Using Inertial Sensors to Automatically Detect and Segment Activities of Daily Living in People With Parkinson's Disease

Hung Nguyen, Karina Lebel, Sarah Bogard, Etienne Goubault, Patrick Boissy, and Christian Duval

***Abstract*— Wearable sensors such as inertial measurement units (IMUs) have been widely used to measure the quantity of physical activities during daily living in healthy and people with movement disorders through activity classification. These sensors have the potential to provide valuable information to evaluate the quality of the movement during the activities of daily living (ADL), such as walking, sitting down, and standing up, which could help clinicians to monitor rehabilitation and pharmaceutical interventions. However, high accuracy in the detection and segmentation of these activities is necessary for proper evaluation of the quality of the performance within a given segment. This paper presents algorithms to process IMU data, to detect and segment unstructured ADL in people with Parkinson's disease (PD) in simulated free-living environment. The proposed method enabled the detection of 1610 events of ADL performed by nine community dwelling older adults with PD under simulated free-living environment with 90% accuracy (sensitivity = 90.8%, specificity = 97.8%) while segmenting these activities within 350 ms of the "gold-standard" manual segmentation. These results demonstrate the robustness of the proposed method to eventually be used to automatically detect and segment ADL in free-living environment in people with PD. This could potentially lead to a more expeditious evaluation of the quality of the movement and administration of proper corrective care for patients who are under physical rehabilitation and pharmaceutical intervention for movement disorders.**

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I. Introduction

PARKINSON's disease (PD) is a neuro-degenerative disorder that progressively deteriorates motor functions in the affected person, which can affect the quality of life by hindering the ability to perform simple task in daily living. Symptoms of PD and the effects of its treatment can manifest in form of tremor, bradykinesia, and dyskinesia. Effective patient-care through real-time feedback of rehabilitation [1], [2] and pharmaceutical intervention [3], [4] can help manage and improve the quality of life by minimizing the effects of these motor dysfunctions on daily living movement. Wireless body-worn sensors provide a practical ambulatory system to capture these movements in free-living environment that might be difficult with laboratory-based optical motion capture system. However, currently, the focus of these ambulatory systems has been on analyzing the *quantity* of physical activity rather than the *quality* of the movements behind the activity. This process can be difficult without a system that could accurately identify the movement (detection) as well as determine the beginning and ending (segmentation) of each movement.

Inertial Measurement Unit (IMU), which comprises of a 3D accelerometer, a 3D gyroscope and a magnetometer, has been used to measure physical activity through differentiation between active and sedentary lifestyle in healthy population [5]–[7] and people with PD [8] based on the quantity of time spent performing certain activities in daily living (ADL) such as lying, sitting, standing, and walking. More recently, Moncada-Torres *et al.* [9] used a set of inertial and barometric pressure sensor to classify additional ADL such as drinking, writing, and brushing. However, the transitions between these activities were often ignored, which are critical to the evaluation of the quality of the movement. Some studies have used inertial sensors to segment the transition of the activity [10], [11]; however, they were often limited to *sit-to-stand* transition perform in laboratory setting and under controlled condition.

In clinical settings, many movement performance parameters calculated during activities such as *sit-to-stand* [12], *walking* [13], [14], and *turning* [15], [16] have been determined to be useful in identifying the altered functional capacity in people with PD. Parameters such trunk angle [17], freezing of gait [18]–[20], gait parameters during walking [21]–[23] (stride time, cadence, angle, etc.) and turning [24]–[26] (speed and number of steps) have been extracted using inertial sensors to evaluate the movement quality of people with PD. Within each segment, outcome measures of movement performance associated with different activities (e.g. stride time in gait) could be evaluated and quantified to measure mobility in movement disorders. Furthermore, within those activities, a proper detection of symptom could be done in people with PD (e.g. tremor, bradykinesia, freezing, etc.). However, before we can analyze the quality of the movement, it is important to accurately detect and segment these activities, especially during free-living environment.

While some studies have concentrated on developing classification algorithms of physical activities in free-living environment of healthy population [13], [27], [28], few studies have focused on PD population [8], [25], [26]. This is important since the goal should be to equip these sensors on patients with movement disorder and let them live their lives while we detect what they are doing and how well they are doing them in an automated fashion. Previously, we have developed detection algorithms using healthy elderly during a Timed Up and Go task [29] and a cleaning task in a simulated free-living environment [30], [31]. Free-living environment poses a new challenge to the detection and segmentation of these activities due to its unrestricted nature as well as the movement difficulty and variability in people with PD. The aim of this study was to develop detection and segmentation algorithms based on IMUs to isolate ADL in people with PD in a simulated free-living environment.

