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Combined analysis of sensor data from hand and gait motor function improves automatic recognition of Parkinson's disease

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***Abstract*—Objective and rater independent analysis of movement impairment is one of the most challenging tasks in medical engineering. Especially assessment of motor symptoms defines the clinical diagnosis in Parkinson`s disease (PD). A sensor-based system to measure the movement of the upper and lower extremities would therefore complement the clinical evaluation of PD.**

In this study two different sensor-based systems were combined to assess movement of 18 PD patients and 17 healthy controls. First, hand motor function was evaluated using a sensor pen with integrated accelerometers and pressure sensors, and second, gait function was assessed using a sports shoe with attached inertial sensors (gyroscopes, accelerometers).

Subjects performed standardized tests for both extremities. Features were calculated from sensor signals to differentiate between patients and controls. For the latter, pattern recognition methods were used and the performance of four classifiers was compared. In a first step classification was done for every single system and in a second step for combined features of both systems. Combination of both motor task assessments substantially improved classification rates to 97% using the AdaBoost classifier for the experiment *patients vs. controls*.

The combination of two different analysis systems led to enhanced, more stable, objective, and rater independent recognition of motor impairment. The method can be used as a complementary diagnostic tool for movement disorders.

I. Introduction

The diagnosis in Parkinson`s disease (PD) is based on specific motor symptoms, which appear consecutively in all extremities. Bradykinesia, tremor, rigidity, and postural instability are the cardinal symptoms that define the diagnosis of PD [1]. To achieve comparable results of the current state of motor symptoms, the Unified Parkinson Disease Rating Scale (UPDRS) – Part III is most commonly used [2]. To assess these symptoms, physicians perform standardized movement tests focusing on the upper and lower extremities. This examination reflects only the symptoms at a given moment in time and highly depends on raters' experience. To exclude these drawbacks, sensors can be used to objectively measure movement of the upper and lower extremities.

To differentiate between PD patients and controls, Salarian et al. used gyroscopes attached to shoes [3]. The groups of Lord, Mariani and Hausdorff also measured gait impairment with gyroscopes respectively accelerometers to recognize and rate PD [4-6].

Bäzner et al. analyzed the motor function of hands with tapping tests and showed significant differences comparing patients with PD, subcortical vascular encephalopathy and healthy controls [7]. It has been shown by Ünlü et al. that the biometric smart pen, which was used in this study, is able to recognize typical symptoms of PD [8].

Patel et al. published a system that analyzed lower and upper extremities. No distinction between PD and controls was made in this study. However, they rated distinct symptoms like tremor, bradykinesia, dyskinesia with eight accelerometers [9]. Signals of single symptoms are substantially more homogeneous. Therefore a rating of single symptoms with inertial sensors leads to good results [10-12].

Several studies used sensor systems to evaluate gait [3-6, 13], hand motor function [7, 8], or only single symptoms for lower and upper extremities [9-12]. However, a clinical examination, e.g. rating of the UPDRS – Part III, combines tests of upper and lower extremities. Thus, in the presented approach, two different sensor-based systems for data fusion on feature level and unified analysis of hand motor function and gait were used [14]. Analogous to a clinical examination, data from gait and hand motor function are combined to obtain an improved rating. The developed system reveals a comprehensive assessment of movement impairment supporting the clinical examination by a movement disorder specialist.

II. Methodology

A. Sensor platform and setup

Hand motor function analysis

To record hand motor function, the Biometric Smart Pen (BiSP, University of Applied Sciences Regensburg, Germany) was used. This electronic ball-pen measures six sensor signals, which include three acceleration axes, finger grip force during holding the pen, refill force and vibration sound. The BiSP pen measures handwriting, drawing and gesture movements on paper or in free air. A SCA3000-D01 accelerometer (VTI Technologies, Vantaa, Finland) is built in. For grip sensing a Piezo Electric Film (PEF), DT4-028K (Measurement Specialities, VA, USA) is wrapped around the gripping area of the pen. The recordings of refill dynamics

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and acoustics are based on a stack type piezo component PSt150/2x3/5 (Piezomechanik GmbH, BY, Germany), which is placed between end of the refill and body of the pen. Sensor data of piezo element is filtered from 0 to 40 Hz for dynamics and from 100 to 500 Hz for vibration sound, what results in two different signals. Transmission of the data to a recording notebook is done based on a HID-USB interface. The software to record signals was implemented by the University of Applied Sciences Regensburg. The accelerometer range is fixed to ± 2g and the sampling frequency to 1000 Hz.

