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Feasibility of using smartphones for quantification of Parkinson's disease motor states during hand rotation tests

Somayeh Aghanavesi, Hasan Fleyeh, Mevludin Memedi and Mark Dougherty

***Abstract*— The aim of this study is to investigate whether acceleration data collected by smartphone inertial measurement unit (IMU) sensors are sufficient to quantify motor states of Parkinson's disease (PD) patients during hand rotation tests. Method: A healthy subject performed repeated hand rotation tests while wearing a wrist motion sensor and holding a smartphone. The similarity of corresponding magnitude 3D acceleration signals of IMU and wrist sensors was measured by the cross correlation method. A previous study (St1) quantified the motor states of PD patients during hand rotation tests and provided good validity to motor states in relation to Treatment Response Scale (TRS) ranging from -3 to +3 rated by clinicians. To investigate if IMU captures enough information from hand rotation tests, the identified important features in both studies were compared. A machine learning method that was developed and trained in St1 with acceleration data collected with the wristband sensor. Accelerometer data collected by a smartphone IMU were used for evaluating the performance of the method for estimating the TRS state of the healthy control. Results: The mean similarity score between acceleration data from IMUs and wrist motion sensor was 0.84 indicating good similarity. More than 50% of important features were common between IMU and St1 indicating IMU can capture important information with regards to hand rotation tests. The mean predicted score of the motor state of the healthy subject based on IMU data was 0.01 (SD = ±0.03) indicating IMU data provides sufficient information for quantification of the motor state of the subject. Conclusions: Acceleration data collected by smartphone IMUs during hand rotation tests can be used for quantification of motor states. Results need to be further investigated in a larger scale study.**

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I. INTRODUCTION

Parkinson's disease (PD) is a complex neurodegenerative disorder, asymmetrically onset and characterized by motor symptoms such as tremor, bradykinesia, akinesia and rigidity [1]. There is a large amount of inter- and intra- variability in PD motor symptoms. Therefore symptom data need be collected objectively, continuously and individually. Assessing PD symptoms requires engagement of both patients and medical professionals where feedback can be sent to both parties [3]. Current assessment of PD motor symptoms is done by clinical examination using scales during the clinical visits. The most commonly used scale is the Unified PD Rating Scale (UPDRS) [2]. A common PD upper limb motor examination is rapid alternate movements of hands (rotation of hands, vertically and horizontally, with as large an amplitude as possible); this is item 25 in UPDRS scale. However, the clinical assessment of the states using UPDRS is limited. There is a need for care givers to use them and for patients to visit the clinicas. There is also inter- and intra- observer variability when using the scales.

The motor characteristics of PD symptoms can be captured using sensor devices, while they provide low cost, low power, unobtrusive, and accurate measurements [3]. With regard to hand rotation tests, motion sensors have been used for quantification of the PD motor states. In a previous study by Thomas et al. [4] (denoted as St1) wrist motion sensors data comprised of hand rotation tests acceleration and gyroscope data were used to quantify the PD motor states. Spatiotemporal features were calculated, and machine learning methods were developed to predict the motor states of PwPD. The methods provided good validity, reliability, and dose-effect time profile. However, using motion sensors has limits since they are used for passive data collection where the data need to be transferred to a processor for analysis, and to a screen for visualization of the results. These sensors are not widely and personally available in the market as ready to use devices and wearing them is not recognized as comfortable for some patients with PD (PwPD) [5]. On the other hand the acceptability and sustainability of the employed sensor devices in PwPD life is an important matter [5]. In contrast, smartphones are publically available, include embedded memories and processors, and enable active data collection where the tests can be objectively and continuously performed. Plus the interaction of PD patients and clinicians becomes possible using this devices [6]. Investigating the quantification feasibility of standardized hand rotation test with smartphones becomes important since further development of such systems can help to improve the quality of life for PwPD.

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To our knowledge, quantification of PD motor states during hand rotation tasks using a smartphone inertial measurement unit (IMU) has only been performed in one study [7] in which the results were not validated with simultaneous assessments of neurological experts.

In this study we aim to examine the sufficiency of acceleration data collected by smartphone IMU during hand rotation tests for quantification of PD motor states. Due to the high power consumption of gyroscope measurements from devices, only the accelerometer data were considered for the analysis in this study. The similarity of the recorded data by IMUs to wrist motion sensor is measured at two signal and feature levels to ensure IMU data contain similar context to motion sensor data in terms of acceleration and symptom information related to hand rotation movements. The motor state of the subject in this study were estimated by training a

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highly correlated method to clinical ratings of the motor states in PD followed by testing the acceleration data from smartphone IMU [4]. The performance of the method was evaluated for estimation of the subject in this study.

