evaluation of the quality of features and classifiers, the *leave-one-subject-out-cross-validation* was used. This was done to prevent overfitting and to ensure a high generalization performance on unseen data [23] and leads to a high prospective relevance of the results.

In contrast to previous studies [8, 11, 14], only two sensors were implemented in a ready-to-wear shoe. This easy applicable approach improves the adherence and may be easily integrated in daily life of affected patients.

Another benefit is, that presented sensor system is able to classify different levels of gait impairment extending other studies that mainly focus on identification of PD patients [8, 13].

In relation to (1) the presented system can provide an objective diagnostic tool for health care providers. In combination with additional non-motor symptoms it allows to develop an objective risk score for PD [24].

Results from (2) show, that the system can rate different levels of gait impairment. Thus, the developed system may also be applicable to monitor motor fluctuations in individual patients occurring during the course of a day. As the presented system is small and unobtrusive, it could be used for smart home monitoring. This may help to adjust drug treatment on the basis of long term monitoring of motor symptoms. Additionally it might prevent falls and fall related injuries like pneumonia, which are the most frequent cause of death in Parkinson`s disease [25].

V. Conclusion

We presented a sensor based system which is able to identify PD associated gait patterns and to objectively distinguish different levels of gait impairments. Our proposed biometric gait analysis system is lightweight, easy applicable and non-invasive, and may complement clinical data for diagnosis of PD. Additionally the system might be used for smart home monitoring and long term assessment of motor symptoms.

Our aim for future research is to collect an even broader database, to further improve accuracy with an extended feature set and to finally come up with a medically approved system that can be implemented into everyday clinical practice.

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