Validation of a New Model-Free Signal Processing Method for Gait Feature Extraction Using Inertial Measurement Units to Diagnose and Quantify the Severity of Parkinson's Disease

Ali Akbari[1], Richard B. Dewey Jr.[2], Roozbeh Jafari[1]
[1] Embedded Signal Processing Lab, Texas A&M University
[2] Department of Neurology, University of Texas Southwestern Medical Center

***Abstract*—Gait analysis is important in diagnosing and quantifying the severity of Parkinson's disease. Different motion tracking systems such as inertial measurement units (IMU) are widely used to detect gait parameters associated with the severity of Parkinson's disease. Although these systems are accurate enough to measure different gait parameters, they utilize a predefined model of human gait to measure these parameters. Model-based signal processing, that takes into account the kinematics of human body, enforces that sensors be placed in a certain configuration in terms of orientation and location which introduces a burden at the signal processing development phase. In addition, it affects the accuracy and robustness of the system when the user does not place the sensors at their pre-defined locations and with a pre-define orientation. In this paper, we introduce a set of model-free features to estimate gait parameters for the applications of diagnosing and quantifying the severity of Parkinson's disease. A model-free signal processing technique does not limit sensor placement, in addition, it does not require the knowledge on the kinematics of the users and the human subjects. We show that our proposed features, using a model-free signal processing technique, are highly correlated (R-value up to 0.96 for suitable locations) with gait parameters obtained from model-based sophisticated algorithms. Therefore, these simple model-free features may be suitable for ongoing assessment of Parkinson's disease and they can be an alternative for conventional gait parameters used for rapid application development.**

Keywords—Parkinson's disease, IMU, gait parameters, model-free features

I. Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder of the central nervous system with a predilection for dopamine systems early in the disease. About 3% of the population over the age of 65 years suffer from Parkinson's disease [1]. PD is characterized by motor (tremor, limb stiffness, slowing of movement, postural instability) and non-motor (depression, anxiety, apathy, cognitive impairment) clinical features. With disease progression, motor features become increasingly disabling and less treatable non-motor features such as dementia become increasingly problematic.

Quantitative assessment of the severity of PD motor features is important both to inform medication adjustments in routine clinical care and for use as outcome measures in clincial trials. Significant research efforts are now being expended to develop agents which can slow or stop the progression of PD. For these studies, robust, validated measures of disease progression are needed. At present, the most common tool used to measure disease severity is the Movement Disorder Society revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS). It consists of several parts which assess both non-motor and motor symptoms. The scale involves survey questions answered by the patient and examination-based assessments performed by a trained and certified clinician.

The primary limitation of the MDS-UPDRS is that it is intrinsically subjective with significant inter-rater variability in scoring [2]. In addition, it is time consuming to perform and necessitates presentation of patients to a clinic setting where the score can be obtained. Thus, it is not applicable to monitoring patients during their normal daily life at home or at work.

In view of the limitations of clinical scales, efforts have been made to develop objective methods to assess PD severity using motion measurement systems. For instance, camera based motion measurement systems are utilized to measure gait parameters in order to quantify PD severity [3]. These systems are well suited for measuring gait characteristics in terms of accuracy and repeatability, but they are limited to testing in a laboratory setting and can typically be used only to assess short segments of gait. Recent advances in wearable technology have led to the development of inertial measurement units (IMU) which can assess human movement using sensors attached to the body in a variety of different settings [4,5].

IMU is commonly used to measure motion characteristics with the goal to quantify PD severity. An ambulatory monitoring system that used three IMUs to measure the physical activities in patients with Parkinson's disease was previously developed [6]. This system correlated well with UPDRS scores. IMUs have also been used to characterize different gait abnormalities in patients with Parkinson's disease [7]. It has been shown that data mining and artificial intelligence systems may help in recognizing the absence or

presence of PD in addition to quantifying the severity of the disease [8].