II. Materials and Methods

A. Experiment

The hand rotation test in this study was performed by a healthy subject while wearing a wrist motion sensor (shimmer3) on wrist and holding a smartphone with the dominant hand (right hand in this case), as shown in Fig 1.

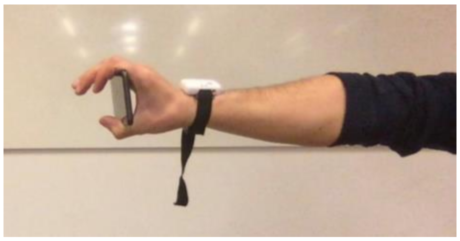

Fig 1. A healthy subject performing a hand rotation tests while wearing a wrist motion sensor and holding a smartphone.

To collect data, first the devices were activated, then hand rotation tests were performed. Each test lasted for about 10-15 seconds. There were experiments of 12, 12, 13, 35 and 10 tests performances during 5 days, each tasks were repeated three times. In total there were 246 trials collected from each instrument.

In St1 there were 22 healthy subjects who performed the standardized hand rotation task together with 19 PwPD in a single center, open label clinical trial in Uppsala, Sweden [8]. Subjects were instructed to sit on a chair without armrests while wearing motion sensors on both wrists. PwPD performed the task up to 15 times and healthy subjects up to 8 times, first with right and then left hand. Each test lasted about 20 seconds. There were three movement disorder specialists who rated the overall mobility of the PwPD on a treatment response scale (TRS) [9], ranging from -3 (Very Off) to +3 (Very Dyskinetic). The total number of observations for healthy subjects was 165, and for PwPD was 229.

B. Sensor measurement

The 3D acceleration data from wrist motion sensor and smartphone IMU were collected. The IMU data was collected using "Sensor Kinetics Pro" application in smartphone. Smartphone sampling rate was 100 Hz, with accelerometer range of +/- 2 g. Motion sensor sampling rate was 102.4 Hz with accelerometer range of +/-16g. The sensor data including *X*, *Y*, and *Z* accelerometer readings from both instruments were saved on external memory and processed offline. The test occasions from both instruments were labelled and their timestamps were matched. From St1, the acceleration data of wrist motion sensor was collected.

C. Pre-processing

The preprocessing of the data was done by first manually segmenting the data captured from both IMU and wrist motion sensor. From the data on the X-axis of the acceleration, the hand rotation tasks were identified. The raw data of IMU and motion sensor including the recordings of the hand rotation is shown in Fig. 2. The 3D acceleration data were segmented starting from 2 second before beginning the task until 2 seconds after the last movement.

D. Feature extraction

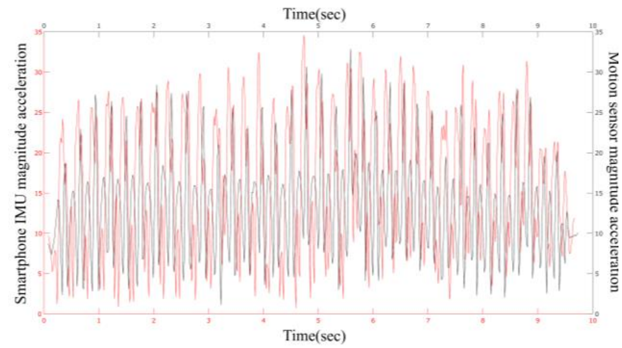

Fig 2. Magnitude acceleration of IMUs (red line) and wrist band (black line). The X-axis presents the time in seconds and Y-axis is the magnitude acceleration from sensors.

Using wrist motion sensor acceleration data in St1, 44 features were calculated for healthy subjects and PwPD which contained 394 observations in total [4]. Using the same methods as in St1 and the two smartphone and wrist motion sensors data in this study, 44 features were extracted. The features are listed in Table I.

TABLE I
IMU AND MOTION SENSORS FEATURES.

