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Segmentation and detection of physical activities during a sitting task in Parkinson's disease participants using multiple inertial sensors

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ABSTRACT

Introduction: The development of inertial sensors in motion capture systems enables precise measurement of motor symptoms in Parkinson's disease (PD). The type of physical activities performed by the PD participants is an important factor to compute objective scores for specific motor symptoms of the disease. The goal of this study is to propose an approach to automatically detect the physical activities over a period time and segment the time stamps for such detected activities.
Methods: A wearable motion capture sensor system using inertial measurement units (IMUs) was used for data collection. Data from the sensors attached to the shoulders, elbows, and wrists were utilized for detecting and segmenting the activities. An unsupervised machine learning algorithm was employed to extract suitable features from the appropriate sensors and classify the data points to the corresponding activity group.
Results: The performance of the proposed technique was evaluated with respect to the manually labeled and segmented activities. The experimental results reveal that the proposed auto detection technique – by obtaining high average scores of accuracy (96%), precision (96%), and recall (98%) – is able to effectively detect the activities during the sitting task and segment them to the proper time stamps.

Introduction

Parkinson's disease (PD) is a degenerative and progressive movement disorder of the central nervous system (Jankovic, 2008). There are several motor symptoms associated with the disease including tremor, bradykinesia, dyskinesia, and rigidity. These motor symptoms can severely affect the normal activities of individuals with PD, particularly in advanced stages. Several medical therapies and surgical interventions such as deep brain stimulation (DBS) are suggested for the treatment of individuals with PD. However, the disease is progressive in many individuals in spite of such therapies. As the disease worsens, treatments need to be modified to provide clinically optimized therapy. Hence, it is essential to monitor PD patients over time in order to accurately modify the treatment and especially target this to the individual patient's need. Thus, patients are required to undergo frequent evaluations to measure motor symptom changes over time. At present, such evaluations have to be performed in the presence of and by an expert clinician in clinic.

The Unified Parkinson's Disease Rating Scale (UPDRS) performed by such an experienced clinician has been accepted as the gold standard for quantitative assessment of the PD motor symptoms. The main drawback of the UPDRS is that the severity of the motor symptoms is assessed subjectively by a human observer with low inter-rater reliability (Chien et al., 2006). This assessment serves as the gold standard for the evaluation of patients in the clinic to grade and categorize a patient's severity of disease. Despite the advances in the interventions for PD including DBS and potentially even more novel disease modifying treatments, the assessment has remained within the domain of clinical expert evaluation, which is at best scale-based and hence subjective.

The advancement of more complex interventions for PD, thus accentuates the need for improved assessment measures that are objective, quantitative, reliable, and portable. Employing a

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quantitative measurement for each motor symptom of PD can help clinicians monitor the patient more effectively and make better individualized clinical decisions. It is also possible to envision remote monitoring of patients that are unable to travel to the clinic. In such scenarios of telemedicine-based assessments, although the expert may be available for discussion, the assessment of the patient is performed in their local setting and often by a non-expert. As immobility advances, having an objective measurement system locally that would provide the expert a consistent assessment would be paramount in adjusting therapy.

Currently, few studies have explored quantitative measurement of motor symptoms in PD using inertial sensors (Dai and DAngelo, 2013; Delrobaei et al., 2014; Printy et al., 2014; Salarian et al., 2007). Inertial sensors have been used to measure bradykinesia (Cancela et al., 2010), motor-fluctuations (Keijsers et al., 2006), fall prevention (Moore et al., 2008) and walking speed (Lord et al., 2008). The quantitative assessment in such studies is mainly based on motion tracking sensors such as magnetic trackers, touch sensors, accelerometers, and gyroscopes. Accelerometer sensors have been widely used for action recognition due to their compact size and reliability (Godfrey et al., 2011). Accelerometers allow for continuous remote mobility monitoring of patients and can be used to evaluate the performance of in-home daily activities. However, the recorded sensor data is extensive and requires manual segmentation of the motor tasks. Briefly, the type of activity within an individual task is identified, and the time stamp for the corresponding activity is entered manually into a computer. Once completed, the mobility parameters associated with each motor symptom can be measured and analyzed.

Manually labeling the activities and segmenting the time stamps during the motor task such as sitting has been utilized as a gold standard. However, depending on how many tasks are done, this process can be very time consuming, and the chance of error is increased. For example, giving one sitting record to different examiners for segmentation, the results were slightly different from each other. Moreover, several examiners would have to be trained to do the time consuming manual segmentation. Thus, automatic detection and segmentation of the various motor tasks would reduce data processing time, reduce human error and may encourage a wider use of these sensors for assessment of PD.

