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Automated Motion Sensor Quantification of Gait and Lower Extremity Bradykinesia*

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Abstract— **The objective was to develop and evaluate algorithms for quantifying gait and lower extremity bradykinesia in patients with Parkinson's disease using kinematic data recorded on a heel-worn motion sensor unit. Subjects were evaluated by three movement disorder neurologists on four domains taken from the Movement Disorders Society Unified Parkinson's Disease Rating Scale while wearing the motion sensor unit. Multiple linear regression models were developed based on the recorded kinematic data and clinician scores and produced outputs highly correlated to clinician scores with an average correlation coefficient of 0.86. The newly developed models have been integrated into a home-based system for monitoring Parkinson's disease motor symptoms.**

I. Introduction

Parkinson's disease (PD) motor manifestations are primarily characterized by tremor, slowed movements (bradykinesia), and rigidity [1]. Additionally, gait and balance disturbances can occur, particularly in patients with advanced PD, which lead to decreased mobility and independence as well as increased fall risk [2], [3].

Accurate assessment of motor symptoms is important to determine treatment efficacy in drug development and therapeutic interventions. The current standard for evaluating motor symptom severities is the Movement Disorders Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS), which rates a range of motor manifestations on a 0 – 4 integer scale corresponding to normal, slight, mild, moderate, and severe [4]. Since these scores are subjective, ratings can vary across clinicians and for an individual clinician at different times [5–8]. Furthermore, MDS-UPDRS score resolution is limited in both amplitude and time, which prevents this scale from adequately capturing symptom fluctuation patterns that may occur throughout the day.

Several systems have aimed to quantify gait in patients with PD; however, most existing systems (e.g. optical tracking) are designed for laboratory use and are too bulky, complex, and expensive for home use. Other systems such as actigraphs focus on monitoring overall activity rather than quantifying specific symptom severities [9–11]. Pressure soles have also been used to quantify abnormal gait; however, an entirely separate system would be needed to assess upper extremity PD motor symptoms [12].

The Kinesia HomeView (KHV) system (Great Lakes NeuroTechnologies Inc., Cleveland, OH) includes a touch-screen tablet computer and finger-worn motion sensor unit (Fig 1A) for guiding patients with PD through an automated motor assessment in their homes. The system includes algorithms that use kinematic data to quantify upper extremity bradykinesia [8], tremor [13], [14], and dyskinesias [15] on a 0 – 4 scale that is highly correlated to clinical ratings. This paper describes the development of novel algorithms for quantifying gait and lower extremity motor function, which, along with a heel clip (Fig 1B), are being added to the KHV system.

II. Methods

Forty-two subjects (31 male and 11 female; age 67 ± 13 years [mean ± SD]; range 40-88 years) with idiopathic Parkinson's disease (PD) meeting research diagnostic criteria [16] were recruited from the Movement Disorders Center of University Hospitals (UH) Neurological Institute (Cleveland, OH). The study was performed in accordance with the Helsinki Declaration (2008) and approved by the UH institutional review board. All subjects provided informed consent prior to their participation. All 42 subjects were on dopaminergic medication during the study and 20 subjects had implanted deep brain stimulation (DBS) systems.

Motion sensor units (KinetiSense, Great Lakes NeuroTechnologies Inc., Cleveland, OH) were placed on each heel, each quadriceps, and the sternum; however, this

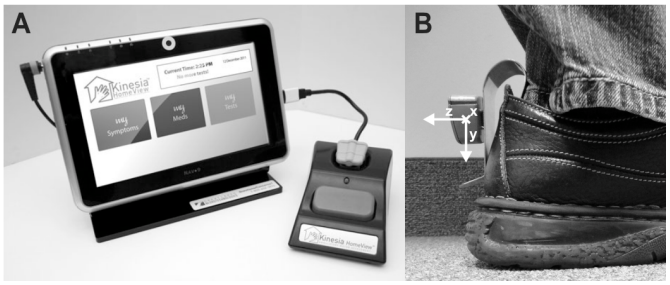

Figure 1. A. The Kinesia HomeView system (Great Lakes NeuroTechnologies Inc., Cleveland, OH) includes a touch-screen tablet computer, a finger-worn motion sensor unit, and docking station. B. The sensor unit can be attached to a heel-clip and used for lower extremity assessments.

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study only examines data collected in each heel motion sensor unit since the Kinesia HomeView system includes only a single motion sensor unit to minimize patient burden. Each KinetiSense motion sensor unit had identical motion sensor specifications to the Kinesia HomeView motion sensor unit, which included three orthogonal accelerometers for measuring linear acceleration along three axes and three orthogonal gyroscopes for measuring angular velocity about each axis (Fig 1B). All data were sampled at 128Hz and transmitted to a computer in real-time via a 2.4 GHz radio.

