Multidimensional Mobility Metric for Continuous Gait Monitoring using a Single Accelerometer

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Abstract – *Mobility has been measured in the form of gait analysis – a method used to assess the physical functioning of a human. Many health-related clinical and pathological gait analysis applications have been proposed in the last decades. Gait analysis research has been predominantly conducted in laboratories in a discipline-specific manner. The main measurement approach is to monitor intrinsic gait patterns in natural settings such as home or work. Our proposed mobility assessment approach is to assess gait along three major gait dimensions: intensity, symmetry, and variability. This multidimensional metric uses a single accelerometer to assess the three dimensions so that the gait metric is continuously applied to mimic the natural human gait in daily life. Initial experimental results demonstrate its practical use in different gait patterns with various gait speeds.*

Keywords: Mobility metric, gait metric, accelerometer, continuous monitoring, gait speed

1 Introduction

Mobility in the recent past has predominantly been studied using gait analysis. Gait analysis is used to assess individual conditions that affect a person's ability to walk. Gait research broadly incorporates quantification and interpretation of gait patterns. Gait analysis was initially developed to assess the subtle changes in human gait patterns that were usually not noticeable by the naked eye. Many measurement approaches and technologies such as infrared cameras and pressure sensor platforms have been used to analyze human gait. For example, in typical gait analysis studies, high-speed digital cameras placed around a walkway are used. Several reflexive markers are attached at many different locations of the body to track motions of the body while walking. Another well-known application of human gait analysis focuses on pathology. The pathological gait analysis measures reflect underlying symptoms of diseases such as cerebral palsy and stroke. This analysis can also be applied to rehabilitation engineering, sports training to improve performance, and biometric identification.

In the last decade, gait analysis has become more popular in the general population, particularly because gait is now well known as a fundamental physical activity for maintaining health levels [2]. With the advent of wearable devices such as Fitbit, many researchers are trying to quantify gait patterns outside of laboratories [13]. Continuous gait monitoring using wearable devices enables us to quantify gait parameters using natural gaits. Many of the available wearable sensors try to measure physical activity by using parameters such as duration, number of steps, and energy consumption. The main advantage of wearable devices is better portability for assessment of gait patterns. For instance, measuring the number of steps using a wearable device on the waist or wrist is a popular way to connect gait to better human physical health. Although gait features from wearable devices are able to represent mobility patterns, the information is still insufficient to apply to a comprehensive understanding of human mobility to make useful predictions of activity [7].

A major problem for people who investigate health issues is to continuously monitor gait functioning and to timely interpret the data to prevent loss of gait functional abilities and improve the quality of life [17]. Although proposed wearable sensor-based gait analysis approaches have introduced great portability to assess gait patterns, many of them are discipline-specific. Moreover, the lack of attempts to comprehensively depict gait patterns has been observed [15]. To address this gap, in this paper we propose a comprehensive mobility evaluation metric for continuous gait monitoring using a single wearable sensor. The mobility metric consists of three gait dimensions: symmetry, variability, and intensity.

The rest of the paper is organized as follows. Section 2 introduces the proposed mobility evaluation metric, which uses wearable sensor-based gait recognition and feature extraction techniques. In section 3, we describe a technique to acquire data on the multidimensional components of mobility. In the next section, we report on an experimental study to demonstrate the efficacy of this metric. In the last section, we discuss the experimental results and their implications.

2 Comprehensive Mobility Measurement

Human gait involves complicated sequential commands by neural control of locomotion to the body muscle [5]. As the center of gravity moves forward based on bipedal motion, potential energy is converted to kinetic energy. Maintaining efficient gait requires minimizing this complicated mechanism smoothly [6]. Based on the literature, human gait is generally defined as a bipedal movement with dynamic balance control [1 and 14]. We propose a comprehensive mobility assessment metric for continuous monitoring using a single accelerometer-based system. We conceptualize that the mobility patterns of a person can be described in terms of the three key dimensions described in Table 1.

Table 1. Mobility dimensions.

Dimension	Definition	Functionality
Intensity	Walking dynamism	Locomotive ability to walk
Symmetry	Bilateral gait balance control	Bilateral balance
Variability	Stride-to-stride variation	Natural fluctuation

2.1.1 Intensity

Intensity describes the active locomotion of a person. As opposed to smooth wheel motion, bipedal human movement generates dynamic and cyclic behaviors. We define active locomotion as a degree of dynamic gait. This functioning eventually enables a person to reach an intended location with a certain degree of dynamic locomotion. By considering the activeness of gait, we are able to measure degrees of active locomotion that describe how active the gait is. If we solely consider gait intensity, a higher degree of intensity demonstrates a better ability to actively propel a center of gravity forward.