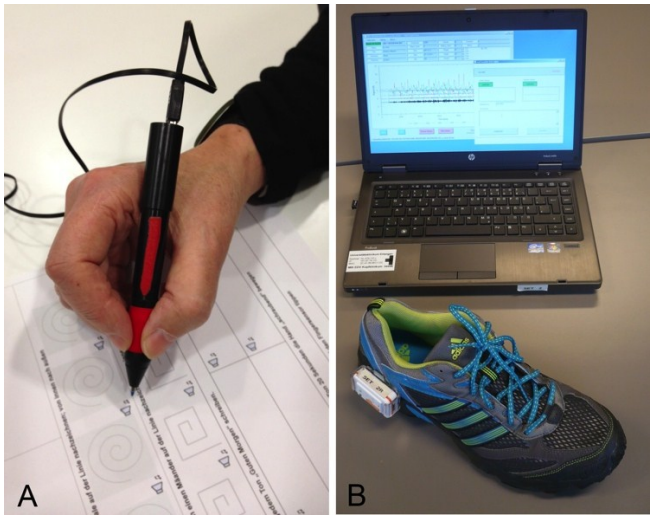

Figure 1 Biometric Smart Pen (BiSP) for analysis of hand motor function (A) and sensor shoe setup – sport shoe with attached Shimmer sensor unit – for gait analysis (B)

Gait analysis

For gait analysis, 3D gyroscopes and 3D accelerometers were used to measure angular velocity and acceleration. These sensors are integrated in the Shimmer sensor unit (Shimmer Research Ltd., Dublin, Ireland), an extensible platform for real-time motion sensing [15]. The sensor platform contains a MSP430F1611 microprocessor running TinyOS with a MMA7260Q accelerometer (Freescale Semiconductors, Austin, TX, USA) and a built-in 500 series MEMS gyroscope (InvenSense, Sunnyvale, CA, USA). Data were directly transmitted via Bluetooth to a notebook for recording. An identical shoe model in different sizes was used to provide comparable conditions for data collection. The sensor units were attached to the lateral heel of both shoes (Fig.1). Data were collected with the software BioMOBIUS (TRIL Centre, Dublin, Ireland). The accelerometer range was set to ± 4g, the gyroscope range to ± 500 degree/sec and the sampling frequency to 50 Hz.

B. Data collection

Data was collected in the movement disorder outpatient unit of the University Hospital Erlangen. Selected patients and controls (Tab. 1) were a subpopulation of an ongoing study with PD patients. In this study patients underwent examination of a movement disorder specialist immediately followed by data recording with the movement analysis systems. To select the subpopulation for this study, including criteria were A) that subjects took part in hand motor function and gait analysis, and B) that selected patients and controls build age matched groups. Participating subjects had to give informed consent based on approval from the ethical committee of the University Hospital of Erlangen (Re.-No. 4208). Included PD patients were able to walk independently (Hoehn and Yahr Scale [16] < 4). Subjects with other upper and lower extremity impairment, due to muscular skeletal disease, were excluded from the study.

Hand motor function tests

For the present study six hand motor function tests were used. The tests consisted of drawing on paper and movements in the air and were partially derived from neurological standard examinations. Movements were executed with the writing hand of a patient.

- *On paper:*
  - Drawing twelve circles at the same place
  - Tracing four preprinted spirals
  - Tracing four preprinted meanders
- *In the air:*
  - Drawing twelve circles around a virtual point
  - Performing pronation/supination movements for 20 s
  - Performing finger tapping on the pen for 20 s

Pronation/supination movements and finger tapping are elements of the UPDRS - Part III and were performed at a convenient speed for the subject.

TABLE I. CHARACTERISTICS OF PATIENTS AND CONTROLS

Characteristics	PD Patients (n=18)	Controls (n=17)
Sex (male:female)*	11:7	4:13
Age (y, mean, ±SD)	61.7 ± 9.7	60.5 ± 8.0
Age of onset (y, mean, ±SD)	54.5 ± 10.4	-
Disease duration (y, mean, ±SD)	7.2 ± 5.6	-
H&Y (±SD)	2.0 ± 0.8	-
UPDRS motor score (±SD)	17.9 ± 12.2	-
Levodopa dose (mg/d, ±SD)	447.7 ±378.1	-
Depression score (Zung, ±SD)**	47.8 ± 10.8	38.8 ± 6.7

Characteristics and clinical parameters of Parkinson`s patients and healthy controls.
* Significant difference in gender (p=0.025 Chi-Square test)
** Significant difference in depression score (p=0.006 Student`s T-test)

Gait tests

In order to generate comparable data, subjects underwent standardized gait tests [17], which partly corresponding to UPDRS – Part III [2, 18].