A variety of auto activity detection techniques and their application in PD have been proposed (Godfrey et al., 2011; Moncada-Torres et al., 2014; Najafi et al., 2002; Nguyen et al., 2015a). These techniques are mainly based on standard signal processing methods, and activities such as *walking*, *sit-to-stand*, and *turning* were detected by processing and analyzing the signals from the sensors. The signals from such activities reveal significant temporal and spatial variations, allowing these activities to be detected using signal processing techniques. However, such techniques may not be helpful for detecting the activities during a sitting task since the signals associated with activities performed while sitting do not show considerable variations. Therefore, new approaches based on pattern recognition and machine learning need to be applied in these scenarios.

The central aim in pattern recognition is to employ machine learning and statistical techniques to classify various patterns and discover the regularities in data (Bishop, 2006). Applications of machine learning techniques are numerous and cover wide scopes with applications in medicine, image processing, business, and geology (Cao et al., 2016; Cobo et al., 2012; Kramar, 1995; Liu et al., 2014; Rustempasic and Can, 2013; Salari et al., 2013). For instance, an intelligent scoring system based on a novel machine learning structure was proposed in (Liu et al., 2014) to predict acute cardiac complications within 72 h for chest pain patients presented in emergency department. Authors in (Cao et al., 2016) recently proposed a novel method based on machine learning techniques for image analysis and image classification. Machine learning techniques are divided into two groups, namely supervised and unsupervised. Supervised techniques use the automatic learning approaches to extract the pattern from the empirical data, and sophisticated decisions can be made based on the learned behaviours. Support Vector Machine (SVM) (Cortes and Vapnik, 1995), decision tree (Utgoff, 1989), extreme learning machine (ELM) (Huang, 2015), and K nearest neighbours (Altman, 1992) are some well-known supervised learning techniques. On the other hand, unsupervised techniques aim to group the patterns which are similar to each other in a set of features without relying on the training samples. Cluster analysis is one of the major unsupervised techniques in pattern recognition. In hard clustering techniques such as K-mean (Hartigan and Wong, 1979), each data point is assigned to exactly one cluster. Fuzzy set theory proposed by Zadeh (Zadeh, 1965) determines the membership function; hence, data points are assigned to the proper cluster with respect to their degree of membership. However, one of the main drawbacks with clustering algorithms is determining the number of clusters.

In order to address the limitations mentioned for signal processing techniques in detecting and segmenting the activities while sitting, and avoid time consuming manual segmentation, we aim to use the pattern recognition technique to automatically and efficiently detect the motor activities done continuously during the sitting task in PD and control participants and segment the time stamps from the inertial sensor data.

Materials and Methods

Participants

Twelve PD participants were recruited from the Movement Disorder Center at the London Health Sciences Center. The inclusion criteria for the PD participants were: (1) idiopathic

Fig. 1. (a): Rest, (b): Posture, (c): Pronation-Supination.

Parkinson's disease, (2) Hoehn & Yahr stage II or III (3) severe motor fluctuations with disabling off periods and dyskinesia during ON phases, (4) able to give informed consent, (5) able to visit the clinic for assessment, and (6) no dementia or psychiatric abnormalities as per formal neuropsychological assessment. Twelve healthy age-matched control participants were recruited from the general public. The inclusion criteria for the age-matched control participants were: (1) no comorbidity, (2) within the same age range as the PD participants, and (3) understand and consent to the study procedures. The study was approved by the Health Sciences Research Ethics Board (HSREB # 103928) at Western University and all participants provided written informed consent prior to participating.

Data collection protocol

Each participant performed several tasks while sitting at each visit. As Fig. 1 illustrates, the tasks include rest, posture, and upper limb pronation-supination. At rest (relaxed position), the participants were asked to rest their arms in neutral position with arms resting on the arm rest. The participants held this position for 20 s. This was followed by the posture task where the arms were fully extended forward with hands in a pronated position at shoulder height for 20 s. In the pronation-supination task, participants were asked to turn their hands one at a time and as fast as possible so that their palms faced up and down alternatively. The participants continued this motion for 10 s for the left hand and 10 s for the right hand.

All these tasks were recorded while the participants were dressed in a lightweight, stretchable, and breathable motion capture system (Synertial IGS-180) over their regular clothing (Fig. 2a). Participants also wore a lightweight cap on which the head sensor was placed, as well as fingerless gloves and shoe attachments on which hand and foot sensors were positioned. The total weight of the suit (including 17 sensors, batteries and internal cable) was 1.5 kg.

The suit was equipped with 17 inertial measurement units (IMUs), positioned on each body part. The system integrates 3D accelerometers, 3D gyroscopes, and 3D magnetometers within each sensing unit as well as a fusion algorithm (using quaternion method (Nguyen et al., 2015b; Sabatini, 2006) – developed by Inertial Labs Inc., Virginia, USA) allowing relative joint angles to be computed from the sensing units. The fusion software is implemented on a main processing unit (MPU) and communicates wirelessly to a receiver linked to a personal computer. Data acquisition was performed at 60 Hz sampling rate using IGS-Bio software Version 2.56 configured for full-body human motion.

First, the suit was calibrated by placing the participant in the middle of a hollow calibration cube constructed using plastic rods.