Description		**Acceleration Data**			
		X-axis	**Y-axis**	**Z-axis**	**Magnitude**[‡]
Mean and SD		1,2	3,4	5,6	7,8
DWT[¥]		9,10	11,12	13,14	15,16
	1st level	17,18	19,20	21,22	23,24
	2nd level	25,26	27,28	29,30	31,32
Abs-sig-diff [‡‡]		33	34	35	36
ApEn [§]		37	38	39	40
Skewness		41	42	43	44

‡ Magnitude is aggregation of squared *X*, *Y*, and *Z* axes for acceleration. ¥ is the discrete wavelet transform coefficients. § ApEn is approximate entropy. ‡‡ Is the absolute mean difference between first and second part

Calculating the features was based on methods described in St1 using acceleration data on *X*, *Y*, *Z* axes (Xacc, Yacc, Zacc), and magnitude of acceleration (Macc). Mean, standard deviation (SD) and skewness were calculated for Xacc, Yacc, Zacc, and Macc to calculate 12 features. Discrete wavelet transform coefficients were extracted from raw data (#9 to 16). The 1st and 2nd level high-frequency components were extracted. Calculating their mean and SD produced 16 features (#16 to #32). The signals were divided into two parts. The absolute mean difference between the first and second parts of the signals was measured to calculate 4 features (#33 to #36). Approximate entropy was used as a method to measure the amount of irregularity in time series which resulted in 4 features (#37 to #40).

E. Data analysis

In order to find out whether the IMU recordings from smartphones could be as sufficient as wrist motion sensors for quantification of the hand rotation tests, first, the similarity of acceleration recordings between IMU and motion sensor was measured. This was to ensure they hold similar contexts.

Second, to ensure that the collected data with IMU contain relevant information to hand rotation tests, the most important features were identified and compared between IMU and the wrist motion sensors in this study as well as in St1. Third, in St1 the validity of different machine learning methods was examined. The scores produced by support vector machine learning (SVM) method provided the best validity to TRS clinical rating. With respect to the TRS scale, the performances of the healthy subjects were considered to be around 0 since this score is defined for normal performances (when PwPD have enough amount of medication and symptoms disappear). In this study, an SVM was trained using acceleration data of hand rotation tests performed during a single dose trial by 19 PD patients and 22 healthy controls in St1 and tested with the acceleration data from IMU and wrist motion sensors to estimate the TRS state of the healthy subject who performed the tests. The performance of the method was evaluated to investigate if IMU data are sufficient for the method to provide an adequate estimation of the healthy control's motor state. The steps are explained in detail as follows:

1) Similarity of the smartphone and shimmer signals

Since the sampling rates of the smartphone and wrist motion sensors were different, in order to be able to compare their acceleration data over a single time scale, first the sampling rates were balanced using the fractional sampling rate conversion method in Matlab [10]. For this, rational factors were obtained by calculating the ratio of the new sample rate to the original sample rate. Using the rational factors one signal was resampled according to the sampling rate of the other signal. Then, using cross-correlation processing technique [11], the similarity between the two signals was measured. Mean of the correlation coefficients were calculated.

2) Similarity of the important features

To assess which features were most important, principal components (PC) analysis was used to calculate the components which contain the most amount of the information extracted from feature sets. Feature sets from IMU and wrist motion sensors, and the features calculated from healthy controls and PwPD data in St1 were used. For each of the feature sets and equal to the number of all features (44), PCs were calculated. The first PC contains the highest variation which decreases over the next PCs. Then based on Kaiser-Guttmann criteria [12], PCs with eigenvalues larger than 1 were retained and the total variance that those PCs accounted in the data were calculated. The eigenvectors comprising the coefficients corresponding to each feature were calculated. When calculating the components, the larger absolute value of the coefficient corresponded to the degree of importance of the feature. The number of retained PCs, the total variance they accounted in data, and the most important features were estimated for feature sets calculated from St1, IMU and wrist motion sensors data.

3) Evaluation of the state by machine learning

In order to estimate the TRS state of the subject in this study, SVM learning method was trained using the feature set from St1 which contained the features of healthy subjects and PwPD. Feature sets of IMU and wrist motion sensors in this study were used one at a time as testing sets. TRS values were used as the response variable. TRS labels for testing sets were predicted by SVM. Mean of the predicted TRS values for IMU and wrist motion sensors were calculated.

III. RESULTS

The mean of the correlation-coefficients calculated by cross correlation similarity measure was 0.84. This indicates that the IMU sensor captures similar acceleration quantities to those of the wrist motion sensor during hand rotation tests.

From each of the IMU, wrist motion sensor, and St1 feature sets, 11 PCs were retained as part of the data that contained the most amount of information from datasets and each of which had eigenvalues higher than 1. The accumulated variances of the PCs were 83%, 80%, and 82% for IMU, wrist motion sensor and St1, respectively. The most 10 important features extracted from PCs of the three feature sets are summarized in Table II. The common features are shown in bold. More than half of the features from the data in this study were in common with the features from St1. These features were the mean, SD of the M_{acc} and Discrete Wavelet Transform (DWT) of M_{acc}, as well as the SD of 2^{nd} DWT on X-axis. In addition, SD of 2^{nd} DWT on z-axis was similar between smartphone and St1.