- *10-meter walk*: Subjects walked 10 m four times at a comfortable walking speed
- *Heel-toe tapping*: While the subject was sitting, heel and toes were tapped alternately on the floor for 20 s
- *Circling*: While the subject was sitting, a circling foot movement (diameter: about 30 cm) was performed 10 cm above the floor for 20 s

C. Feature extraction

For both systems sensor signals underwent different preprocessing steps. Signals were cut manually at the beginning and end of recording. To eliminate measurement noise, sensor data was filtered with a Chebyshev low pass filter [19]. Order and cut-off frequency of the filter were selected feature dependent.

A set of standard features were extracted for **hand motor function analysis**. Two main types of features were calculated from each test and signal channel. *1)* Sequence dependent features from complete writing or movement tests. Length is depending on execution time. *2)* Frequency dependent features, calculated from one movement sequence.

For the spiral and meander drawing, the average of the four features of each single repetition was used. This was preferred in order to obtain more robust features. The number of extracted features from six signal channels and six hand motor function tests was 828 in total.

Biometric gait features were extracted from recorded sensor data of gyroscopes and accelerometers placed on the left and right shoe. Features were calculated analogous to a previous study [17] out of: *1)* Single steps of 10 meter walk, *2)* Gait sequences of 10 meter walk (complete test), *3)* Test sequences (15 seconds) of heel-toe tapping and circling and *4)* from Fourier-transform of gait sequences and test sequences for a frequency-based analysis [19]. Features were computed for sensor units on both shoes and three sensor axes per gyroscope and accelerometer. Step features were calculated for every single step and averaged per person and test. This approach was chosen to make the features more robust resulting in 286 features for the walking test and 204 for each other test.

A subset of extracted features used for classification experiments is listed in Table II.

D. Feature selection and classification experiments

For feature selection two methods were compared and analyzed with every classifier used.

First, linear forward selection was used with a correlation-based feature subset selection (CFS) criterion [20]. Features with a high correlation to class labels were selected. A low inter-correlation was preferred.

The second method was a linear forward selection with a backtracking facility. The criterion for feature subset selection was accuracy of chosen classifier for current classification experiment [21].

There is no single classifier, which is optimal for all classification tasks [22]. Therefore, three different classifiers were compared. Linear Discriminant Analysis (LDA) [22], the Support Vector Machine (SVM) [22] with a linear kernel and AdaBoost [22] were employed.

As classification task, *PD vs. control* group experiments were conducted for features of sensor shoe and smart pen alone, respectively, and afterwards for the combined feature set of both systems [14]. These three classification tasks were evaluated with all three classifiers resulting in nine single classification experiments.

To compute classification accuracy *leave-one-subject-out-cross-validation (LOSOCV)* [22] was used.

TABLE III. BEST CLASSIFICATION RESULTS FOR PD VS. CONTROL

Sensor	Classifier	# features	CR	Sens. / Spec.
Smart pen	AdaBoost [1]	14	89	94 / 83
Sensor shoe	SVM linear [2]	9	91	88 / 94
Combined	AdaBoost [3]	12 (5+7)	97	100 / 94

[1] AdaBoost, 30 iterations, CFS linear forward feature selection
[2] SVM linear, C=4.0, Classifier depending linear forward selection (backtracking=5)
[3] AdaBoost, 50 iterations, CFS linear forward feature selection
CR: Classification rate, Sens.: Sensitivity, Spec.: Specificity

III. EXPERIMENTS AND RESULTS

For each experiment both types of feature selection methods were performed. The classifier depending selection was trained on the current classifier and the backtracking was fixed to five steps.

In experiments with LDA as classifier no parameters had to be determined. Best fitting cost parameter *C* for linear SVM was evaluated in a range of 0.1 to 800 in decadic steps. Best iteration number for AdaBoost was evaluated in a range of 10 to 100 in steps of 10.