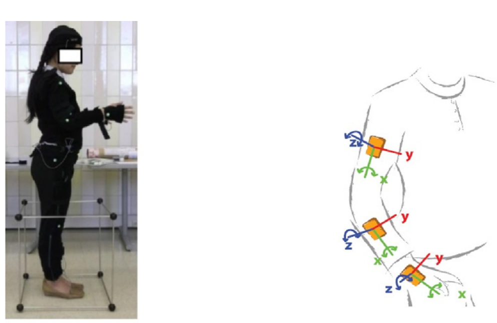

Fig. 2. a: Animazoo Motion Capture System. b: Sensor Set up for Arm (Rustempasic and Can, 2013).

A photo of the participant was taken for calibration purposes and shown in Fig. 2a. The photo was saved under a codified identifier to preserve the anonymity of participant, and the photo was de-identified afterwards.

Sensor selection and feature extraction

The recorded raw data during the sitting task contains several frames. The number of frames or data points for a one-minute recording is approximately about 5000. Each frame or data point is composed of a set of features associated with the sensors attached to the different body joints. Therefore, in order to detect the activities during the sitting task, joint angle data relevant to the upper and lower arms were utilized (Fig. 2b). Joint angles including all degrees of freedom from the wrist, elbow, and shoulder were extracted from the data as the input for the auto detection and segmentation algorithm (Table 1). In other words, such information identifies the suitable features, representing the data for activity detection during the sitting task. Thus, each data point is identified in terms of the features shown in Table 1.

Auto detection and segmentation algorithm based on fuzzy C-mean method

This research is based on the fact that the frames of the record for the tasks performed while sitting and the associated type of the physical activity are unknown. In other words, the training samples are not available to get the classifier trained accordingly. Thus, an unsupervised pattern recognition technique was utilized.

Fuzzy C-mean (FCM) technique was applied for detecting the relevant activity during the sitting task. FCM is a clustering technique where similar data points should be in the same cluster while dissimilar ones are assigned to different clusters. FCM was first presented by (Dunn, 1973) and developed by (Bezdek, 1981). FCM as a soft clustering technique measures the degree of membership of each data point to the particular cluster. Such membership values fall in the range of [0,1] and exhibit the consistency of the relationship between the data point and the cluster. As discussed earlier, the raw data contained several frames (data points), and each frame was composed of a set of features associated with the sensors attached to the different joints. The feature space for the sitting task includes the information from the selected sensors attached to the upper and lower arms (Table 1). Each activity is counted as one cluster. Since the number of activities performed by the participants is known and specified in advance, determining cluster number for the FCM clustering algorithm is no longer a limitation in our application. The number of clusters is equal to the number of activities performed by the participant during the sitting task. *Rest (R)*, *Posture (P)*, for the right and left upper limbs together and *Pronation-Supination* with right hand (ProSup-R), and *Pronation-Supination* with left hand (ProSup-L) constituting four activities performed in a consecutive manner. The data points or the transition points between two successive activities like *Rest* and *Posture* are labeled as *NoAction* using FCM algorithm. Thus, the total number of clusters or C-value is equal to five in the FCM algorithm.

Let N be the total number of data points in the recorded raw data and m be the exponential weight of membership. The fuzzy data clustering is done with respect to the minimization of the following objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} U_{ij}^{m}.X_i,$$

Table 1
Joint Angles and all the Degrees of Freedom Associated with the Selected Sensors.

Joint Angle and Degrees of Freedom for the Left and Right arms	
Right-Wrist -Flexion/Extension (FE)	Left-Wrist -Flexion/Extension (FE)
Right-Wrist- Ulnar/Radial (UR)	Left-Wrist- Ulnar/Radial (UR)
Right-Wrist-Pronation/Supination(PS)	Left-Wrist- Pronation/Supination(PS)
Right-Elbow-Flexion/Extension (FE)	Left-Elbow-Flexion/Extension (FE)
Right-Elbow-Pronation/Supination(PS)	Left-Elbow-Pronation/Supination(PS)
Right-Shoulder-Flexion/Extension (FE)	Left-Shoulder-Flexion/Extension (FE)
Right-Shoulder-Rotation (RO)	Left-Shoulder-Rotation (RO)
Right-Shoulder-Abduction/Adduction (ABD)	Left-Shoulder-Abduction/Adduction (ABD)

where X_i is the distance of the ith frame to the jth cluster center $S_j=\{s_R, s_P, s_{PS-R}, s_{PS-L}, s_{NoAction}\}$ and matrix $U=[u_{ij}]$ measures the membership degree between ith data point to the jth cluster. To minimize the objective function, FCM algorithm subjected to the following process:

1. Set the termination threshold $\varepsilon\in[0, 1]$, iteration step $q=0$
2. Initialize membership matrix $U=[u_{ij}]$, $U^{(0)}$
3. At q^{th} iteration, calculate the cluster centroid $S^{(c)}=[S_j]$ with $U^{(q)}$

$$S_j = \frac{\sum_{i=1}^{N} U_{ij}^{m}.X_i}{\sum_{i=1}^{N} U_{ij}^{m}}.$$

4. Update the membership function

$$U_{ij} = \frac{1}{\sum_{K=1}^{C}\left(\frac{\|x_i-S_j\|}{\|x_i-S_K\|}\right)^{\frac{2}{m-1}}},$$

Where S_K is the cluster centroid of the previous iteration, $1\leq j\leq C$ and $1\leq i\leq N$

5. If $\| U^{q+1} - U^{q} \| < \varepsilon$ then stop; otherwise, $q=q+1$ and go to step 3.

The kinematic pattern of the joint angles, presented by the selected sensors, is used to identify the type of the activity during the performance.

Evaluation metric

In the manual segmentation, examiners watched the avatar through the IGS BIO software and labeled the start frame and end frame for each activity during the sitting task. Manual Segmentation has been utilized as a gold standard for segmenting the time stamps for activities during a motor task like sitting; hence, it is considered as the "ground truth" for evaluating the performance of our detection technique based on the FCM algorithm. However, as discussed earlier, the manual segmentation done visually by the examiner is very time consuming since the recorded sensor data is extensive, and this process might be erroneous since it is done by visual segmentation. Thus, a detection and segmentation method based on FCM was proposed in this study to do the segmentation efficiently and in an unsupervised manner. The performance of the proposed method is evaluated in terms of the evaluation metrics like precision, recall, f-measure and accuracy.

Precision of each detected activity or cluster (C_i) is the number of data points correctly clustered using the detection technique (i.e. True Positive (TP)) divided by sum of TP and the number of data points which are identified or labeled as C_i but they actually belong to other clusters or activities (i.e. False Positive (FP)). So the precision of each detected activity denoted as (Act_i) is computed using the following equation:

$$Precision_{Act_i} = \frac{TP_{Act_i}}{TP_{Act_i} + FP_{Act_i}} \times 100$$

While precision measures the fraction of data points correctly put in the same cluster (activity), recall is the fraction of actual data points that were identified, and F-measure is the harmonic mean of precision and recall. Recall score is calculated based on the following equation:

$$\mathrm{Recall}_{Act_i} = \frac{TP_{Act_i}}{TP_{Act_i} + FN_{Act_i}} \times 100,$$

Where FN_{Act_i} is the number of data points that actually belong to Cluster C_i or Activity i, but they are incorrectly identified as being in other clusters using the detection technique, and F_measure is formulated as below:

$$F_{measure} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}.$$

Accuracy shows the fraction of data points correctly clustered using the proposed detection technique among the total number of examined data points. Thus, the accuracy of the model is calculated as below:

$$Accuracy = \frac{\sum_{i=1}^{C} TP_{Act_i}}{\sum_{i=1}^{N} i} \times 100,$$

Where C equals to total number of clusters which is 5 in our case, and N is the total number of data points (i.e. frames). As discussed earlier, TP_{Act_i} is the number of data points correctly identified as belonging to activity i (Act_i).

Results

The FCM algorithm was applied in a blinded fashion to all datasets. Therefore, the segmentations, manual and automatic were

Table 2
Performance of the Proposed Method in Detecting Rest Activity.

Number	Precision Rest		Recall Rest		F-measure Rest	
	Participants		Participants		Participants	
	Patients	Controls	Patients	Controls	Patients	Controls
1	99%	100%	98%	99%	99%	100%
2	97%	100%	100%	95%	98%	97%
3	100%	100%	99%	99%	99%	99%
4	98%	99%	97%	100%	98%	99%
5	98%	100%	100%	98%	99%	99%
6	98%	100%	100%	94%	99%	97%
7	98%	99%	100%	100%	99%	100%
8	95%	100%	100%	99%	97%	100%
9	98%	100%	100%	98%	99%	99%
10	97%	96%	100%	100%	99%	98%
11	100%	97%	99%	100%	99%	97%
12	100%	100%	99%	100%	100%	100%
Mean	**98%**	**99%**	**99%**	**99%**	**99%**	**99%**

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Table 3
Performance of the Proposed Method in Detecting Posture Activity.

Number	Precision Posture		Recall Posture		F-measure Posture	
	Participants		Participants		Participants	
	Patients	Controls	Patients	Controls	Patients	Controls
1	91%	100%	100%	96%	95%	98%
2	97%	99%	100%	99%	98%	99%
3	99%	98%	98%	100%	99%	99%
4	96%	97%	100%	100%	98%	98%
5	99%	99%	96%	100%	98%	99%
6	97%	95%	100%	99%	98%	97%
7	92%	95%	100%	96%	96%	96%
8	98%	100%	100%	94%	99%	97%
9	93%	100%	100%	98%	96%	99%
10	100%	95%	96%	100%	98%	98%
11	100%	100%	99%	99%	99%	99%
12	95%	100%	100%	100%	98%	100%
Mean	**96%**	**98%**	**99%**	**98%**	**98%**	**98%**

Table 4
Performance of the Proposed Method in Detecting ProSup_R Activity.