2.1.2 Symmetry

Symmetry is a dimension that reflects the degree of bilateral balance of gait. Symmetry has been defined as a good balance between the actions of the limbs [3 and 11]. When a person has the capability to locomote between two locations, there will be patterns of locomotion. The bilateral balance of each stride is one of the gait functionalities that represents bilateral balance while walking. Bilateral balance is considered to be an efficacious method to analyze the balance control ability of humans. Gait symmetry includes the effect of limb dominance and different levels of muscle contributions in gait in order to achieve control and propulsion in gait mechanisms [10]. Gait symmetry has been used to understand the risk for falls. When a difference between two successive bilateral gait parameters increases, we can interpret this tendency as a more asymmetric gait pattern in a stride.

2.1.3 Variability

As a person keeps maintaining gait cycles, there will be a natural fluctuation over multiple strides. The intrinsic stride-to-stride fluctuation is natural due to bipedal movement, and it is also an important aspect of human gait characteristics. The gait cycle variation is considered as a signature of individual gait patterns or an indicator of malfunction of balance control. The dimension of variability can then be defined in terms of the stride-to-stride fluctuation in human gait patterns and the natural variations that occur in locomotive performance for multiple gait cycles [8]. Variability in gait is a useful indicator of impaired locomotor control in a clinical study and a parameter in the evaluation of mobile abnormality [4]. The ability to mitigate gait variability within certain criteria is important in order to maintain effective mobility. Generally, increased variability in a movement pattern indicates less cooperative behavior among the components of the underlying control system. Decreased variability generally indicates highly stable and cooperative behavior [12].

3 Measurement of Mobility Dimensions

Each mobility dimension is measured using attributes collected from our wearable sensor system. Because a single accelerometer is used for the wearable measurement, attributes are derived from three-dimensional acceleration to assess gait parameters.

3.1.1 Intensity

The vector magnitude (VM) of 3-D acceleration is used to identify the intensity of gait. Although step time easily represents locomotive capability to get to a destination, measuring time to reach the intended destination is inappropriate for a continuous monitoring design. Instead of time to get to a destination, we propose to directly use the magnitude of acceleration while walking. In particular, by taking the vector magnitude of acceleration, we can measure pure acceleration generated for center of gravity propulsion. A person who generates greater intensity in each gait cycle will tend to have a higher center of gravity propulsion.

3.1.2 Symmetry

The symmetry index (SI) proposed by Robinson et al. is used to assess asymmetry of gait [9]. Using SI, we quantify left and right step time gap as a degree of gait symmetry. Although the symmetry relies on complicated mechanisms from several components of the body, comparing a temporal gait parameter that is the left and right step time of each stride is an effective way of measuring symmetry.

3.1.3 Variability

Stride time fluctuation is used to evaluate gait variability. Since we define gait variability as a natural inconsistency of gait over multiple strides, the natural variation of a temporal gait parameter is efficiently represented by the accelerometer-based sensor system used to measure gait. The standard deviation (SD) of multiple stride times is used to calculate the degree of variability in this study.

4 Mobility Metric Computation

Mobility in terms of the gait metrics proposed in the previous section is measured using a single sensor wearable system. The three-dimensional acceleration measured by the sensor is used to recognize each step and extract associated gait features. Initially, a gait recognition algorithm is applied to determine the initiation timing of each step. Once the algorithm detects gait cycles, gait parameters are extracted from each gait cycle. In order to make this work self-contained, we briefly revisit the technical achievements in our preliminary studies and relevant background information [16].

4.1 Gait Recognition

For accurate gait cycle recognition, the gait recognition technique searches peaks stemming from heel-strike actions. In Figure 1, we observe regular peaks from heel strikes. The actions also substantially change jerk, which is defined as a change in the rate of acceleration as shown in Figure 2.