Table II shows an overview of features, which are selected for best results. Best results and depending parameters for classification experiments are listed in Table III.

IV. DISCUSSION

The current study aimed to develop a system for combined analysis of hand and gait motor function impairment. The system was trained to differentiate between PD patients and healthy controls with sensors analyzing movement of lower and upper extremities.

TABLE II. SELECTED FEATURES FOR BOTH SENSOR SYSTEMS

Feature	Name	Category	Description
1	Mean	Signal sequence	Average of complete signal sequence
2	Variance	Signal sequence	Measure for signal spreading, defined as the square of standard deviation
3	Regression line gradient	Signal sequence	Local extreme values are extracted and regression line is fitted through
4	Standard deviation of minima	Signal sequence	Standard deviation of local extreme values
5	Maxima minima difference	Signal sequence	Difference between mean of maxima and mean of minima
6	Autocorrelation maximum	Signal sequence	Maximum value of cross-correlation of the signal with itself
7	Integral	Signal sequence	Expresses the area of the region in xy-plane bounded by the signal
8	Root mean square	Signal sequence	Root Mean Square or quadratic mean is a statistical measure, useful especially for signals which vary in positive and negative range
9	Dominant frequency	Frequency analysis	Characterizes the main speed of an test
10	Energy ratio	Frequency analysis	Complete signal sequence energy divided by energy value of dominant frequency
11	Energy in frequency band	Frequency analysis	Energy in a frequency band describes parts of distinct frequencies in the signal, typical frequency bands for specific movements can be defined
12	Regression line of windowed energy in frequency band	Frequency analysis	Regression line is fitted through energy values calculated for every window of a windowed Fourier-transform
13	Fall gradient of stance phase	Step feature	Gradient from maximum positive rotation of stance phase to heel-off

List of classification relevant features: step features extracted from gyroscope z-axis (sagittal plane), signal sequence and frequency features usable for all axes of accelerometer, gyroscope, force and sound signals of sensor pen and sensor shoe

To deal with the substantial amount of features and to beat the curse of dimensionality [22], it was necessary to select the most important features for classification. Feature selection improves computational time as well as classification results [23]. Two methods were used to reduce the feature space from 1522 dimensions for combined analysis to a maximum of 32 dimensions. Resulting number of features for CFS method varied from 12 to 32 features. The excellent results for classifier dependent linear forward selection with a backtracking facility result in a feature space of 3 to 9. The reasons for this small feature space from the second method are possibly the high specification to the current classifier and the backtracking facility.

In a first classification step both systems were evaluated independently and best classification results were calculated. In general, PD motor symptoms appear first in upper extremities [24]. With disease progression symptoms also affect lower extremities. Therefore a higher recognition rate from the sensor pen was expected. However results show recognition rates of PD patients from hand motor function of 89% and for gait analysis of 91%. A possible explanation is that all tests with the sensor pen were done with the writing hand, which was in 17 of 18 patients the right hand, yet 10 of 18 patients were left side affected.

In a combined analysis an excellent classification accuracy of 97% was reached. It shows that a combined set of features could improve classification results again.

For evaluation and calculation of classification accuracy *LOSOCV* was used. This evaluation method ensures a high generalization performance on unseen data and prevents overfitting [25]. To get rid of a possible overfitting during feature selection an independent test set will be evaluated in a further study.

One important issue to note was the missing sex match between both groups. Significantly more male subjects were in patient group compared to healthy controls. The gender dependent movement differences could lead here to a bias in the results. Other studies showed that these results are similar for age and sex matched groups for gait and hand motor function individually [3, 7, 12].

Results of this and past studies [13, 17] are very promising for the sensor-based analysis in movement disorders. These concepts will bring excellent tools to support physicians and improve clinical care.

V. Outlook

Future classification experiments will aim to differentiate between mild, intermediate and severe disease stages. A large set of patient and control data will be used to do an individual assessment for early diagnosis and disease monitoring. The goal is to build up a system for an immediate rating of the movement impairment. Therefore a recording of more patient and control data is needed to get age and sex matched groups.

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References

[1] Jankovic, J., *Parkinson`s disease: clinical features and diagnosis.* Journal of Neurology, Neurosurgery & Psychiatry, 2008. **79**: p. 368.

[2] Goetz, C.G., et al., *Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): scale presentation and clinimetric testing results.* Mov. Disord., 2008. **23**: p. 2129-2170.