Subjects were evaluated on four MDS-UPDRS motor assessment items focusing on the lower extremity: toe-tapping, leg agility, gait, and freezing of gait. Toe-tapping was evaluated for each foot and consisted of the subject tapping his/her toes as big and as fast as possible for ten seconds. Leg agility was evaluated for each leg and consisted of the subject raising and lowering his/her foot as high and as fast as possible for ten seconds. Gait and freezing of gait (FOG) were evaluated by having the subject walk 15 feet, turn 180 degrees, and walk back. Data were collected from each non-DBS subject once and each DBS subject twice (once with DBS turned on and once with DBS turned off) to capture a wide range of severities. Kinematic data were recorded via the motion sensor unit while each task was performed, and the subjects were videoed for subsequent clinician scoring. The video scoring was performed by three movement disorder neurologists per MDS-UPDRS guidelines [4]. The scores given by the three clinicians were averaged to minimize scoring variability.

Several quantitative features were extracted from the kinematic data recorded on a single heel sensor unit during each task. For toe-tapping and leg agility, the sensor on the heel being evaluated was used, while for gait and FOG, the motion sensor unit on the left heel was used. The quantitative features chosen were previously found to be highly correlated to clinician UPDRS scores [17], [18] and used as inputs to models for objectively rating symptom severities.

For both toe-tapping and leg agility, data were low-pass filtered at 10Hz using a second order Butterworth filter to remove high-frequency noise. The signals recorded from the gyroscope measuring angular velocity about the x-axis were processed for toe-tapping since toe-tapping produces primarily angular movement about the heel, while the signals recorded from the accelerometer measuring motion along the y-axis were processed for leg agility since the leg agility task produces linear motion of the heel. For toe-tapping, excursion angle was calculated by integrating the angular velocity and high-pass filtering at 0.3 Hz (Butterworth, second order) to remove drift. The logarithm of the root mean square (RMS) of both angular velocity and excursion angle were calculated. The coefficient of variation (CV) of time between toe-taps was calculated from peaks in the angle signal using a threshold at half of the RMS angle. For the leg agility task, linear velocity was calculated by integrating linear acceleration and high-pass filtering at 0.3Hz (Butterworth, second order) to remove drift. Amplitude was calculated by integrating a second time. The logarithm of the RMS of both linear velocity and amplitude were then calculated. The CV of time between leg lifts was calculated from peaks in the linear velocity signal using a threshold at half of the RMS velocity.

For gait and FOG, data collected by the motion sensor unit were low-pass filtered at 5Hz (Butterworth, second order) to remove high-frequency noise. Each forward step was identified by marking the peaks in angular velocity about the x-axis from the leg swing using a threshold of half the RMS angular velocity. For gait, the mean leg swing peak angular velocity, mean leg swing range of motion, and CV of the time between leg swings were calculated from the gyroscope measuring angular velocity about the x-axis and used in the model. For FOG, all of the previous mentioned gait features plus the time it took for the subject to perform the 180-degree turn were used. Turn time was determined by integrating angular velocity recorded on the gyroscope measuring rotation about the y-axis and calculating the time required to rotate the sensor unit between 40 and 150 degrees.

Multiple linear regression models were developed for the four evaluations correlating the quantitative features to the average clinician MDS-UPDRS scores. Each model had the following form:

$$R = b_0 + \sum_{j=1}^{n} B_j P_j \quad (1)$$

where R is the average clinician rating, the n values of Pj are quantitative variables extracted from kinematic data, and b_0 and B_j are regression coefficients. Generalization to new data was evaluated using a "one left out" technique. This meant a single regression was computed using all but one data point. The resulting regression model and coefficients were then used to compute an output score for the data point left out. The analysis was repeated leaving each data point out once. The correlation coefficient and RMS error between the regression model outputs and average clinician scores were computed for all generalization data. This analysis was computed separately for toe-tapping, leg agility, gait, and FOG.

III. Results

Each of the 22 non-DBS subjects completed the motor tasks once, while each of the 20 DBS subjects completed the tasks twice (once with DBS on and once with DBS off). Therefore, each task was performed 62 times. Since the scoring algorithms were designed to function with only a single sensor unit on the heel and separate clinical scores were given for left and right toe-tapping and leg agility tasks, the data were pooled resulting in 124 total toe-tapping and leg agility task scores. Since gait and FOG were scored independent of body side, only the motion sensor unit on the left heel was used, resulting in 62 scores each for gait and FOG.

