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Capturing Whole-Body Mobility of Patients with Parkinson Disease Using Inertial Motion Sensors: Expected Challenges and Rewards

Fariborz Rahimi PhD, *Member, IEEE,* Christian Duval PhD, Mandar Jog MD, Carina Bee BSc, Angela South MA, Monica Jog BSc, Roderick Edwards PhD, and Patrick Boissy PhD, *Member, IEEE*.

***Abstract*—While many studies have reported on the use of kinematic analysis on well-controlled, in-laboratory mobility tasks, few studies have examined the challenges of recording dynamic mobility in home environments. This preliminary study evaluated whole body mobility in eleven patients with Parkinson disease (H&Y 2-4). Patients were recorded in their home environment during scripted and non-scripted mobility tasks while wearing a full-body kinematic recording system using 11 inertial motion sensors (IMU). Data were analyzed with principal component analysis (PCA) in order to identify kinematic variables which best represent mobility tasks. Results indicate that there was a large degree of variability within subjects for each task, across tasks for individual subjects, and between scripted and non-scripted tasks. This study underscores the potential benefit of whole body multi-sensor kinematic recordings in understanding the variability in task performance across patients during daily activity which may have a significant impact on rehabilitation assessment and intervention.**

I. Introduction

THE identification of intrinsic obstacles imposed by age and illness and extrinsic obstacles imposed by the physical environment is critical in helping elders and persons with disease maintain an optimal level of functional mobility, personal independence and quality of life. Without intervention, these barriers increase the risk of adverse events such as falls, as well as causing reduced mobility due to fears of these adverse events. Mobility has traditionally been measured using laboratory (instrument), clinical (observational) and community (self-report) approaches. These approaches have trade-offs in terms of precision/accuracy, validity/reliability, time/cost, training/expertise, participant burden and real-world generalizability. Laboratory research is fundamental to understand mechanistically how these intrinsic and extrinsic obstacles affect mobility in aging or diseased populations. However, the impact of intrinsic and extrinsic obstacles described in laboratory research does not necessarily reflect those observed when a person is navigating within their home or community. It is then difficult to make inferences about the real-life challenges facing aging individuals and those having motor impairments such as patients with Parkinson disease (PD).

Wearable sensors for home monitoring of different aspects of physiology related to health status have been extensively used for applications such as post-operative evaluation [1], increased telepresence in telerehabilitation and fall detection [2,3], general emergency situations [4], crude movement & heart monitoring [5], and vital signs monitoring [6,7]. Numerous biomechanical sensing approaches have been proposed to enhance in-home monitoring [8,9]. Systems for estimating the risk of falls based on standing up and sitting down movement analysis [10] or gait analysis [11] have been proposed. Similar studies have investigated ambulatory monitoring and quantification of motor conditions in PD, such as in tremor [12,13,14] bradykinesia [15] ON-OFF states [16,17] and dyskinesia [18,19]. However, for most of these studies, the number of sensors and sensor placement on the body has been decided based on educated guesses and depending on the specific questions to be examined. This means that the collected data only provided information about one specific aspect of mobility, neglecting potential features of mobility that might be more relevant to identify home mobility challenges. This is not to say that two sensors cannot for some purposes do the work of many. In fact, data reduction, i.e., reducing the number of sensors to a minimum, should be the ultimate goal for practical application. However, restricting the data collected at the outset may lead to important information being missed. For a particular group of subjects navigating in their home environment, the following questions can be considered: (1) which key feature(s) best reflect their mobility characteristics, (2) how do those key features differ for different tasks, and (3) what is the optimal sensor placement to capture the key mobility features examined? Based on these questions, it would be preferable to examine home mobility using a 'top-down' approach, using enough sensors to recreate whole-body movement. This data allows for the potential identification of any key mobility features that can separate motor performance based on age, or compare the mobility of healthy aging individuals against that of persons with motor disorders. Once those key features are identified, sets of markers (i.e., minimal number of sensors, optimally placed) could then be applied to best represent the mobility behaviors of subjects. This is different from the 'bottom-up' approach used in previous studies where the minimal number of sensors is used based on educated guesses. Accordingly, there is a need for a system that can capture whole-body mobility in the home.