II. Methods

A. Participants

Participants were recruited through the Centre de Recherche de l'Institut Universitaire de Gériatrie de Montréal (CRIUGM) in collaboration with the Québec Parkinson Network (QPN).[1] Nine community dwelling older adults who were diagnosed with early stages of PD were recruited for the study to form a homogenous motor symptom. In order to avoid extreme fluctuation in motor symptoms often associated with late stages of PD, one inclusion criterion required participants to be diagnosed in the early stages of PD by their neurologists and had a score of 2 or less on the Hoehn & Yahr scale [32]. The sample included two females (mean±std; age = 65.5±12.0 years old, height = 1.65±0.03 m, weight = 56.7±12.0 kg, years of diagnostic = 4.5±1.5 years) and seven males (age = 66.1±2.7 years old, height = 1.75±0.03 m, weight = 80.1±18.6 kg, years of diagnostic = 4.8±5.6 years). Participants were screened for cognitive deficits using the Montreal Cognitive Assessment (MOCA) test (mean of 27±2 SD) [33]. One participant was classified as a dependent in ADL using the Nottingham Extended Activity of Daily Living Scale [34]. Participants did not exhibit any severe motor dysfunctions that would hinder their ability to perform the task; however, some participants displayed motor symptoms common in PD such as rigidity, tremor, and bradykinesia. The institutional ethics review board of the CRIUGM approved this research and each participant read and signed an informed consent form.

[1]Quebec Parkinson Network is a group of researchers, clinicians and patients, all collaborating to fight against Parkinson's disease. Currently directed by Edward Fon, it was created in June 2013 and now counts over 800 patients and over 150 members (including neurologists, researchers and people working on Parkinson's disease) who join forces to promote multidisciplinary research. One of its main roles in research is the participant registry and the bio-bank that facilitate access to valuable information on patients for research team projects.

B. Experiment Protocol

A simulated free-living apartment (7m x 8m) was set up to induce a daily living task of cleaning. A more descriptive layout of the environment was described in these studies [31]. In brief, color-coded objects were strategically placed throughout the apartment at different locations and heights. Participants were asked to navigate the apartment and collect these objects and placed them in their corresponding color-coded baskets located throughout the simulated apartment. Objects were placed at three different height levels: ground level, mid-level (60-120 cm from the ground), and high-level (160-180 cm from the ground). Baskets were placed at ground and mid-level only. Walls and corridors were constructed to prompt participants to walk along a specific path and to induce turning in sharp angle (90°). Three plastic armchairs were also included in the apartment to induce sit down and stand up activities.

Participants were tested in the morning during their OFF state or at least 10 hours after their last medication. Participants performed one trial of 3-, 4-, and 5-minute duration. Participants first performed the 5-minute trial. Then the 3- and 4-minute trials were completed with the order randomized. Five 5-minute trials, randomly selected from the nine participants using the same cohort, were used to train and optimize the algorithms. The 3- and 4-minute trials from all nine participants (18 total trials) were used to validate the algorithms. Participants were required to satisfy certain activity count to ensure that all the activities were performed during each trial of the cleaning task. For example, they must sit in each chair at least once and each basket must have at least three items. The only strict restriction imposed on the participants was that they could only carry one object at a time.

Participants performed these activities while wearing the IGS-180 motion capture suit (Synertial UK Ltd, Brighton, UK). The IGS-180 is equipped with 17 IMUs (OS3D, Inertial Labs, VA, USA) positioned on each limb, trunk, and head segment to capture full-body 3D movement. Each module contains a 3-axis accelerometer (linear acceleration), a 3-axis gyroscope (angular velocity), and magnetometer (magnetic north heading). Raw data (acceleration, angular velocity) and 3D orientation (estimated from a proprietary fusion algorithm developed by Inertial Labs) from each IMU were acquired at 60 Hz. A local reference frame of each IMU was expressed