Number	Precision ProSup_R		Recall ProSup_R		F-measure ProSup_R	
	Participants		Participants		Participants	
	Patients	Controls	Patients	Controls	Patients	Controls
1	98%	96%	99%	100%	99%	98%
2	89%	90%	100%	100%	94%	95%
3	70%	96%	100%	100%	82%	98%
4	94%	98%	100%	100%	97%	99%
5	80%	99%	100%	98%	88%	98%
6	81%	97%	100%	96%	90%	96%
7	87%	100%	100%	95%	93%	97%
8	100%	98%	100%	97%	100%	97%
9	91%	87%	100%	99%	95%	93%
10	100%	87%	100%	100%	100%	93%
11	95%	88%	100%	93%	97%	90%
12	94%	80%	100%	100%	97%	88%
Mean	**90%**	**93%**	**100%**	**98%**	**94%**	**95%**

Table 5
Performance of the Proposed Method in Detecting ProSup_L Activity.

Number	Precision ProSup_L		Recall ProSup_L		F-measure ProSup_L	
	Participants		Participants		Participants	
	Patients	Controls	Patients	Controls	Patients	Controls
1	94%	100%	93%	98%	96%	99%
2	95%	94%	94%	95%	94%	94%
3	97%	100%	97%	90%	97%	95%
4	76%	99%	100%	97%	86%	98%
5	92%	100%	100%	94%	96%	96%
6	100%	100%	88%	97%	94%	98%
7	97%	100%	94%	88%	95%	94%
8	84%	95%	100%	86%	92%	91%
9	96%	99%	99%	90%	98%	94%
10	99%	89%	100%	100%	99%	94%
11	99%	93%	100%	98%	99%	96%
12	94%	82%	100%	100%	97%	90%
Mean	**94%**	**96%**	**97%**	**94%**	**95%**	**95%**

performed completely independently prior to the comparisons discussed below. The proposed method was tested on twelve PD participants and twelve control participants performing the sitting task for about one minute. The proposed method aimed to use the sensor information from the motion capture system and automatically identify the physical activities and segment the time stamps. Such information is essential for further analysis to compute the objective scores for motor symptoms of PD.

The percentages of precision, recall, f-measure for activities like *Rest, Posture, ProSup_R, and ProSup_L* during the sitting task and across 24 participants are shown in Tables 2–5, respectively. The first 12 participants are the PD participants, and the second half includes the control participants.

The last row in Table 2 is the mean of precision, recall, and f-measure scores for all participants calculated separately for PD and control participants. As Table 2 indicates, the mean of precision score for *Rest* is about 99% indicating that the data points or the frames of *Rest* activity are correctly identified using the detection technique. The high recall value suggests that very small numbers of data points are incorrectly identified as belonging to other activities. F-measure score which is calculated based on precision and recall reveals that the proposed method performed very effectively in detecting *Rest* activity.

As Table 3 demonstrates, the mean of evaluation metrics for *Posture* activity is close to 100%, confirming one more time that the proposed detection technique based on FCM algorithm can effectively detect and identify the activities performed by the participant.

The scores of the evaluation metrics for *ProSup_R* and *ProSup_L* indicated in Table 4 and Table 5, respectively, are slightly lower than *Rest* and *Posture*. The reason could be that the recording time for the Pronation-Supination activity is half of *Rest* and *Posture* as it is divided into right and left arm. Since pattern recognition techniques aim to find the regularity of the data, the more the

Table 6
Summary of the Method's Performance across the Different Evaluation Metrics and the Performed Activities.

Motor Task	Precision Rest		Recall Rest		F-measure Rest	
	Participants		Participants		Participants	
	Patients	Controls	Patients	Controls	Patients	Controls
Rest	98%	99%	99%	99%	99%	99%
Posture	96%	98%	99%	98%	98%	98%
ProSup_R	90%	93%	100%	98%	94%	95%
ProSup_L	94%	96%	97%	94%	95%	95%

Table 7
Accuracy of the Detection Model for Each Participant.

Number	Accuracy	
	Participants	
	Patients	Controls
1	96%	98%
2	95%	95%
3	94%	97%
4	95%	98%
5	95%	97%
6	95%	95%
7	93%	95%
8	96%	95%
9	95%	95%
10	98%	93%
11	98%	93%
12	96%	94%
Mean Accuracy	**96%**	**95%**

specific pattern occurs in data, the more precise the algorithm can detect the activity.

Table 6 summarizes the information of Tables 2–5. So mean of precision, recall, and F-measure for each activity and across all participants shown in Table 6. F-measure score which is calculated based on precision and recall indicates that the proposed auto segmentation method is able to detect the correct activity by obtaining the F-measure of at least 95%. The mean scores of F-measure for Rest and Posture are very satisfactory and demonstrate that if a specific activity lasts for about 20 s, the algorithm can detect that activity more effectively.