To date, whole-body mobility has been constrained to the laboratory where several systems exist to capture 3D human motion. They include magnetic, sonic and optical systems

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using passive or active markers. While each of these systems provides fairly accurate 3D representation of human movement, they are not suited for home recording. Over the last 10 years, inertial sensing has proven to be a suitable ambulatory alternative to traditional image-based tracking systems [20]. Inertial sensing for motion tracking is most commonly performed using nine-axis sensor modules or so called Inertial Measurement Units (IMUs), each containing three orthogonally mounted triads of angular rate sensors, accelerometers, and magnetometers. The accelerometers are used to measure the linear acceleration vectors that are relative to the coordinate frame of the sensor module. The magnetometers serve a similar function for the local magnetic field vector. Angular orientation is determined by integrating the output from the angular rate sensors. Using a combination or fusion of this triad of sensor signals and various signal processing techniques, it is possible to estimate the orientation of the module. The accuracy of this estimation varies with the type of sensor used, the motion being tracked, the environmental presence of ferrous objects and the performance of the fusion algorithm used. IMUs are used in aerospace, marine and automotive fields and are now increasingly used for human motion tracking in clinical applications.

Inertial sensor nodes are generally limited in their number and location, but recently several off-the-shelf portable full body recording systems have been introduced, such as the MVN® from Xsens Technologies, IGS-190 from Animazoo, and FAB from Biosyn™. These systems contain 16 to 19 inertial motion sensors. While there is potential to use such systems for measuring body motion in humans [23-27], they are by no means perfect. In fact, they are understandably less accurate than camera-based systems [21, 22], because of drift, potential loss of data due to poor transmission, etc. Nonetheless, they currently represent the best method available for capturing whole-body mobility in the home.

The objective of this study was to quantify the variability/repeatability of movement profile components during daily tasks among elderly patients with PD. This study considered 11 PD patients who needed medication adjustments. The participants' mobility was studied both pre-, and post-medication alteration. However, the results that are presented in this paper mainly reflect comparisons in pre-medication differences in order to focus on short-term variability in aspects of mobility.

Among various tools that can be used for quantitative assessment of mobility, Principal Component Analysis (PCA) has been chosen to reveal the internal structure of each routine task performed by individual participants.

II. METHODS

A. Patients

The inclusion criterion for study participants was that they had to be ambulatory patients with PD experiencing mild to moderate medication inefficacy, demonstrating wearing off of drug, or dyskinesia. These patients were included because they lead a range of active daily lifestyles representative of the range of PD patients seen at the Movement Disorders Centre clinic. The patient demographic for the study was as follows: 11 patients, 8 males, 3 females, ages ranging from 56-78 years, weight ranging from 57-107kg, 2 drug-naïve, 2 requiring walking aid, 8 leading fairly active lifestyles.

B. Experimental Procedure

In-home mobility was recorded using an IMU based motion analysis system. These visits lasted 1.5 hours each. During this session, the participants were equipped with 11 inertial motion units (IMUs) of the FAB system (Functional Assessment of Biomechanics ™, Biosyn Systems, Inc.) on their upper and lower limbs, trunk, pelvis, and head (Fig. 1). Data recorded from the sensors were wirelessly transmitted to a signal receiver and laptop computer placed within the environment. The system was calibrated for 15s with the participant stationary in neutral position (standing upright, head facing forward, feet shoulder width apart, arms by sides, palms inward).

Before the experiment, participant height and weight were entered into the FAB software to calibrate a personalized biomechanical model of the sensor system placed across standard body locations (Fig. 1). In the first part of the experiment, participants performed nine scripted tasks, consisting of specific movements such as walking and turning, sitting and rising from a chair, figure 8 turns, and reaching tasks (TABLE II). Participants unable to complete certain tasks were asked to complete only those with which they felt comfortable. At the end of each recording, time series related to orientation of the 11 sensors were translated to joint angles and joint angular velocities using the biomechanical model by the FAB software.

In the second part of the experiment, the system was recalibrated and participants were instructed to go about their routine household activities while wearing the FAB system. They were also instructed to remain indoors within 40m of the signal receiver to allow for optimum signal reception. Free motion capture occurred for one hour. Also, a miniature video camera clipped to the shirt collar was used to identify the environment in which the individual was moving. Researchers involved with data collection left the premises for the duration of the hour to avoid experimenter bias.