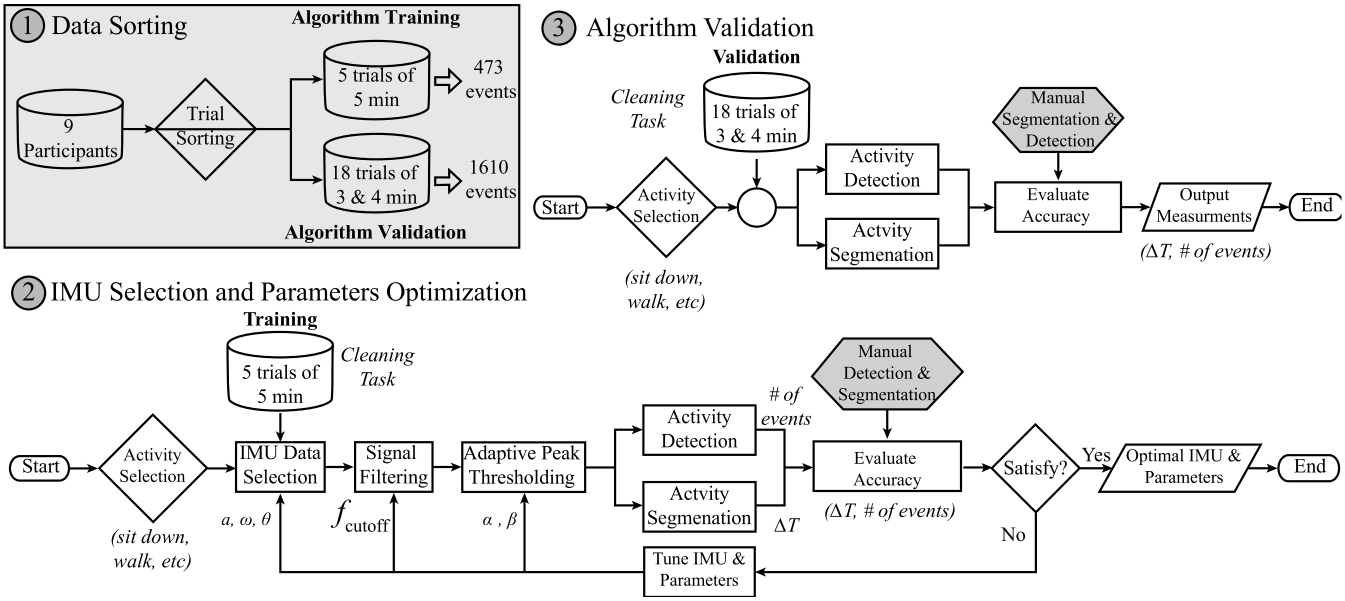

Fig. 1. Schematic of the process to train and validate the algorithms to classify activities of daily living in free, living environment. Five 5-minutes trials, randomly selected from the population, were used to train the algorithm to find the optimal set of sensor signals and parameters to accurately detect and segment these activities during an unstructured cleaning task.

with the y-axis aligned along the length of the IMU and the z-axis perpendicular to the width of the IMU. IMUs were normally aligned so that the y-axis was positioned along the limb segment, except for the head sensor, where head axial rotation was aligned along the x-axis. Further detail of the IMUs can be found here [29]. Since there was no *a priori* expectation as to which sensors were suitable markers for detection and segmentation, all 17 modules were active during the recording.

An examiner also segmented the activities during the cleaning task using a visual full-body avatar generated from IGS-180 motion capture software (IGS-Bio v. 2.59). The results from the manual identification and segmentation were used to evaluate the accuracy of the algorithms. The examiner was given general instruction on how to visually identify the beginning and ending of different activities during the cleaning task without imposing specific markers to account for the variability in how patients perform these activities. For example, the beginning of *reach* was marked by the initiation of hand movement and the ending was noted when the hand reached the object. *Turn* was identified when there was a change in direction of the body. *Turn* could occur gradually (during walking) or sharply during abrupt change of direction (turn180°). *Sit down* was segmented when the participants started to lower themselves onto the chair and ended when they were completely stable in the chair. *Stand up* was initiated when participants propelled their bodies upward and terminated just before the initiation of gait. Participants were instructed to perform the activities at their own speed; therefore, the examiner must use his judgment to account for the variability in how participants perform these activities. For example, during *stand up*, some participants transitioned directly into walking before completely reaching upright.

C. Activity Detection

ADL such as *sit down* (on a chair), *stand up* (from a chair), *reach* (*ground*, *mid*, *high*), *walk,* and *turn* were identified for detection and segmentation. The algorithms developed in this study were based on previously presented method using nonlinear transform and adaptive threshold [30], [31] to detect for peaks that correspond to different activities. While the method was developed using a continuous Timed Up and Go task, the fundamental processes of detecting and segmenting these activities remained the same. In the cleaning task, kinematics peaks were used to identify an activity and the maximum/minimum to the left/right of these peaks were used to estimate the duration (segmentation) of an activity. The schematic of the process to train and validate the algorithms is shown in Fig. 1. The algorithms were trained and optimized by using five 5-minute trials that were randomly selected from nine participants. In total, there were 473 events in the training data set. The optimization process was used to determine the cutoff frequency, the adaptive threshold parameters, and the IMU signals needed to accurately detect and segment each activity. The optimal parameters were found with respect to the training data set. The algorithms were then validated using the 3- and 4-minute trials from all nine participants (1610 events).