As described above, quantitative features extracted from the heel motion sensor unit were used to develop models that output 0 – 4 scores. The "one left out" technique evaluated the model's accuracy to predict MDS-UPDRS scores. Figure 2 shows model output scores plotted versus the average

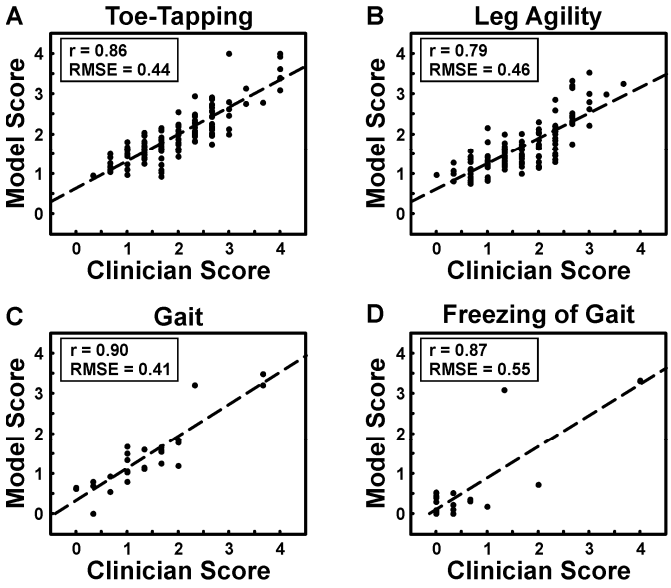

Figure 2. The scored output from the "one left out" models are plotted versus the average clinician MDS-UPDRS scores for (A) toe-tapping, (B) leg agility, (C) gait, and (D) freezing of gait. The correlation coefficient and root-mean-square error between model outputs and average clinician scores are included for each item.

clinician MDS-UPDRS scores along with correlation coefficients and RMS errors. The average correlation coefficient and RMS error were 0.86 and 0.47, respectively.

IV. Discussion

The models for quantifying toe-tapping, leg agility, gait, and FOG using data recorded on a single motion sensor mounted on the heel produced outputs highly correlated to the average of three clinicians' MDS-UPDRS scores. The high correlations were similar to what we had achieved previously for upper extremity bradykinesia [8] and tremor [13], [14]. Although clinical rating scales can suffer from poor inter- and intra-rater reliability, particularly for bradykinesia [8], the MDS-UPDRS remains the gold standard for PD motor assessment. Additionally, outputting scores on a 0 – 4 scale correlated to the MDS-UPDRS improves the likelihood of clinical acceptance since clinicians are quite familiar with the MDS-UPDRS scoring system. However, the models developed in this study output scores on a continuous scale and therefore provide higher resolution than the MDS-UPDRS, which permits only integer scores. One limitation of the current study was the lack of mild to moderate freezing of gait in the study population, which likely contributed to the greater RMS error.

We have previously demonstrated that patients with PD have little trouble using the KHV system in their homes to assess tremor and upper extremity bradykinesia via a single finger-worn motion sensor unit [19]. The new algorithms for assessing gait and lower extremity bradykinesia use a single heel-worn motion sensor unit, which should add little burden to patients. The ability to assess gait in the home has several important implications. Home monitoring of gait could greatly aid in the assessment of DBS and determining an optimal set of DBS stimulation parameters. A major limiting factor with current DBS programming practices is that the time required to achieve a stable motor symptom response following a single change in stimulation settings may exceed the total time of the entire programming session. That is, studies capturing motor symptom severity response after stimulation is turned off showed that while tremor severity may reach baseline within minutes, other Parkinsonian symptoms including bradykinesia need up to an hour and gait three to four hours [20], [21]. Programming sessions in the clinic are typically limited to two hours; therefore, it is not feasible to evaluate a full range of stimulation settings and capture the full motor response following each adjustment. As a result, in-clinic programming may significantly underestimate the full effect of stimulation and set the stimulation amplitude too high. This may cause adverse effects once the patient returns home, such as stimulation of the internal capsule. Additionally, stimulator battery life may be reduced, leading to more frequent battery replacement surgeries and associated surgical risks.

Access to movement disorder specialists for effective gait and balance symptom monitoring and management is critical for a geographically disparate subset of the PD population or those unable to travel. Movement disorder centers are generally located in urban settings, which can limit access to well-trained clinicians and effective symptom management [22]. Rural patients can have a significantly worse quality of life than their urban counterparts [23]. Telehealth technologies such as Kinesia HomeView can have a significant impact on the equity, accessibility, and management of PD for patients who live in rural and remote communities or for those unable to travel [24–27]. The willingness and ability of patients with PD to wear a heel-worn motion sensor unit is an area of future research. Nevertheless, the algorithms developed in this study have been incorporated into the Kinesia HomeView system, which now provides home-based assessment of tremor, upper and lower extremity bradykinesia, dyskinesias, and gait.

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