Instrumented gait parameters are helpful indicators for discriminating PD from control subjects as well as for quantifying the severity of the disease in PD subjects [9]. However, the main limitation of existing sensor based gait measurement systems is that they utilize model-based signal processing methods to extract gait features from raw sensor data. Leveraging kinematic models, the system identifies certain templates in the signals to detect steps and to calculate parameters like cadence, stride length, stride velocity, range of motion, joint angles, maximum swing velocity, sit to stand and stand to sit transition times, turn time, turn peak velocity, etc. These parameters have shown significant correlation with PD diagnosis and PD severity quantification [1, 6, 9]. Model-based systems that require the knowledge of human kinematics have several limitations. First, sensor locations and orientations must be fixed and known since this method needs to match the signals with particular templates in each axis of motion. If the location or orientation of the sensors changes, the models would need to be adjusted and modified accordingly. Without proper adjustment, incorrect sensor placement results in incorrect computation of gait parameters. Second, in order to compute certain parameters such as stride length, it is necessary to know additional information about the subject such as height.

We previously evaluated gait and balance parameters in PD and control subjects at a single visit using the model-based Mobility Lab (APDM Inc., Portland,OR) system consists of six IMUs [9]. Each subject performed the instrumented Timed-Up-and-Go (iTUG) test using the APDM system and the clinical severity of PD was measured by the MDS-UPDRS. The APDM system includes six movement sensors consisting of 3-axis accelerometer, gyroscope and magnetometer and generates 101 different measurements for the iTUG test. The correlation between ten mostly correlated features of gait and the severity of PD ranged from 0.18 to 0.61.

The goal of the present study is to offer insights into design of a wearable solution using model-free signal processing to assess the severity of PD. We propose a model-free signal processing and feature extraction technique that can realize this goal. Our system does not require any specific placement of the sensors or the subject kinematics information. In other words, this system can generate features alternatively quantify the gait parameters required to assess the severity of PD. In this paper, we first introduce our proposed features and then we characterize correlation between our features and those APDM measurements that are most correlated with the severity of PD.

This technique can also improve wearability of the system by leveraging less number of sensors, while in the model-based approaches reducing the number of the sensors often leads to breaking the kinematic models. In addition, simple and general features used in our proposed technique can be expanded to other applications while using the model-based techniques, redesigning and remodeling is required when a new application and measurement model is present.

II. METHODS

A. Experimental design

Fifty Parkinson patients participated in this study. PD patients were recruited from the Clinical Center for Movement Disorders at UT-Southwestern Medical Center (UTSWMC). The protocol and the consent were approved by the IRB at UTSWMC. Subjects were required to perform iTUG test, wherein subjects are required to stand up from the chair, walk to the line, turn around, walk back, and sit down.

Subjects completed the tests while six sensors of type Opals® (Mobility Lab, APDM Inc., Portland,OR) were attached to their body. Two sensors were placed on the ankles, two sensors were placed on the wrists, one sensor was placed on the waist and one sensor was placed on the trunk. The sampling rate was 128 Hz.

B. Preprocessing

Figure 1 illustrates the block diagram of our signal processing. Gyroscope, accelerometer, and magnetometer signals were used to extract features without considering any model for the gait. Signals were pre-processed before extracting the features. All signals were passed through a low pass filter with a cut-off frequency of 2Hz to remove high frequency noise and then passed through a high pass filter with a cut-off frequency of 0.034 Hz to eliminate the bias and baseline wandering.

The accelerometer measures the Earth's gravity in addition to the acceleration produced by the motions. In order to extract motion features from the acceleration signal, we need to remove the gravity component. To do that, we calculate the orientation of the sensor. Using accelerometer and magnetometer signals in addition to those of the gyroscope, we calculate the orientation and remove the drift. In this study, we used the Madgwick filter to calculate the orientation [10]. When the orientation is calculated, we can rotate the acceleration signal from sensor body coordinates to the global coordinate system. In the global coordinate system, we know that the gravity vector is equal to 9.8 m/s^2 in Z direction, so we can subtract it from the acceleration signal as shown in (1) below:

$$A_g = q \otimes A_b \otimes q^* \qquad (1)$$
$$A_{net,g} = A_g - [0, 0, 9.8]$$

where A_g is the acceleration represented in the global coordinate system, A_b is the acceleration represented in the sensor body coordinate system, q is the orientation of the sensor represented in quaternion form, q^* is the conjugate of q, and $A_{net,g}$ is the acceleration produced by human motion which is calculated by removing the gravity.