TABLE II
FIRST 10 MOST IMPORTANT FEATURES (NUMBERED IN TABLE I), FOR IMU, WRIST MOTION SENSOR, AND ST1.

	IMU	MOTION SENSOR	ST1
Mean M_{acc}	**2**	**2**	**8**
Mean Acc on X-axis		9	
Mean DWT on M_{acc}	**3**	**3**	**7**
SD of M_{acc}	**5**	**8**	**2**
SD Acc on X-axis		5	
SD Acc on Y-axis	4		
SD of Z-axis	9	7	
SD of DWT on M_{acc}	**1**	**1**	**3**
SD DWT on X-axis		4	
SD DWT on Z-axis	8	10	
SD 1^{st} level DWT on M_{acc}			9
SD 1^{st} level DWT on X-axis	10		6
SD 2^{rd} level DWT on M_{acc}			1
SD 2^{rd} level DWT on X-axis	**6**	**6**	**5**
SD 2^{rd} level DWT on Y-axis			10
SD 2^{rd} level DWT on Z-axis	7		4

Macc is magnitude of acceleration. SD is standard deviation. Acc is accelration. DWT is discrete wavelet transform method.

A machine learning method was used to map the sensor data to the states defined in TRS. Using the feature sets from IMU and wrist motion sensors as individual testing sets, the performance of the method for estimating the state of the healthy subject was explored. The best prediction performance was expected to be 0. Using the feature set from wrist motion sensor data as testing set in SVM, the absolute mean value of the predicted TRS scores was 0.05. With the same approach but using IMU feature set as a testing set, the absolute mean of the predicted TRS scores was 0.01.

IV. DISCUSSION AND CONCLUSIONS

Comparison of acceleration data recorded by smartphone IMU and wrist motion sensors during hand rotation tests in this study resulted in high similarity indicating the recordings contain similar quantities. More than 50% of the most important features excerpted from calculated PCs of IMUs and motion sensors data were similar. This level of similarity shows that the IMUs capture relative information to hand rotation tests similar to motion sensors. It was needed to further investigate whether features calculated from IMU data are enough for a valid method that was trained with 394 observations recorded from PwPD and healthy controls to estimate the motor state of the subject correctly [4]. The mean SVM-based predicted score using IMU for estimating the state of the subject was alike to TRS state of healthy control indicating IMU data provided enough information to the method for predicting the motor state of the subject adequately.

However, the data in this study was limited and the methods need to be examined with a larger data set where IMU sensor data collected from several healthy subjects and PwPD. The inclusion of the collected data is suggested to be from patients at various disease stages so the complete range of the motor states could be captured for an accurate analysis [13]. In addition, mounting the sensor on the back of the hand for sufficient detection of symptoms during hand rotation is recommended [13]. While in this study smartphone was horizontally held by subject's hand (Fig 1) and knowing that the accelerometer is placed in the middle of the smartphone, the placement of it can be further investigated to identify at which location of hand the smartphone can collect more information related to symptoms. With respect to objective motor symptom measurements, separating the controlled and uncontrolled movements are recognized to be important in a study incorporating opinions of a panel of experts in PD [14]. We know that the accelerometer is positioned in the middle of the smartphone. Mounting or strapping smartphone on the back of the hand may help to capture the uncontrolled movements since performing a test while holding the device might cause the voluntary micro movements to disappear. This may provide more accurate symptom information and it could be even more convenient for PwPD in the advanced disease stage when lots of fluctuations appear e.g. extreme tremor. Since differentiating dyskinesia from tremor and motor fluctuations from non-motor fluctuations are difficult for PwPD, while early fluctuations need an accurate measurement of the movements, micro-level data need to be collected. Mobile technology is expanding quickly towards improving the quality of PwPD life [6]. A comprehensive explanation of wearable technology from 26 different aspects expressed that mobile computing power of smartphones will likely play a key role in wearable technology innovations providing quick, robust and easy solutions regardless of place and time [15]. In our previous studies processing the motion sensors data of tests like walking and foot tapping showed promising results for the assessment of PD symptoms [16], [17]. Although smartphone-based quantification of the symptoms data can provide integrated solutions for dose individualization where collection, processing, analysis and dose suggestion can be provided in one unit. The results in this study indicate that the smartphone IMUs can collect acceleration data and capture symptom information present in hand rotation movements similar to motion sensors. Smartphone IMUs can provide sufficient information for quantification of the motor states during in hand rotation tests.

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