[3] Salarian, A., et al., *Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring.* IEEE Transactions on Biomedical Engineering, 2004. **51**: p. 1434-1443.

[4] Mariani, B., et al., *3D gait assessment in young and elderly subjects using foot-worn inertial sensors.* J. Biomech., 2010. **43**: p. 2999-3006.

[5] Lord, S., et al., *Concurrent validity of accelerometry to measure gait in Parkinsons Disease.* Gait & Posture, 2008. **27**: p. 357-359.

[6] Hausdorff, J.M., *Gait dynamics in Parkinson's disease: common and distinct behavior among stride length, gait variability, and fractal-like scaling.* Chaos, 2009. **19**: p. 26113.

[7] Bäzner, H., et al., *Differential pattern of hand-tapping compromise in vascular versus idiopathic parkinsonism: a study based on computerized movement analysis.* Mov. Disord., 2005. **20**: p. 504-508.

[8] Ünlü, A., R. Brause, and K. Krakow, *Handwriting analysis for diagnosis and prognosis of Parkinson's disease.* Biological and Medical Data Analysis, 2006. **4345**: p. 441-450.

[9] Patel, S., et al., *Monitoring motor fluctuations in patients with Parkinson's disease using wearable sensors.* IEEE transactions on information technology in biomedicine a publication of the IEEE Engineering in Medicine and Biology Society, 2009. **13**: p. 864-873.

[10] Hoff, J.I., et al., *Accelerometric assessment of levodopa-induced dyskinesias in Parkinson's disease.* Mov. Disord., 2001. **16**: p. 58-61.

[11] Cancela, J., et al. *A comprehensive motor symptom monitoring and management system: the bradykinesia case.* in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2010.

[12] Keijsers, N.L.W., M.W.I.M. Horstink, and S.C.A.M. Gielen, *Ambulatory motor assessment in Parkinson's disease.* Mov. Disord., 2006. **21**: p. 34-44.

[13] Klucken, J., et al., *Mobile biosensor-based gait analysis : A diagnostic and therapeutic tool in Parkinson's disease.* Der Nervenarzt, 2011. **4345**: p. 441-450.

[14] Hall, D.L. and J. Llinas, *An introduction to multisensor data fusion.* Proceedings of the IEEE, 1997. **85**: p. 6-23.

[15] Burns, A., et al., *SHIMMER - A Wireless Sensor Platform for Noninvasive Biomedical Research.* IEEE Sensors Journal, 2010. **10**: p. 1527-1534.

[16] Goetz, C.G., et al., *Movement Disorder Society Task Force report on the Hoehn and Yahr staging scale: status and recommendations.* Mov. Disord., 2004. **19**: p. 1020-1028.

[17] Barth, J., et al. *Biometric and Mobile Gait Analysis for Early Diagnosis and Therapy Monitoring in Parkinson`s Disease*. in *Engineering in Medicine and Biology Society EMBC 2011 Annual International Conference of the IEEE*. 2011.

[18] Steffen, T. and M. Seney, *Test-retest reliability and minimal detectable change on balance and ambulation tests, the 36-item short-form health survey, and the unified Parkinson disease rating scale in people with parkinsonism.* Phys. Ther., 2008. **88**: p. 733-746.

[19] Girod, B., A. Stenger, and R. Rabenstein, *Signals and Systems*. Electrical Engineering. 2000: Prentice Hall.

[20] Hall, M.A., *Correlation-based Feature Selection for Machine Learning*. 1999, PhD Thesis, University of Waikato.

[21] Hall, M., et al., *The WEKA data mining software.* ACM SIGKDD Explorations Newsletter, 2009. **11**: p. 10.

[22] Duda, R.O., P.E. Hart, and D.G. Stork, *Pattern Classification (2nd Edition)*. 2 ed. 2000: Wiley-Interscience.

[23] Hastie, P., *The Elements of Statistical Learning*. 2003: Springer Verlag.

[24] Uitti, R.J., et al., *Defining the Parkinson's disease phenotype: initial symptoms and baseline characteristics in a clinical cohort.* Parkinsonism related disorders, 2005. **11**: p. 139-145.

[25] Fukunaga, K. and D.L. Kessell, *Estimation of Classification Error.* Computers IEEE Transactions on, 1971. **20**: p. 1521-1527.