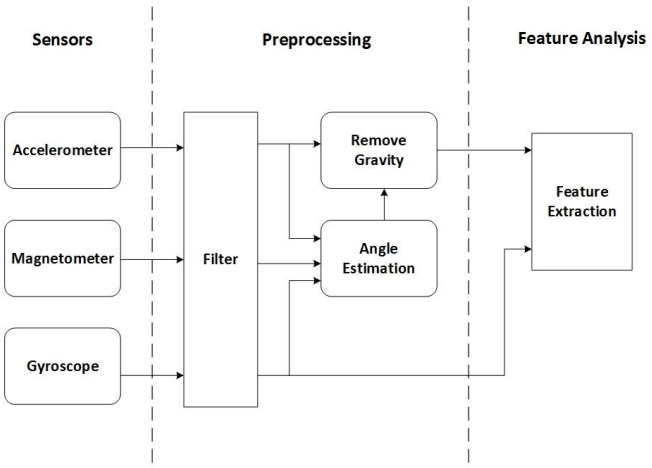

Figure 1 – Block diagram of the signal processing

As highlighted earlier, sensor location and orientation do not impact our feature extraction method. In order to remove the effect of different sensor placements, we summed up the square of three axes of the accelerometer as well as those of the gyroscope, called the total acceleration and the total angular velocity, respectively. We apply all subsequent analyses and processing to the total acceleration and the total angular velocity. In the following section, we will introduce the features extracted from these signals.

C. Features

Human biomechanics studies show that there is a synchronization rhythm between the swinging of the hand and the foot motion during walking [11]. Therefore, each peak in the acceleration signal of the hand could be an indicator for each step in normal walking. Based on this assumption, our first feature is produced by detecting the peaks in total acceleration signal detected from the hand. Figure 2 represents a sample total acceleration signal on the hand and time difference between detected peaks. Similarly, time difference of the peaks were calculated for total angular velocity signal on the ankle. After detecting peaks, we calculate the time difference between every two consecutive peaks. We then calculate the average of time differences between consecutive peaks as a feature.

Some patients suffer from sever rigidity and tremor of the hand. For these patients, hands do not move synchronous to the feet and hence there are no significant peaks in hand's signal. As a result, we could not find those peaks related to each step as shown in Figure 2. For these patients, we used a similar approach of detecting peaks for sensor on the waist instead of sensor on the hand. Detecting peaks associated with gait from the acceleration signal on the waist is a bit more challenging since the amplitude of the fluctuating signal on the waist is lower than the signal of the hand. However, in case that patient's hand does not move synchronous with the feet, using the waist sensor appears to be the next feasible option.

After detecting the average of the time difference between consecutive peaks, we create a window and slide it over the total acceleration and angular velocity signals to extract the features over time. The size of the window is equal to the average of the time difference between consecutive peaks of the acceleration, with overlap equal to a quarter of window size. The size of the window was determined to be 1.2 seconds on average through our experimental study.

The next feature is the mean difference between the maximum and the minimum of the acceleration and angular velocity signals in each window (Figure 3).

Global maximum of the total acceleration and total angular velocity are among other features. In addition, we calculate the absolute integration of the total acceleration and the total angular velocity signals over each window as a feature.

When the subject turns, a large peak occurs in the angular velocity signal on the waist. The amplitude of this peak is much larger than the peaks that are related to the walking. We detect first zero crossing instances before and after this peak and difference between these zero crossing instances is another feature (Figure 4).