Table 7 indicates the accuracy of the detection technique in terms of all activities for each participant. Overall, the detection model can detect the activities very effectively by getting the mean

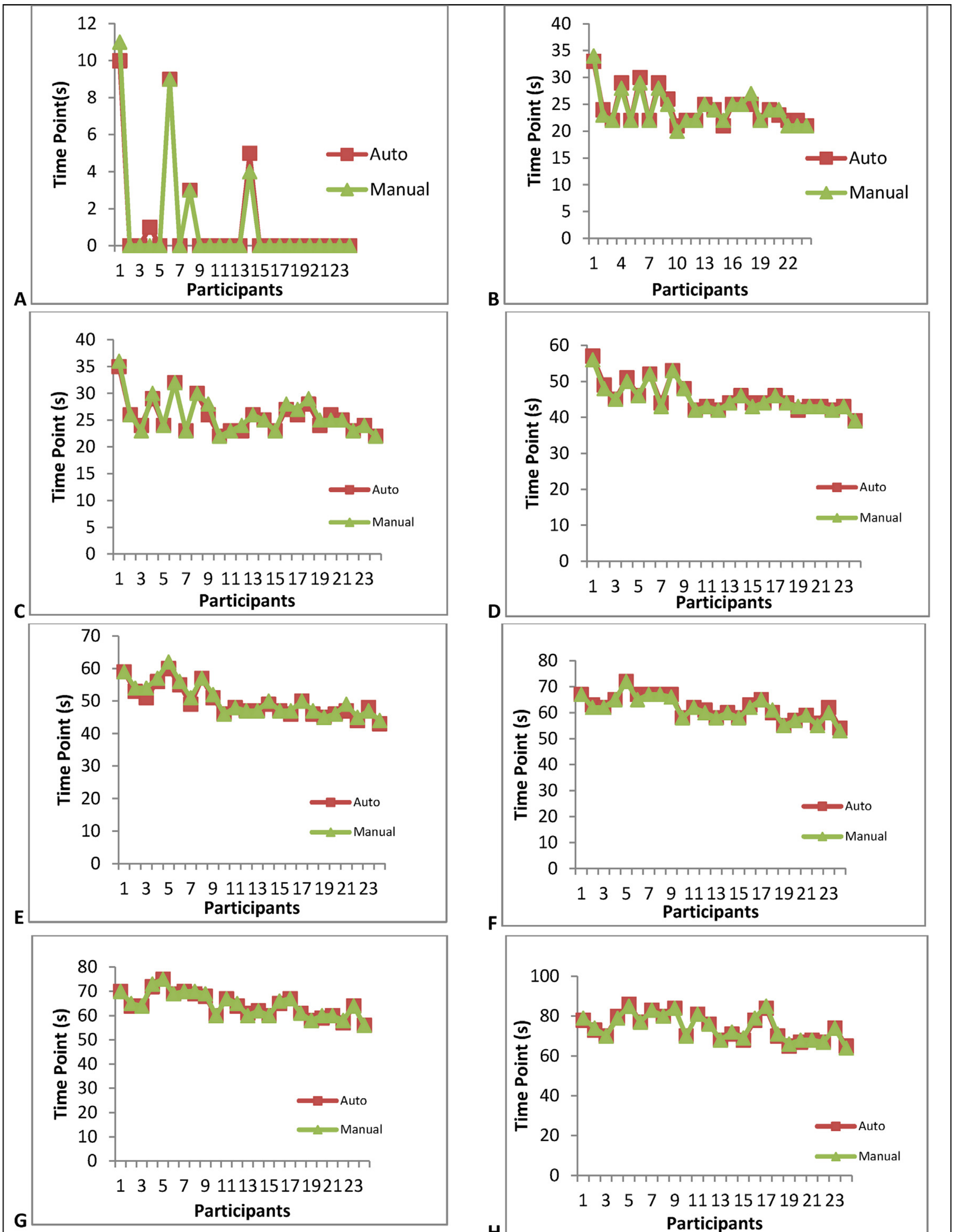

Fig. 3. Start Time Point and End Time Point of Auto and Manual Segmentation for each Activity and across All Participants.