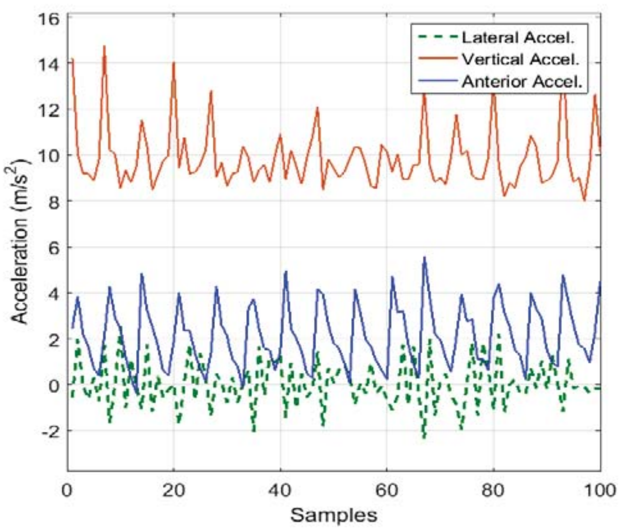

Figure 1. Raw acceleration data.

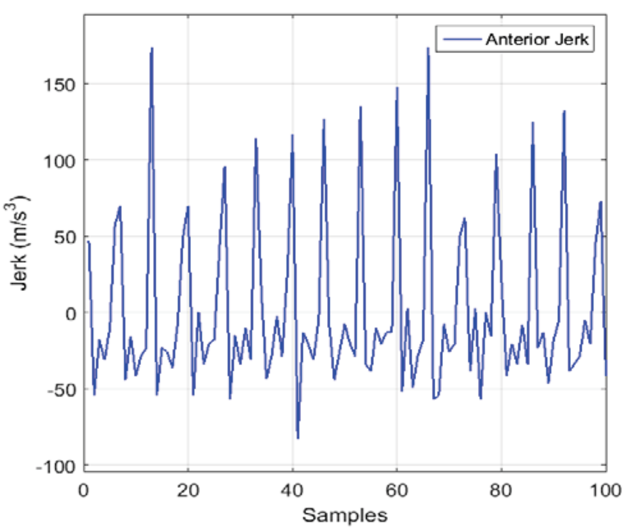

Figure 2. Jerk data from acceleration.

Compared to an acceleration pattern, a jerk pattern shows clear peak moments as shown in Figure 2. In particular, the anteroposterior directional jerk is used to identify each heel strike, rather than other directional jerks. In Figure 3, recognized gait cycles are shown. The vertical dotted lines indicate calculated gait cycles. Horizontal distances of each vertical line as step times are computed at this phase in order to extract gait dimension.

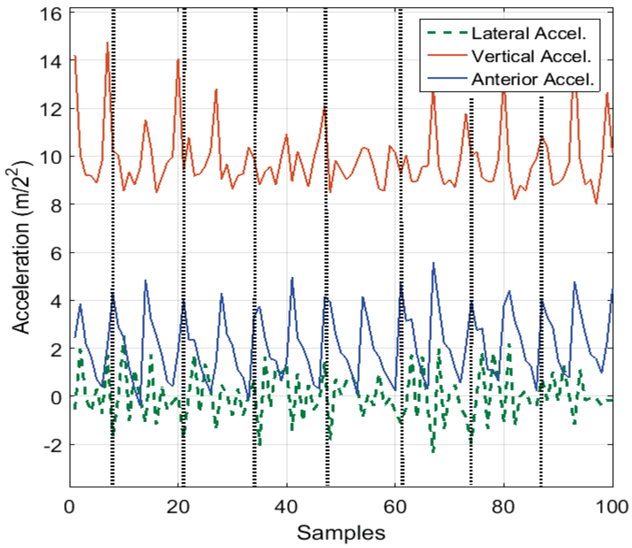

Figure 3. Recognized steps with vertical dotted lines.

Basic gait parameters listed in Table 2 are used to determine gait dimensions in the proposed dimensions for mobility. The gait parameters are directly calculated from raw acceleration data.

Table 2. Basic gait parameters extracted from sensor.

Type	Name	Description
Acceleration	Step acceleration	3-D acceleration of each step
Step time	Step duration	Individual step time
Stride time	Standard deviation	Duration of two successive step times

4.2 Mobility Dimension Extraction

The three mobility dimensions are eventually obtained at the end of the following extraction process. Using mathematical approaches briefly discussed in section 2 regarding gait attributes, the basic gait parameters are translated to associated mobility dimensions using the following equations (refer to Table 3).

Table 3. Attributes of gait metric.