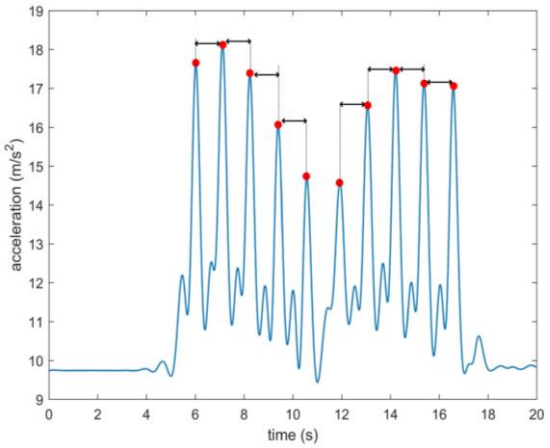

Figure 2 – Sample of total acceleration signal on the hand. Peaks are detected and time difference between every two consecutive peaks is calculated. Each peak is associated with a step.

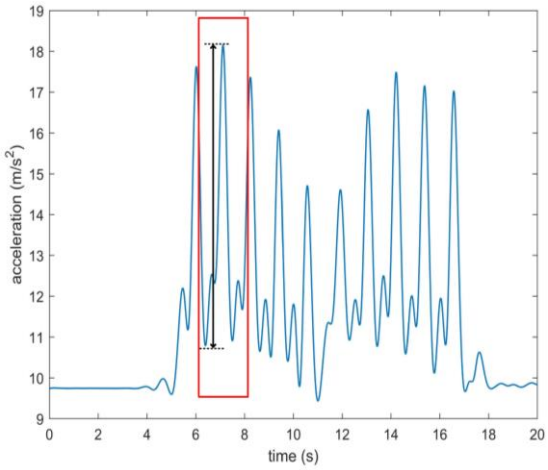

Fig. 3 – A sample window on total acceleration signal and difference between maximum and minimum in the window

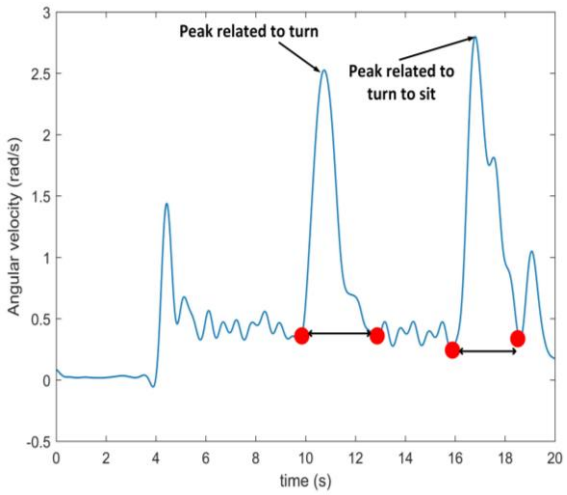

Figure 4 – Total angular velocity of the waist and peaks related to turning instances. Zero instances before and after these peaks are detected and the time differences is considered as a feature.

III. Results

The correlation coefficient (R-value) and p-value between our proposed features using sensors on the hand and the waist, and some gait parameters created by APDM system are illustrated in Table I. The p-value tests the hypothesis of no correlation against the alternative that there is a nonzero correlation. Small p-values, less than 0.05 rejects the hypothesis of no correlation or in other words, shows that there is a significant correlation between two signals.

R-value and p-value between gait cycle time or cadence and features extracted from the upper body, as shown in Table I, sensor showed significant correlation. It indicates that significant peaks produced by the walking, which are detectable using total acceleration of the hand and the waist, are correlated with the walking steps. By using the total acceleration instead of using unique axes of the sensor, we do not need to consider the orientation of the sensor on the body.

Features extracted from hand did not show any significant correlation with the stride length as well as the stride velocity (p-value greater than 0.05). However, the distance between valleys to peaks of the acceleration signal on the waist shows relative correlation with stride length and stride velocity. In order to calculate exact stride length, additional information on subjects like their height would be required; however, current correlation between the features extracted from the waist and the stride velocity or stride length shows that these features could be useful for diagnosing or quantifying the severity of PD.