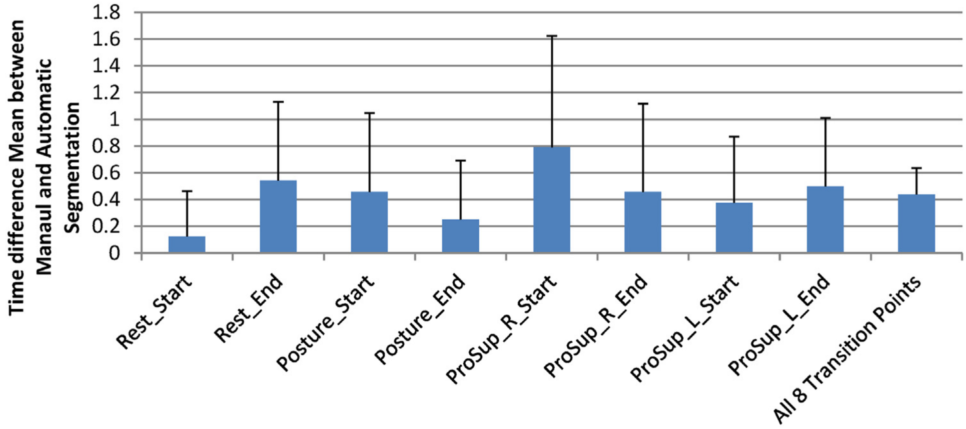

Fig. 4. Mean of Time Difference between Manual and auto Segmentation across 24 Participants for Start time and End Time of each Activity.

accuracy score of 96% for the PD participants and 95% for the control participants. Based on the experimental results, the accuracy above 90% is perfect as the proposed technique is evaluated w.r.t. the manually labeled data points done visually by the examiners. Such manual segmentation is not absolutely consistent among the examiners. So the accuracy of 90% for the auto detection activity technique is acceptable. This issue is clearly shown in Figs. 3 and 4.

The recorded raw data contains several frames. Since all activities are performed in a continuous fashion during the sitting task, the auto activity detection model determines the start frame and end frame for each activity similar to what examiners do for manually segmenting and labeling the frames. The start time point and the end time point of all activities include 8 transition points. Fig. 3 indicates each transition point based on the auto detection algorithm and manual segmentation method across all participants. The frame was converted to seconds w.r.t. the sampling rate. Raw data (acceleration, angular velocity) were recorded at the sampling rate of 60 Hz during the performance. For example, if the start frame for the *Rest* activity is equal to 200, it means that *Rest* actually starts at about 200/60HZ = 3 s of the record. The exact start time (in s) and end time (seconds) for each activity using manual and automatic segmentation are provided in the Appendix A.

All graphs in Fig. 3 suggest that the proposed auto segmentation method perfectly overlaps with the manual or visual segmentation. For example, in Fig. 3A, the start time of rest activity for participant #1 is at 11th second based on the auto segmentation, and such a score is at second 10 using the manual segmentation. Hence, based on the graphs in Fig. 3, start time points and end time points achieved using the auto segmentation method is pretty close to manual segmentation for all activities.

The mean of differences and variances between manual and auto segmentation of the sitting task for all activities and across all participants are computed in terms of seconds and indicated in Fig. 4. Fig. 4 suggests that the time stamp difference between auto and manual segmentation is negligible, and such differences can be observed among different examiners that manually label and segment the raw data. This issue confirms that the accuracy with the cut-off score of 90% is a good estimation showing that the proposed technique performs effectively enough in detecting the activities and segmenting the time stamps. The average of differences between the auto and manual segmentation, across 8 transitions shown in the last column of Fig. 4, is ΔT_{avg} = 0.43s. This difference is not significant, allowing the proposed technique to be an efficient and effective alternative for the time consuming manual segmentation.

Discussion

Detecting the activity and segmenting the time stamps during a motor task is the initial and significant step in kinematic analysis. Once the activity is detected and segmented to the corresponding time stamp, the objective score can be measured for the motor symptoms. For instance, bradykinesia (Dai et al., 2016) score is computed based on Pronation-Supination activity with both left and right hands, and the scores of motor symptoms such as dyskinesia (Goetz et al., 2013) and tremor (Das et al., 2011) are calculated w.r.t. the *Rest* and *Posture*, respectively while sitting. So, having an intelligent algorithm to automatically and effectively detect the performed activities and segment the time stamps is an essence.

Manual segmentation of extensive sensor data for finding the time stamp associated with certain activities is very time-consuming, and it requires qualified examiners to get trained on this task. In order to tackle such limitations of manual segmentation, the auto detection and segmentation technique proposed in the current study made use of information from the inertial sensors to identify and segment the activities performed during the sitting task.

Several studies have addressed the problem of auto activity detection for different purposes (Godfrey et al., 2011; Moncada-Torres et al., 2014; Najafi et al., 2002; Nguyen et al., 2015a). Most of these studies processed and analyzed the signals from the sensor in order to detect the specific activities. For example, in (Godfrey et al., 2011), the proposed activity detection algorithm (*VESPA*), which is based on Scalar (dot) product method, utilized the information from a chest mounted accelerometer for detecting the *sit-to-stand* and *stand-to-sit* activities. The same activities were detected in (Najafi et al., 2002) using a miniature gyroscope attached to the chest and a portable recorder placed on the waist. The authors in (Nguyen et al., 2015a) proposed a method to detect different types of activities like *Standing, walking, turning, and sitting* during the TUG (Time-Up-And-Go) task, performed by PD participants. The techniques used in the previous works are mainly based on signal processing techniques where the signals from sensors were detrended to remove sensor drift, normalized, and band pass filtered with optimal frequencies to reveal kinematic peaks that corresponded to different activities. In the current study, the activities, shown in Fig. 1, could not be detected using such signal processing techniques. The kinematic peaks cannot be revealed due to small temporal and spatial variations of the signals associated to the activities of the sitting task.