Name	Attribute
Intensity	Vector magnitude of 3-D acceleration
Symmetry	Symmetry index of successive step time
Variability	Standard deviation of stride times

Intensity is defined as an average vector magnitude of 3-D acceleration for each step. Equation 1 below is used to calculate intensity using 3-D step acceleration. Equation 1 is used to calculate the average vector magnitude of each step, where $\boldsymbol{m}$ is the number of acceleration samples in each step and x, y, and z represent each directional acceleration.

$$VM = \frac{1}{m}\sum_{i=1}^{m}\sqrt{\left(x_i^{\ 2} + y_i^{\ 2} + z_i^{\ 2}\right)} \qquad (1)$$

Symmetry is assessed using the symmetry index [Robinson, 1987] as shown in Equation 2. Symmetry of gait is calculated using two consecutive step times, where T_{odd} is the odd number step time and T_{even} is the even number step time.

$$SI = \frac{T_{odd} - T_{even}}{\frac{1}{2}\left(T_{odd} + T_{even}\right)} \times 100 \qquad (2)$$

Finally, variability is computed using recognized stride times. We previously defined gait variability as a standard deviation of stride times. Stride times are entered into Equation 3 to compute the variability of gait. In this equation, T denotes stride time and $\overline{T}$ is the mean of the stride times.

$$SD = \sqrt{\frac{\sum (T - \overline{T})^2}{N - 1}} \qquad (3)$$

5 Experimental Study

We conducted an experimental study using the proposed multidimensional mobility metric. We chose varied walking speeds as an experimental protocol to demonstrate the practical use of the proposed gait metric. Because previous studies found that gait patterns changed when walking speed changed, we hypothesized that the proposed gait metric would reflect previous findings at various walking speeds.

5.1 Protocol

Table 4. Gait speed table.

Gait Speed	Gait Speed Control
Slowest	40 percent slower speed than the preferred
Slower	20 percent slower speed than the preferred
Preferred	Self-determined gait speed
Faster	20 percent faster speed than the preferred
Fastest	40 percent faster speed than the preferred

Twelve healthy subjects volunteered to participate in our experiment. Five male and seven female subjects with ages between 21 and 33 participated in the experiment. Subjects were required to walk a 30-meter long walkway in a building. They wore comfortable shoes for the experiments. Before the data collection, the subjects walked the walkway twice in order to determine their preferred walking speeds. Table IV shows five different gait speeds that were computed from their preferred gait speeds. A single accelerometer was worn at the lower back of the trunk in each subject.

5.2 Results

Using the data collected from our experiment, we analyzed gait acceleration for five different gait speeds. Figure 4 shows the typical acceleration patterns from the slowest, preferred, and fastest gait speeds as an example.

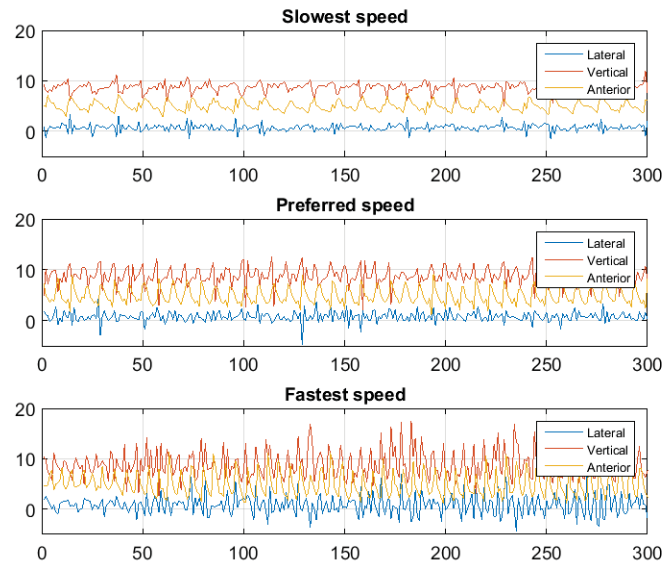

Figure 4. Acceleration from three different gait speeds.

The proposed comprehensive mobility measurement evaluated each gait pattern, Figures 5-7 illustrate these experimental results. As shown, five different gait speeds showed a distinctive status of gait using our proposed metric.

Figure 5 shows the intensity pattern for each gait speed. Intensity highly correlates with gait speeds with clear boundaries between different speeds. For example, the intensity value for the fastest and faster gait speed distributes independently without overlap between them. Figures 6 and 7 show similar patterns along with gait speeds. Typically, both gait dimensions yield the highest values of symmetry and variability at the lowest gait speeds. The results reflect previous findings; slow walking requires more tight dynamic balance control than faster gait, hence a slow gait likely has more inconsistency.