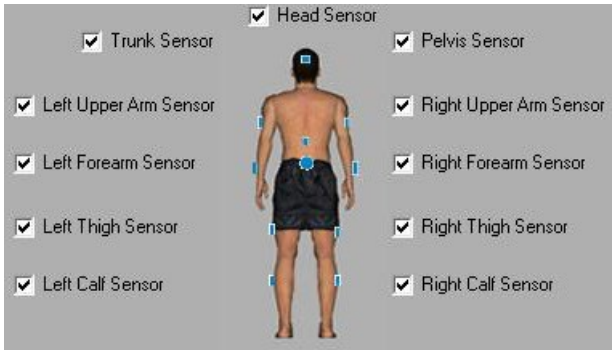

Fig. 1. Placement of 11 sensors on the body limbs, trunk, pelvis, and head (image taken from FAB Recorder software, Biosyn Systems). Head sensor is fixed to a cap worn by the participant. The remaining 10 sensors are held in place by Velcro straps.

C. Data Analysis

Movement of body limbs was recorded at a sampling rate of 100 Hz. Three dimensional accelerations and angular velocities from 11 IMUs were converted to body joint angles and joint angular velocities (Fig. 2 (b) and (c)) using the individualized biomechanical model generated for each participant. For analysis, fifty-nine joint variables provided by FAB software included 10 angular velocities and 48 joint angles (TABLE I). Of these, pelvic heading velocity relative to Earth's magnetic North was extracted based on the initial calibration.

Time segments of each task and trial were manually extracted for analysis by watching the avatar animation time-synchronized with the recorded data.

All joint variables were averaged over 0.5sec bins to capture gross volitional movements less than 2Hz. PCA analysis with the covariance method was applied to the normalized and binned data for each task. Since PCA is amplitude-sensitive, both velocities and angles were separately normalized to the greatest data point in either group, to make the two groups equally important. The covariance matrix was calculated in MATLAB® (R2007b), based on which the scores were ranked by importance. The PCA scores were used to evaluate the relative contribution of individual joint variables to each specific task. A joint variable with higher PCA score had greater contribution to the variance in the data. It was assumed that similar PCA profiles across trials/tasks/participants would indicate reliability among repeated samples.

Inter-trial variability was assessed for both scripted and non-scripted walking (T1) at baseline. Inter-subject variability was assessed for scripted walking. Inter-task variability was assessed using the nine scripted tasks (TABLE II).

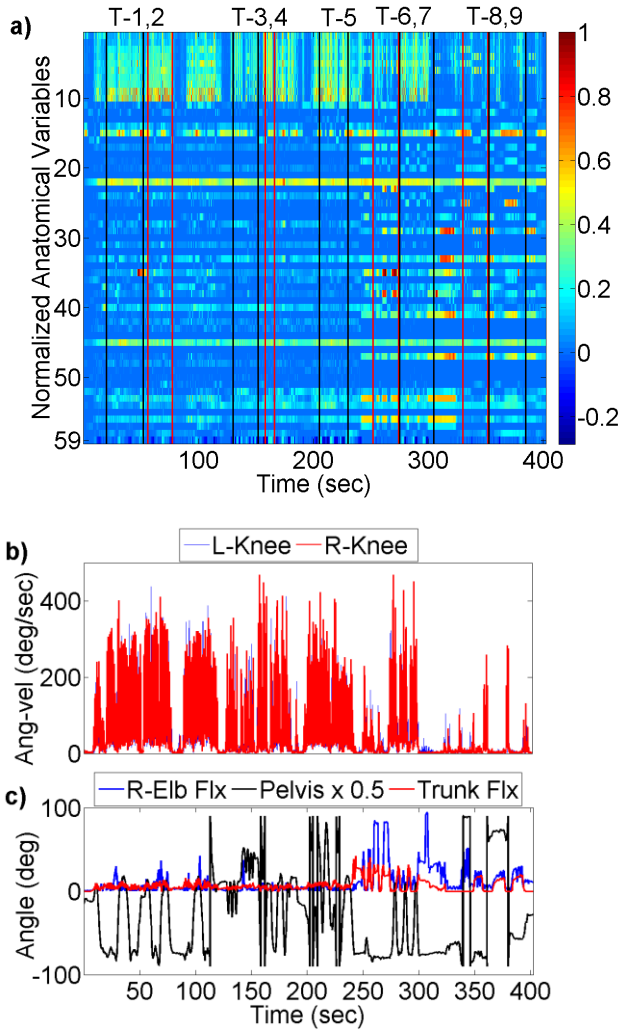

Fig. 2. Participant #11 sample of scripted movement involving 9 tasks (T1-T9, TABLE II). All 59 joint variables were averaged over 0.5 sec bins and normalized to either maximum velocity or maximum angle, (a). Left-right knee velocities as samples of time-domain joint angular velocities, (b). Right elbow flexion, pelvis heading, and trunk flexion as samples of time-domain joint angles, (c).