The correlation between the peak swing velocity and feature extracted from the angular velocity of the hand, as illustrated in Table I, tends to be less obvious since for this parameter, we need to detect stance and swing phases of the gait which was not investigated in this paper.

Range of motion for the arm, peak arm swing velocity and turn peak velocity are among parameters that can be extracted from upper body sensors. The distinction with the ADPM toolset here is that their model-based algorithms use information from sensors on the lower body to detect and separate each stride and then calculate these parameters over each stride. However, Table I shows that our model-free features, without any requirements on the identification of the strides by using gait models, can be a strong alternative for those measurements.

Table II represents correlation coefficient and p-value for our proposed features extracted from the ankle, and gait parameters created by APDM system. We observe that using the sensor on the lower body, the correlation between gait parameters and the proposed feature sets is more significant than the sensor on the upper body. This indicates that using these model-free features to diagnose or quantify the severity of PD, either of the two options offer potential solutions with varying accuracy.

Table II shows that simple model-free features proposed in this study have significant correlation with the values measured by the APDM system. Thus, these simple features can offer an alternative solution for measurements acquired through sophisticated model-based signal processing such as the ones offered through the APDM.

Our model-free features representing peak swing velocity and range of motion of the shank exhibit slightly smaller correlation with those of the APDM tool. That is because for these parameters, detecting swing and stance phases for each stride is very important and since our algorithm does not use any template or models for the gait, we observe larger error in estimating those parameters.

Table I – Correlation between our features extracted from upper body sensors, and APDM gait measurements which are correlated with PD severity

Oure proposed features	**APDM measurements**	**R-value**	**P-value**
Time difference between peaks of acceleration	Gait cycle time	0.90	1.1e-18
	Cadence	- 0.88	2.1e-16
Acceleration peak to valley distance (waist)	Stride velocity	0.57	2.7e-5
	Stride length	0.59	1.94e-5
Maximum angular velocity (waist)	Peak swing velocity	- 0.35	0.01
	Turn peak velocity	0.69	1.2e-8
Maximum angular velocity (hand)	Peak arm swing velocity	0.75	5.9e-11
Acceleration peak to valley distance (hand)	ROM arm	0.70	8.e-9
Difference between zero crossing instances before and after largest peaks	Turn duration	0.73	3.4e-5

Table II – Correlation between our features extracted from sensor on the lower body, and APDM gait measurements which are correlated with PD severity

Oure proposed features	ADPM measurements	R-value	P-value
Time difference between peaks of angular velocity	Gait cycle time	0.95	6.7e-39
	Cadence	- 0.96	3.7e-53
Integration of acceleration signal	Stride velocity	0.86	6.8e-9
	Stride length	0.74	1.1e-5
Maximum angular velocity	Peak swing velocity	0.69	3.2e-8
Integration of angular velocity signal	ROM shank	0.65	7.7e-4

The main difference between our proposed features, and the features created by APDM is that our system, based on model-free signal processing, does not need to know about the sensor placement and the underlying human body kinematics. Our proposed features accelerate application and signal processing development and leads to reduce computational complexity, which is of principal importance in wearable devices with low-power processing units.

IV. Conclusion

A model-free signal processing system is presented in this paper to extract general gait features. These features can be used to diagnose Parkinson's disease as well as to quantify the severity of the disease. Simple and scalable features were extracted without using specific models for the gait or human kinematics, and without reliance on the knowledge of sensor location or orientation. Moreover, this study showed that we can use less number of the sensors, for instance only the sensors on the upper body, to generate some of the desired features. This will improve the wearability of the system. We showed that our proposed features are highly correlated with gait parameters measure by the APDM system. This system and other similar systems which measure gait parameters, require the knowledge on the orientation and the location of the sensors. These signal processing suite need to adjusted or redesign if any changes are applied to the type or configuration of the sensors. Our generic and scalable model-free features on the other hand can offer alternative solution while do not suffer from these limitations. This study validated the feasibility of using model-free features in estimating parameters required to quantify the severity of PD. Designing a system to quantify the severity of PD using proposed features is among the objectives of our future investigations.

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