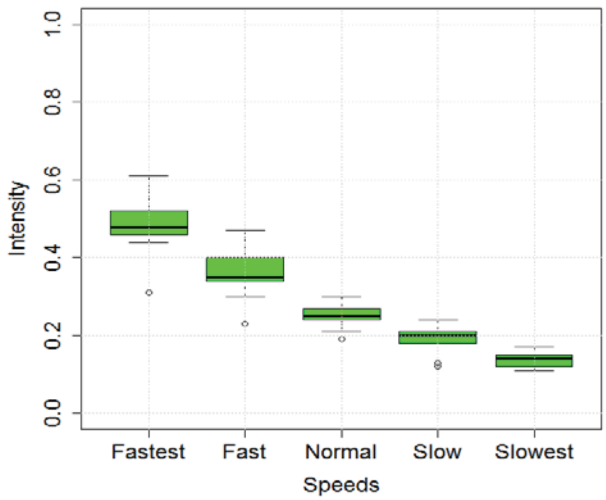

Figure 5. Intensity result for five different gait speeds.

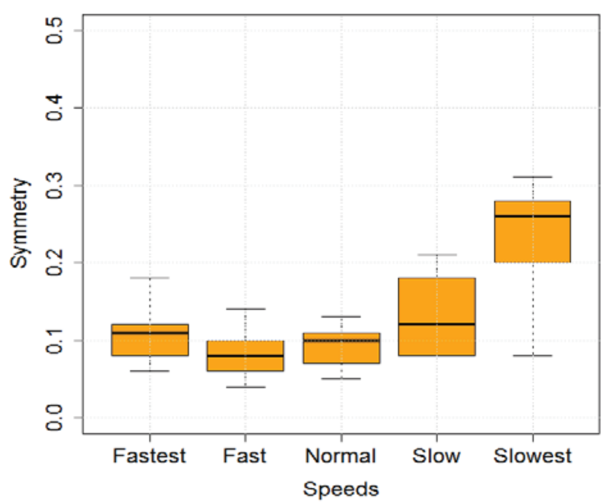

Figure 6. Symmetry result for five different gait speeds.

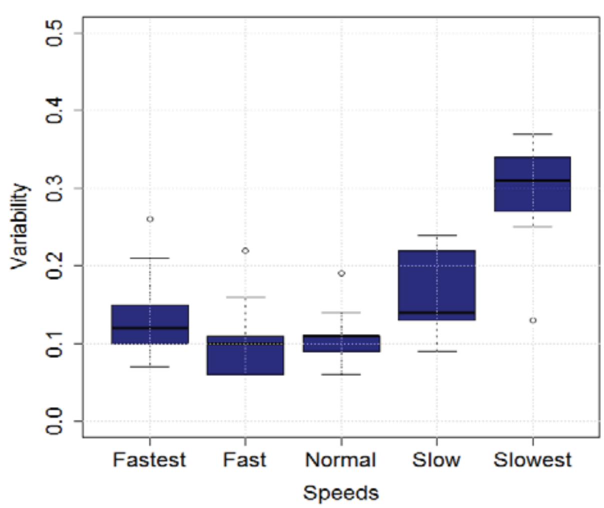

Figure 7. Variability results for five different gait speeds.

6 Conclusion

Gait analysis has attracted a great deal of interest in the domain of clinical and biomechanical research. Gait analysis using wearable devices provides continuous and repeatable results in daily activity with inexpensive cost and convenient portability [13]. However, using basic temporal and spatial gait parameters such as the number of steps, step length, and step duration are insufficient to get informative gait interpretation.

We propose a multidimensional view of mobility that uses a gait metric that includes notions of balance control and gait agility. We conducted an experimental study for various gait speeds using the proposed concept. The results illustrate that different speed gait is efficiently identified using our comprehensive mobility metric. It addresses the inherent spatial limitation of laboratory-based gait analysis. Moreover, the mobility metric can be extended and applied to continuously tracking human gait in daily living and work settings.

We expect that our wearable sensor-based mobility metric can be adopted for long-term mobility monitoring to monitor general gait patterns. As a next step of the study, the multidimensional mobility concept is being applied to a physical activity classification system in order to capture various types of gait in natural setting to assess daily and weekly gait pattern changes.

7 References

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