III. Results

PCA analysis compared across trials for the walking task indicated large inter-trial variability (Fig. 3). This was the case for 10 of 11 participants.

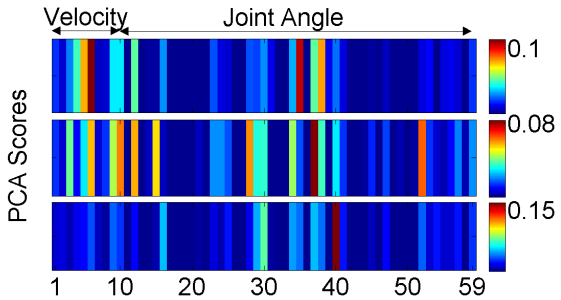

Fig. 3. Typical inter-trial variability demonstrated in scripted walking task for participant #9, prior to medication adjustment. Warmer colors indicate higher PCA scores which represent greater contribution to the variance in the data.

We also report variability between scripted and non-scripted tasks for walking in baseline condition (Fig. 4).

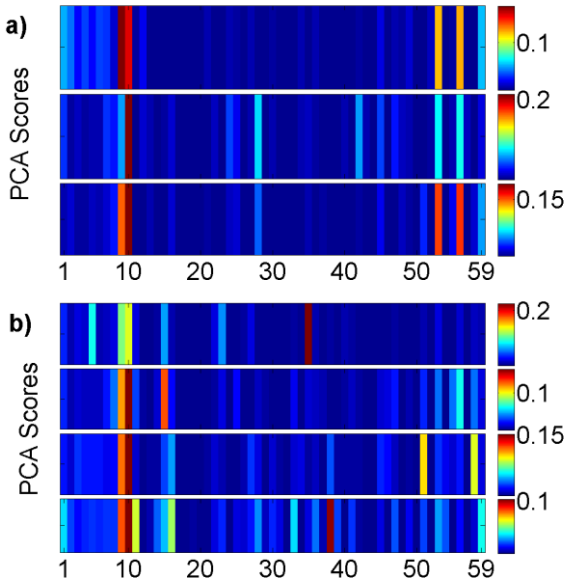

Fig. 4. Even for the participant who demonstrated low inter-trial variability for the scripted walking task (a), inter-trial variability increased for the non-scripted walking task (b). Warmer colors indicate higher PCA scores which represent greater contribution to the variance in the data.

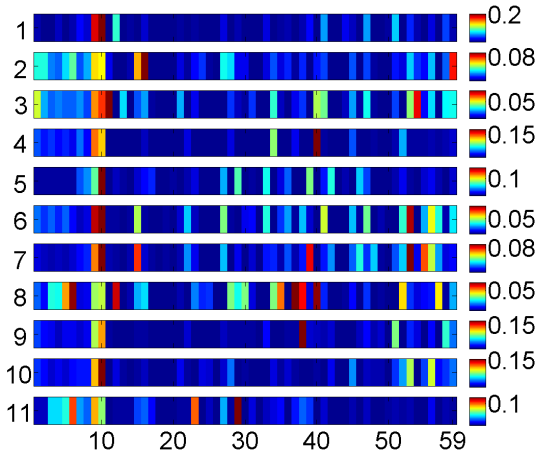

Fig. 5. Inter-subject variability for scripted walking task presented by PCA scores. Warmer colors indicate higher PCA scores which represent greater contribution to the variance in the data. Data presented for 11 participants, three trials of walking each, at baseline (pre-medication intervention).

Inter-subject variability for the scripted walking task is also reported (Fig. 5). Inter-task variability is reported across all participants in nine scripted tasks (Fig. 6).

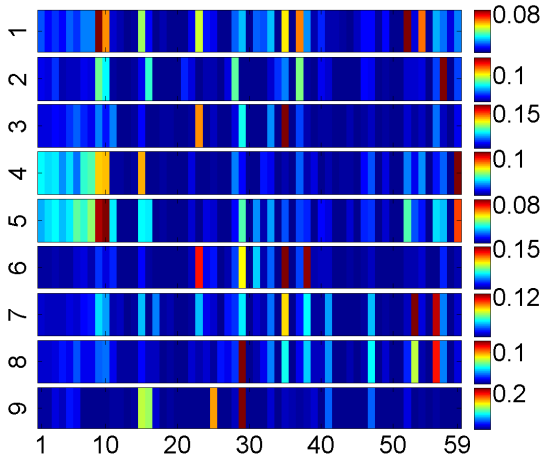

Fig. 6. Typical inter-task variability demonstrated across 9 scripted tasks for Patient#12. Warmer colors indicate higher PCA scores which represent greater contribution to the variance in the data.