Sit down and *stand up* was detected using several kinematic data extracted from different IMUs (Fig.2a) and segmented using the acceleration of the trunk ($a_{z,\mathrm{Tr}}$) (Fig 2b). Other IMUs were used to help detect and differentiate these activities from other confounding activities within the cleaning task. The sacrum acceleration ($a_{z,\mathrm{S}}$) was added to ensure synchronicity of movement of the trunk and the hip during these activities. Similarly, the symmetry of the left and right hip flexion (θ_{H}) was used to discriminate from other activities such as *reach ground*, where PD participants often performed with one

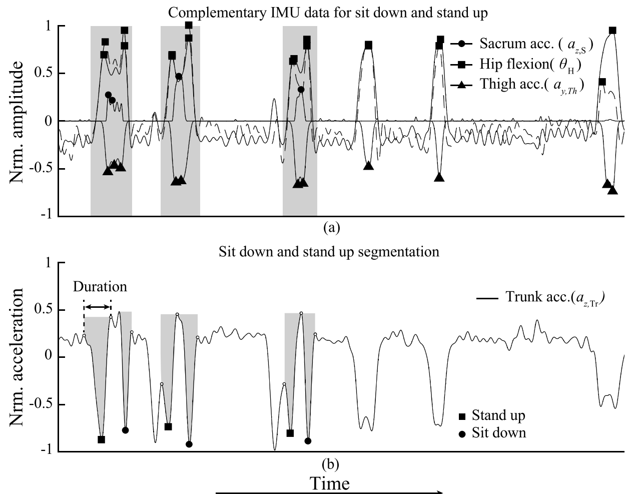

Fig. 2. Detection and segmentation of *sit down* and *stand up* using a set of sensor signals that included the acceleration of the sacrum in the z, direction ($a_{z,S}$) and the acceleration of the thigh in the *y*,direction ($a_{y,Th}$), and the flexion angle of the hip (θ_H).

knee touching the ground. Lastly, the derivative of the thigh acceleration ($\dot{a}_{y,Th}$) was used to distinguish between *sit down* and *stand up*. This define as:

$$a_{y,Th}(k)\begin{cases}\text{if } \dot{a}_{y,Th} \geq 0 \Rightarrow & \text{sit down}\\ \text{if } \dot{a}_{y,Th} < 0 \Rightarrow & \text{stand up}\end{cases} \quad 1 \leq k \leq n \tag{1}$$

where $n$is size of the recorded signal during a trial and k are the location of the detected peaks within the signal.

Turn was detected using the angular velocity of the trunk ($\omega_{y,\mathrm{Tr}}$), sacrum ($\omega_{y,\mathrm{S}}$), and thigh ($\omega_{y,\mathrm{Th}}$) (Fig. 3a). These IMUs were used to restrict *turn* to when the upper and lower body both rotate in concert.

Walk was classified using the magnitude of the linear acceleration of the left and right IMU on the shin in the x and z direction ($||a_{xz,Shin}||$) (Fig. 3b). However, to independently detect *walk*, other signals were used to reject non-walking bouts thus reducing confusion with other activities. For example, the linear acceleration of the trunk ($a_{z,\mathrm{Tr}}$) and sacrum ($a_{z,\mathrm{S}}$) in the z direction were used to nullify false positives detected during *reaching* and their angular velocities about the y-direction ($\omega_{y,\mathrm{Tr}}$,$\omega_{y,\mathrm{S}}$) were used to negate false positives detected during *turn* activity. Lastly, the magnitude of the acceleration of the thighs ($||a_{xz,\mathrm{Th}}||$) was used to neutralize false positives detected during *sit down* and *stand up* while providing a redundant check on walking activity.

Reaching activities were detected using the normalized angle of the trunk (θ_{Tr}), hip (θ_{H}), knee (θ_{K}), and shoulder (θ_{Shld}) (Fig 4a). These reaching angles were normalized in each trial using the absolute maximum angle recorded during the trial. Segmentation of reaching was achieved using the shoulder angle (Fig. 4b-d). The trunk, knee, and hip angle were used to refine the biomechanics of reaching to separate sub-activity such as *reach ground*, *reach mid,* and *reach up*. For example, during *reach up*, these angles were set to