Some studies employed classification techniques for activity detection (Kwapisz et al., 2011; Maurer et al., 2006; Moncada-Torres et al., 2014; Wang et al., 2012). For example, in (Moncada-Torres et al., 2014), a KNN classifier was applied to predict and detect the activities like *walking* and *sit-to-stand* using the information from inertial and biometric sensors located on different body limbs. However, the main drawback with such supervised classification techniques is providing the training samples for the classifier from the previously labeled data points. Moreover, the training samples might not be suitable enough to effectively train the classifier, and this issue can have an adverse effect on the accuracy of the classifier. In our case, PD participants were asked to perform the activities at their own pace, and their performances varied w.r.t. their mobility conditions. Therefore, using the labeled data from one examined case as the training samples for the classifier is not reliable. On the other hand, it is not feasible to provide training samples from the data associated to each participant. The main goal in this study was therefore to do the activity detection and segmentation task in an unsupervised manner.

The proposed technique in this study was based on an unsupervised machine learning algorithm. FCM clustering algorithm was applied to detect the activities during the sitting task using the information from the inertial sensors attached to the upper and lower arms. Our method is able to be efficiently applied to any number of tasks performed continuously regardless of how long each task may last. The proposed detection technique was evaluated w.r.t. the ground truth, and it was able to effectively detect the activities with average accuracy of 96%. The results of precision, recall, and F-measure, calculated for different activities across PD and control participants, are very satisfactory and encouraging, confirming that the proposed technique is a better alternative and significantly more efficient than the manual segmentation method in dealing with big data. As a future application of this work, the auto detection algorithm, which allows automatic segmentation, can determine the time stamps for different motor tasks, and hence the objective scores can be computed for different PD motor symptoms associated to a motor task. Thus, individuals with mobility impairment can be remotely monitored during daily living and assessed over time.

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Relevant conflicts of interest/financial disclosures

The authors have no conflicts of interests.

Appendix A.

Table A1
(Fig. 3): Start time and End time for each Activity using Auto and Manual Segmentation.

Participant Number	Rest Auto		Rest Manual		Posture Auto		Posture Manual		ProSup_R Auto		ProSup_R Manual		ProSup_L Auto		ProSup_L Manual	
	Start time	End Time	Start Time	End Time	Start Time	End Time	Start Time	End Time	Start Time	End Time	Start Time	End Time	Start Time	End Time	Start Time	End_Time
1	10	33	11	34	35	57	36	56	59	67	59	67	70	78	70	79
2	0	24	0	23	26	49	26	48	53	63	54	62	64	73	65	74
3	0	22	0	22	24	45	23	45	51	62	54	62	64	70	64	70
4	1	29	0	28	29	51	30	50	56	65	57	65	72	80	73	79
5	0	22	0	22	24	46	24	46	60	72	62	72	75	86	75	85
6	9	30	9	29	32	52	32	52	55	67	56	65	69	77	69	77
7	0	22	0	22	23	44	23	43	49	67	51	67	70	83	70	83
8	3	29	3	28	30	53	30	53	57	67	57	67	69	80	70	80
9	0	26	0	25	26	48	28	48	51	67	52	66	68	84	69	84
10	0	21	0	20	22	42	22	42	46	58	46	58	60	70	60	70
11	0	22	0	22	23	43	23	43	48	62	48	62	67	81	67	81
12	0	22	0	22	23	42	24	42	47	61	47	60	64	76	65	76
13	0	25	0	25	26	44	26	44	47	58	47	58	61	68	60	68
14	5	24	4	24	25	46	25	46	49	60	50	60	62	71	62	72
15	0	21	0	22	23	44	23	43	47	58	47	58	60	68	60	69
16	0	25	0	25	27	44	28	44	46	63	47	62	65	78	66	79
17	0	25	0	25	26	46	27	46	50	65	50	65	67	84	67	85
18	0	25	0	27	28	44	29	44	46	60	47	61	61	70	61	71
19	0	22	0	22	24	42	25	43	45	55	45	55	58	65	58	66
20	0	24	0	24	26	43	25	43	46	57	46	57	59	67	60	68
21	0	23	0	24	25	43	25	43	47	59	49	59	60	68	60	68
22	0	22	0	21	23	42	23	42	44	56	45	55	57	67	58	67
23	0	22	0	21	24	43	24	43	48	62	47	60	64	74	64	74
24	0	21	0	21	22	39	22	39	43	54	44	53	56	65	56	64

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