IV. Conclusion

While recording from just one or two sensors has proven useful in quantifying certain aspects of mobility for healthy elderly populations, our preliminary results suggest that reducing the number of sensors may lead to loss of potentially relevant information, at least for a PD population. Perhaps the profile of movements in PD patients is more confounded by hypo and hyper kinetic motions across the limbs compared to those in healthy individuals. It can be suggested that in the capture of mobility through natural movements, certain variables associated with disease may be lost if assessed with reduced number of sensors, particularly movements present within the home environment in a population with Parkinson disease.

The data were analyzed to determine possible variability between tasks, between subjects, and between trials. PCA assumes that a linear relationship exists among the variables. While this is by no means demonstrated for the variables used here, PCA provides a reasonable first attempt at identifying movement patterns.

While it is expected that the PCA profile of joint activities varies between tasks, as shown in Fig. 6, a conserved movement profile amongst patients for each separate task was looked for, but was not found. In comparison to standardized movement patterns typical of laboratory settings, monitoring of natural movements requires more sensors to capture those combined limb activities more relevant to everyday life. To examine scripted and non-scripted tasks further, walking was highlighted as the most repeated and distinct movement facilitating this comparison. Even for the patient showing the least inter-task variability for scripted tasks, non-scripted walking demonstrated higher variability (Fig. 4).

In addition, the inter-subject variability seen across participants within the same non-scripted task demonstrates inconsistency expected among patients with PD. Parkinson disease is a condition with a large degree of heterogeneity in

phenotypic presentation. Such variability suggests that sensor reduction should be sparingly and conservatively employed in this population, for personalized mobility assessment.

As demonstrated by the inconsistency of variables identified by PCA, patient movement profiles were not replicated across multiple trials within the same scripted task (Fig. 3,4). This shows that there is, in fact, a wide range of movement patterns adopted by patients with PD, which might not be captured in recordings from only one or two sensors. These differences in movement patterns may reveal important aspects of mobility changes. Common features of the movement patterns may also emerge as more patients are tested. Further studies in this area may provide great benefit to rehabilitation assessment and intervention.

APPENDIX

TABLE I
JOINT MEASUREMENT VARIABLES USED IN THE STUDY

Variable #	Quantity
	Angular Velocity (deg/sec)
1	Cervical
2	Trunk
3-4	Left- Right Shoulder
5-6	Left- Right Elbow
7-8	Left- Right Hip
9-10	Left- Right Knee
	Joint Angle (deg)
11-12	Cervical (Flexion, Extension)
13-14	Cervical Lateral Flexion (Left, Right)
15-16	Cervical Rotation (Left, Right)
17-18	Trunk (Flexion, Extension)
19-20	Trunk Lateral Flexion (Left, Right)
21-22	Trunk Rotation (Left, Right)
23-28	Left Shoulder (Flexion, Extension, Abduction, Adduction, Internal Rotation, External Rotation)
29-34	Right Shoulder (Flexion, Extension, Abduction, Adduction, Internal Rotation, External Rotation)
35-37	Left Elbow (Flexion, Supination, Pronation)
38-40	Right Elbow (Flexion, Supination, Pronation)
41-46	Left Hip (Flexion, Extension, Abduction, Adduction, Internal Rotation, External Rotation)
47-52	Right Hip (Flexion, Extension, Abduction, Adduction, Internal Rotation, External Rotation)
53-55	Left Knee (Flexion, Internal Tibial Rotation, External Tibial Rotation)
56-58	Right Knee (Flexion, Internal Tibial Rotation, External Tibial Rotation)
59	Pelvis Incremental Rotation

TABLE II
DESCRIPTION OF THE SCRIPTED TASKS

Task	Description
T1	Walking in a straight line at a normal speed. Performed over 5m
T2	Walking in a straight line at a fast speed Performed over 5m
T3	90° Rotation on one spot, both sides
T4	180° Rotation on one spot, both sides
T5	Walking at a normal speed and turning around two spots (Figure-8 shape), performed over 5m with pivot points at 1.5 and 3m
T6	Rising out from a standard chair without supporting armrests
T7	Rising out from a standard chair without supporting armrests and walking forwards
T8	Reaching in front and on both sides for object held just beyond reach at chest height
T9	Bending down in front and on both sides for reaching an object held beyond reach on the ground

All the tasks were repeated three times.

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