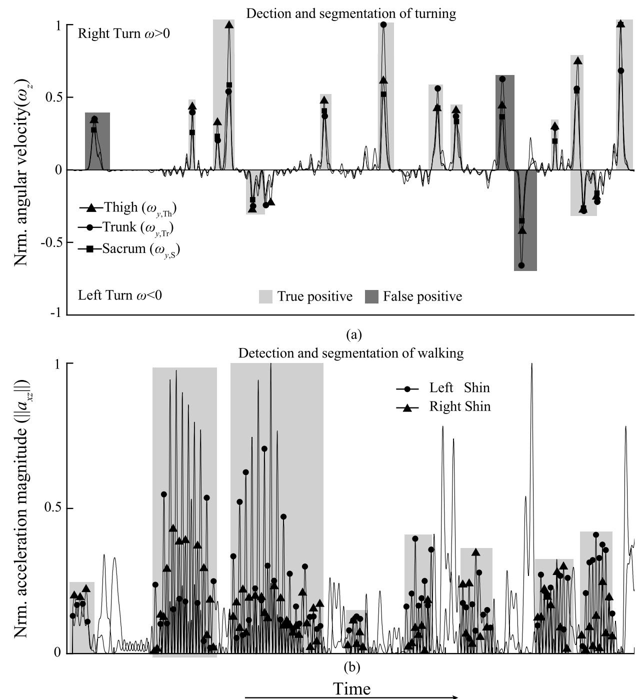

Fig. 3. (a) Detection and segmentation of turning using a set of three IMUs (angular velocity of trunk, Thigh, and Sacrum) that connect the upper and lower limb rotation. (b) Walking was detected and segmented using IMUs on the left and right shank.

$\theta_{\mathrm{T}} = \theta_{\mathrm{H}} = \theta_{\mathrm{K}} \approx 0$ to define that the participant was upright during *reach up*. This region is referred to as region of low range of motion (low ROM) (Fig. 4a). During *reach mid*, the condition was relaxed to $\theta_{\mathrm{H}} = \theta_{\mathrm{K}} \approx 0$. In contrast, *reach ground* was detected during segment of high ROM of these angles. However, these requirements were not sufficient to isolate *reach up* and *reach mid* due to the variability in the height of the participants and the fixed position of the objects at these levels. Therefore, the shoulder angle was discretized using the peak value (PV) and peak prominence (PP) of the activity peak to separate these sub-reaching activities. The peak prominence is defined as the vertical height of the activity peaks to the lowest contour line (minimum) of lower neighboring peaks.

Reach up was defined when PV and PP of θ_{Shld} satisfied these conditions:

$$\begin{aligned}\theta_{\mathrm{Shld},PP} &\geq 0.7 \cdot \max\left(\theta_{\mathrm{Shld},PP}\right)\\ 30^\circ \leq \theta_{\mathrm{Shld},PV} &\leq 0.7 \cdot \max\left(\theta_{\mathrm{Shld},PV}\right)\end{aligned} \tag{2}$$

Reach mid was classified when the PV and PP satisfied these conditions

$$\begin{aligned}\theta_{\mathrm{Shld},PP} &\leq 0.9 \cdot \max\left(\theta_{\mathrm{Shld},PP}\right)\\ \theta_{\mathrm{Shld},PV} &\leq 0.9 \cdot \max\left(\theta_{\mathrm{Shld},PV}\right)\end{aligned} \tag{3}$$

D. Activity Segmentation

Segmentation of the activity was accomplished by finding the first maximum or minimum to the left or right of these activity peaks. This method was thoroughly presented in

TABLE I
SENSOR SIGNALS TO DETECT AND SEGMENT ACTIVITIES

Task	Detection				Segmentation		
Sit down/Stand up	Trunk a_z	Sacrum a_z	Hip θ	Thigh a_y	Trunk a_z		
Reach up	Shoulder θ	Knees θ	Hip θ	Trunk θ	Shoulder θ		
Reach mid	Shoulder θ	Knees θ	Hip θ		Shoulder θ		
Reach ground	Shoulder θ	Knees θ	Hip θ	Shoulder a_x	Shoulder θ		
Turn	Sacrum ω_y	Thigh ω_y	Trunk ω_y		*Sacrum ω_y	Thigh ω_y	Trunk ω_y
Walk	Thigh $\|\|a_{xz}\|\|$	Shin $\|\|a_{xz}\|\|$	Trunk a_{z} & ω_y	Sacrum a_{z} & ω_y	Shin $\|\|a_{xz}\|\|$		

a denotes the linear acceleration, ω is the angular velocity, and θ represents the angular displacement. Quaternions of two adjacent IMUs that define the joint rotation were used to calculate θ.
* Segmentation was confirmed when at least two sensors detected similar activity peaks nearby

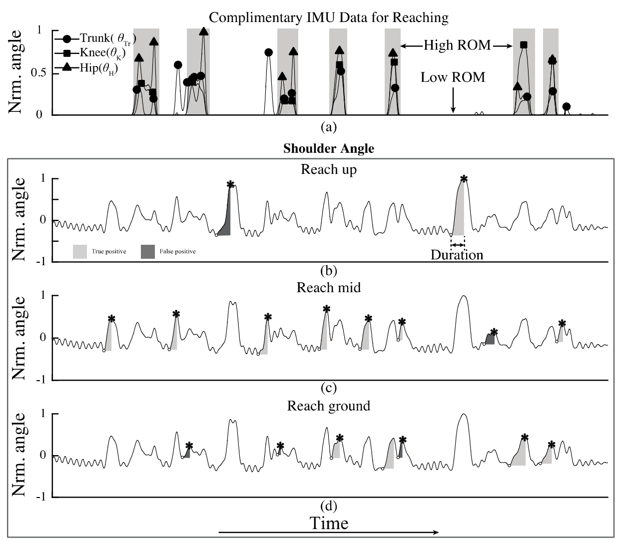

Fig. 4. Reaching activity. (a) The angle of the knee, hip, and trunk were used to differentiate three levels of reaching: *reach up*, *reach mid*, and *reach ground*. (b) The shoulder angle was used to segment these reaching activities.

previous study [29]. However, reaching was modified with the ending of the activity corresponding to the peak of the activity, denoting the ending of the reaching activity when the hand reaches the objects.

In addition, segmentation of *turn* was calculated using the average time marked using the angular velocity of the sacrum ($\omega_{y,S}$), thigh ($\omega_{y,Th}$), and trunk ($\omega_{y,Tr}$). This redundancy was needed to account for the unstructured nature of the cleaning task and the variability in how participants performed the *turn* activity. The complete sensor signals used for detection and segmentation is tabulated in Table I.

E. Statistical Analysis

Sensitivity, specificity, and F-score were used to measure the detection accuracy of these activities. Sensitivity measures the proportion of true positive (TP) while specificity measures the proportion of true negative (TN). The accuracy, F-scores, was defined as:

$$\text{F-score} = \frac{2 \cdot \text{TP}}{2 \cdot \text{TP} + \text{FN} + \text{FP}} \tag{4}$$

where FN is the numbers of false negative and FP denotes the numbers of false positive. Segmentation accuracy was evaluated using the absolute difference of the time (beginning and ending) marked manually by the examiner and automatically using the sensors for each activity ($\Delta T = |T_{manual} - T_{sensor}|$). The Shapiro-Wilk test ($\alpha = 0.05$) was used on the ΔT of each activity to determine the normality of the data distribution. Predictive confidence interval ($\alpha = 0.05$) was also used to evaluate the reliability and robustness of the algorithms. The boxplot of the ΔT was generated using a 95% confidence interval (CI) to demonstrate the predictive reliability of using the sensor to segment these activities.

III. RESULTS

A. Activity Detection

Eighteen trials of the 3- and 4-minute were used to validate the algorithms. In total, there were 1,610 events of seven classified activities (*sit down*, *stand up*, *reach up, reach mid*, *reach ground*, *turn,* and *walk*). *Sit down* ($n = 50$) and *stand up* ($n = 63$) were detected with 100% sensitivity and 99.9% specificity. For reaching, *reach up* ($n = 51$) was detected with 80.4% sensitivity and 99.9% specificity while *reach mid* ($n = 223$) was identified with 80.4% sensitivity and 96.0% specificity. *Reach ground* ($n = 174$) was classified with 93.1% sensitivity and 98.9% specificity. *Turn* ($n = 692$)was identified with 82.7% sensitivity and 92.6% specificity. Lastly, *walk* ($n = 357$) was detected with 91.9% sensitivity and 99.4% specificity. Across all activities, classification using the sensors signals was about 90% accurate (sensitivity = 89.8%, specificity = 97.9%).

The confusion matrix of the ADL is shown in Table II. The largest percentage of confusion was during *reach up* activity, where the algorithms falsely detected *reach mid* (21.2%). In contrast, confusion of *reach up* during *reach mid* was only 8.4%.

B. Activity Segmentation

During *sit down* (N = 84), the median of the time difference (ΔT) between the manual and sensor segmentation was 0.34s (Fig. 5). There were four outliers, which comprised of 4.8% of *sit down* events ($\%n_0$). The maximum predictive CI of the data was 1.16s. *Stand up* (N = 114) was segmented with a median difference of 0.18s with six outliers ($\%n_0 = 5.3$) and a predictive CI of 0.65s. The average median ΔT during the three reaching activities (N = 587) was 0.2s (*reach up*: N = 80, median = 0.23s; *reach mid*: N = 233, median = 0.18s; *reach ground*: N = 274, median = 0.20s). During

TABLE II
ACTIVITY DETECTION CONFUSION MATRIX

	Sit Down	Stand Up	R Up	R Mid	R Ground	Turn	Walk
Sit Down (*n*=50)	100	0.0	0.0	0.0	3.8	0.0	0.0
Stand Up (*n*=63)	0.0	100	0.0	0.0	0.0	3.1	0.0
R Up (*n*=51)	0.0	0.0	80.4	21.2	0.0	0.0	0.0
R Mid (*n*=223)	0.0	0.0	8.4	80.3	8.0	1.7	6.3
R Ground (*n*=174)	0.0	0.0	1.1	3.4	93.1	1.7	0.6
Turn (*n*=692)	0.2	0.3	0.0	3.4	2.2	85.4	1.7
Walk (*n*= 57)	0.0	0.0	0.3	1.8	0.0	0.3	91.9
F-score	0.98	0.98	0.80	0.78	0.92	0.83	0.95
Sen (%)	100.0	100.0	80.4	80.3	93.1	82.7	91.9
Spec (%)	99.9	99.9	99.3	96.0	98.8	92.4	99.4

Confusion matrix of the seven activities detected in the simulated cleaning task expressed as a percentage (%). *n* denotes the number of samples of each activity. F-score represents the accuracy of activity detection. *Reach up*, *reach mid*, and *reach ground* are denoted by R UP, R Mid, and R Ground. The true positive and true negative of the algorithms are denoted by the sensitivity (Sen) and specificity (Spec). Darker shading indicates higher detection percentage.

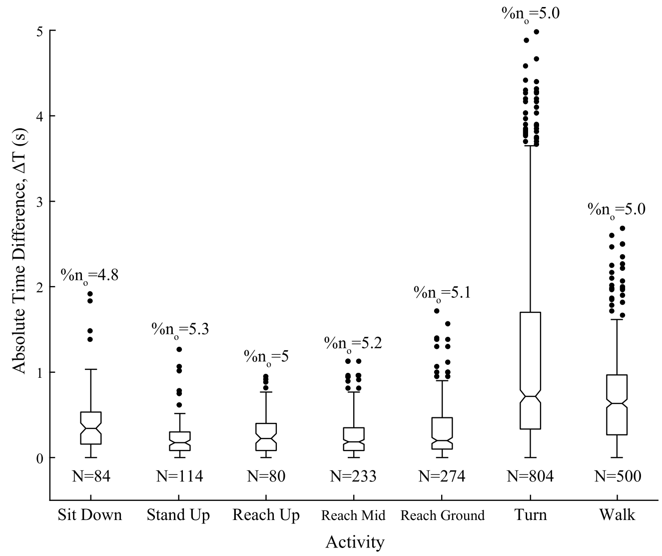

Fig. 5. Comparing the absolute time difference (ΔT) marked manually by the examiner and automatically using the sensors. N denotes the sample size in each activity while $\%n_o$ indicates the percentage of outliers outside the 95% confidence interval within each activity.

reaching activities, the largest predictive CI was 0.95s, which occurred during *reach ground*, while *reach up* and *reach mid* has a maximum predictive CI of 0.78s and 0.75s respectively. The median ΔT of the *turn* (N= *804)* was 0.72s with 40 outliers ($\%n_0 = 5.0$) and a maximum predictive CI of 4.58s; however, 75% of the ΔT was less than 1.60s. *Walk* (N = 500) was segmented with a median difference time of 0.63s with 25 outliers ($\%n_0 = 5.0$) and a predictive CI of 1.71s. Across all activities (N = 2089), the average ΔT was about 0.35s.

IV. Discussion

There is an immense potential of using inertial sensors as clinical tools to assist and improve patient-care during physical rehabilitation and pharmaceutical intervention by analyzing the movement and motor dysfunction under free-living condition. However, for clinical application, such system must robustly detect and segment these activities with high accuracy and automation. This study demonstrated high efficacy of using IMUs to accurately detect and segment common daily living activities in a simulated free-living environment in participants with early PD during an unstructured task.

While most studies on activity classification in free-living environment have focused on healthy and elderly adults [5], [9], [35], [36], few studies have applied classification methods to a challenging population such as PD. In a similar study, Jalloul *et al.* [37] used a set of six sensors to measure daily living activities such as walking, standing, and sitting in patients with PD. These activities were detected with a sensitivity of 92.4%, 91.8%, and 88.6%, respectively. However, it is noted that the results were based on a very small sample size (n = 2). In this study, we could detect these activities with comparable or higher sensitivity and in a larger cohort with PD (n = 9). Salarian *et al.* [8] used a set of three inertial sensors attached to the trunk and shanks to measures the *sit-to-stand* transition and ADL such as walking, standing, and sitting. The study showed a detection sensitivity of 98.5%, 83.6%, and 99.5%, respectively. In addition, transition of *sit-to-stand* was segmented with 83.8% sensitivity. Here, we demonstrated great accuracy in the detection of *sit down* and *stand up*, which could be used to measure performance in PD population [38], [39]; they were segmented with a median difference of 0.26s across all participants. Furthermore, the algorithm used by Salarian involved a set of fuzzy classification rules to sectionalize the activities thus reducing the risk of false detections. Here, all the activities were independently detected using an optimal set of sensors; therefore, it did not depend on the classification of other activities. This is important in the context of free-living, where movements are unstructured. Lastly, this study provided the first strategy to use inertial sensors to detect reaching activities at different stratifications (*reach ground*, *reach mid*, and *reach high*). These reaching activities are critical components of independent living in people with movement disorders.

Beyond activity classification, this study is unique in that it presents the first experiment on the segmentation of activity during free-living in a PD population. This is significant because it could potentially lead to evaluation of the *quality* of the movement rather than the *quantity* of the movement using inertial sensors. Ultimately, the goal is to deploy these sensors in a free-living environment on patients with movement disorders and extract relevant clinical parameters within each segment of activity to determine the progress of rehabilitation and pharmaceutical intervention. The results in this study show that segmentation of these activities based on IMUs can be comparable to manual segmentation, in addition to requiring significantly less time. Manually segmenting these activities can be a time consuming and tedious process. For example, to manually classify and document the seven activities in one 3-minute trial required nearly four hours of work.

Reaching activities were detected with almost 90% sensitivity; however, the accuracy decreases when reaching tasks are separated by levels. However, the decrease in the accuracy of the sub-activity of reaching could be attributed to the fact the heights of the mid- and high-level were not scaled to the participants' height. This led to a higher confusion of *reach mid* as *reach high* (21%), especially in taller participants (height $\geq$1.8 m). The beginnings and endings of *turn* were segmented with a median difference of 0.68s within the manual segmentation even though it was the most challenging activity to visually segment. *Turn* can occur abruptly during sharp angle (turn 180° or 90°) or more gradually during walking. Yet, even with the largest variation (std = 1.09s), *turn* was detected with almost 83% accuracy. Lastly, there were over 350 bouts of walking classified manually by the examiner and about 92% of it was detected using the sensors. Within the detected walking bouts, the differences between the manual and sensor segmentation was approximately 0.63s. The high detection rate and low segmentation time differences illustrate the potential of using IMUs in clinical setting to quickly measure and analyze the quality of movement in PD population.

While 17 IMUs were active during the experiment, only 10 IMUs were used in the final detection and segmentation algorithms. This amount of IMUs was needed to account for possible asymmetry in PD population as well as to provide coverage for handedness. Participants were not restricted to the use of the left or right hand; therefore, IMUs from both hands were monitored to detect reaching activities. Similarly, participant adopted varying strategies to reach for objects on the ground level. Some participants bent both knees on the ground during the execution of this activity while other bent only one knee. IMUs on the left and right side of the lower limbs were monitored to accurately detect these differences. In addition to outputting linear acceleration and angular velocity, uses of fusion algorithm also generate orientation data, which allows for the calculation of the range of motion between two contiguous limb segments. The availability of orientation data enables detection of similar movements like *reach up* and *reach mid* that would have been difficult using only accelerometric or gyroscopic information. The accuracy of these orientation data has been shown in previous experiments [40].

The present study highlights the fact that for unscripted, free-living movements, limiting the number of sensors could be counterproductive, especially if detection, segmentation, and assessment of movement are the goals. However, we also recognize that deploying a 17-IMUs system might be cumbersome in the home environment; therefore, sensors optimization is necessary before such system could practically be deployed for patients to use at home. The present study enabled us to identify key sensor locations for the detection and segmentation, which in the long term may help us propose a more reasonable number of sensors for real life recordings. The strain on the patient could be further alleviated by taking advantage of the modularity of these sensors and analyze targeted movements to further miniaturize the system for implementation in the home environment.

The results in this study showed the robustness of the algorithms to classify and separate many different activities over varying degrees of symptomology in the participants. Yet, despite the variability, the algorithms could detect these activities with high accuracy during a cleaning task and its segmentation precision is comparable to manual segmentation. This is an important first step in developing these sensors for performance analysis. These sensors could also potentially be used to measure and characterize symptoms of PD (tremor, dyskinesia, bradykinesia, etc.) to betterunderstand the evolution of these symptoms during treatment using method such as the signal-to-noise ratio (SNR) approach [41], where the signal is the voluntary movement and the noise is the symptom detected. If the SNR is high, then the symptom is irrelevant to the performance of the person tested. Furthermore, these wireless sensors are an ideal medium to be used for remote monitoring [42]–[44] of patients in their natural environment.

We acknowledge that the present algorithms may not respond as well for more advance cases of PD. Nonetheless, it represents a significant leap forward; a proper detection and segmentation of ADL in free-living environment is imperative to develop fully automated evaluation tools that can be used to monitor patients in their natural environment. The outcomes of this study will prompt the analysis of PD patient during performance of more natural activities in free-living environment to better understand and evaluate the effect of rehabilitation and pharmaceutical intervention. Accurate real-time assessment of performance will greatly enhance the ability of clinicians to administer corrective intervention to improve the quality of life of people living with movement disorders.

V. Conclusion

IMUs could potentially be used to detect, segment, and assess ADL during an unstructured task in a free-living environment in PD population. This is a critical step in developing and validating algorithms using inertial sensors to accurately extract targeted activities during daily living to assess movement and motor dysfunction.

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