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# Estimation of spatio-temporal parameters for post-stroke hemiparetic gait using inertial sensors

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ABSTRACT

This paper represents the first step in developing an inertial sensor system that is capable of assessing post-stroke gait in terms of walking speed and temporal gait symmetry. Two inertial sensors were attached at the midpoint of each shank to measure the accelerations and angular velocity during walking. Despite the abnormalities in hemiparetic gait, the angular velocity of most of the testing subjects (12 out of 13) exhibited similar characteristics as those from a healthy population, enabling walking speed estimation and gait event detection based on the pendulum walking model. The results from a standardized 10-meter walk test demonstrated that the IMU-based method has an excellent agreement with the clinically used stopwatch method. The gait symmetry results were comparable with previous studies. The gait segmentation failed when the angular velocity deviates significantly from the healthy groups' profile. With further development and concurrent validations, the inertial sensor-based system may eventually become a useful tool for continually monitoring spatio-temporal gait parameters post stroke in a natural environment.



## 1. Introduction

Stroke is a leading cause of adult disability in western countries [1]. According to World Health Organization estimates, 15 million people suffer from stroke each year, of which 5 million are permanently disabled [2]. Since gait impairments and mobility disorders can negatively impact independence, regaining community-based ambulatory mobility has been identified as a major rehabilitation goal for many stroke survivors [3]. Walking speed and gait symmetry have been widely used to evaluate post-stroke gait [4,5]. Self-selected walking speed has long been recognized as a proxy measure of ambulation quality and is used to quantify the progress of gait rehabilitation [6,7]. A widely accepted clinical assessment of short distance walking speed is the standardized 10-meter walk test (10 MWT) [8,9], which makes use of a stopwatch and the results reflect general physical function. On the other hand, temporal gait symmetry has been found as a significant predictor of hemiparetic walking performance and motor recovery [10,11]. Instrumented walkways (*e.g.*, the GAITRite system, CIR Systems Inc., NJ, USA), are commonly used to determine the temporal gait parameters, such as swing time and stance time of the paretic and nonparetic legs [12,11]. A limitation is that these systems are not typically available in clinical settings due to their size and cost. An inexpensive and easy-to-use system capable of assessing walking speed and gait symmetry simultaneously in a natural environment could be a cost-effective means for monitoring recovery during post-stroke rehabilitation.

Previous studies have demonstrated that miniature inertial sensors are well suited to evaluate the spatio-temporal parameters of human gait in activities of daily living. Inertial sensor based walking speed estimation methods have been developed and validated for healthy gait in the past several years [13–15]. Inertial sensors with more sophisticated strapdown algorithms have been developed for personal navigation applications as a potential alternative to the GPS system [16,17]. With the aid of the zero velocity update and Kalman filter, these systems were able to estimate the location of a pedestrian in a 3D indoor or outdoor environment [16,17]. Despite the progress in healthy gait and personal navigation, the use of inertial sensors in post-stroke hemiparetic gait analysis is mostly limited to the detection of gait events or counting steps [18,19].

Recently, triaxial ankle accelerometers combined with a machine learning algorithm have been used to recognize gait events and estimate walking speed in stroke survivors [20]. A limitation of this method is that subject-specific calibration using data collected from known distance walking at three different speeds over a known distance is required. The calibration

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procedure is often performed in a clinical setting, which limits its generalizability to daily living environments. The objective of this study is to develop and evaluate an inertial sensor-based system that is capable of estimating walking speed and simultaneously evaluating gait symmetry for stroke survivors without the need of pre-calibration.

## 2. Methods

### 2.1. Apparatus

The Inertia-Link (MicroStrain, Inc., Williston, VT, USA) is an IMU sensor that consists of a triaxial accelerometer ($\pm 5$ g, where $g$ is the gravitational acceleration) and a triaxial gyroscope ($\pm 600^{\circ}$/s). Only two accelerometer axes and one gyroscope axis were used since we focused on the motion in the plane of progression (*i.e.*, sagittal plane). The accelerations and angular velocity data were collected at 100 Hz wirelessly.

### 2.2. Sensor configuration

Two IMU sensors were attached to the midpoint of each shank on the lateral side using athletic tape (Fig. 1). Before each experiment, subjects were asked to stand still with the shank vertical (longitudinal axis perpendicular to the floor) and the IMUs were adjusted such that the normal and tangential axes were aligned to vertical and horizontal directions of the global coordinate system, respectively.

### 2.3. Signal conditioning

Signal processing was performed using MATLAB (The MathWorks, Natick, MA, USA). In the gait event detection algorithm for the gait symmetry evaluation, a second-order Butterworth low-pass filter with a cut-off frequency of 10 Hz was used to remove noise from the raw angular velocity and acceleration measurements. For the gait segmentation, a second-order Butterworth low-pass filter with a cut-off frequency of 2.3 Hz was applied to the gyroscope signals.

### 2.4. Walking speed estimation

For each inertial sensor, the gait segmentation algorithm was implemented to divide a walking sequence into a series of stride cycles, and the average walking speed for each stride cycle was calculated for the paretic and non-paretic leg separately. The starting point of each stride cycle was defined as the shank vertical event, when the longitudinal direction of the shank was parallel to the direction of gravity. This specific gait event has been determined from the characteristics of the shank angular velocity (Fig. 2(a)) for healthy subjects [14]. Despite the differences in amplitude, the major characteristics (shape and peaks) of the angular velocities for both the paretic and non-paretic legs resemble the pattern of those of a healthy subject, as shown in Fig. 2(a) and (b). The similarity in features in the angular velocity profile enables the use of a single procedure segmentation of the gait cycle. The instantaneous shank velocities were calculated through direct time integration of the global coordinate accelerations, and then the walking speed was calculated for the corresponding stride cycle [14]. The use of gait segmentation did reduce the speed estimation error. However, further experiments identified that this method consistently underestimated walking speed [14]. To deal with this issue, an off-line linear regression-based calibration procedure was developed to correct the speed estimation error [15].

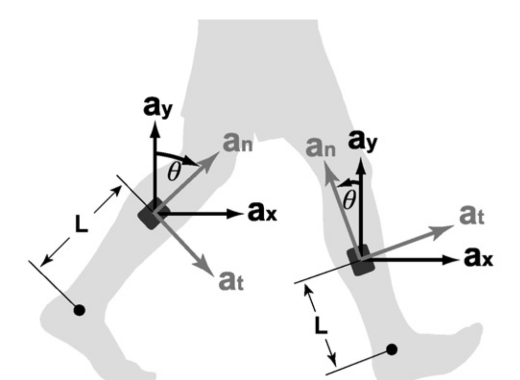


**Fig. 1.** Sensor configuration. An IMU is attached to the shank in the sagittal plane on the lateral side. Since only the shank motion in sagittal plane was considered in the method, the normal acceleration $a_n$ is measured along the $n$ direction, the tangential acceleration $a_t$ is measured along the $t$ direction, and the axis of the gyroscope is perpendicular to the sagittal plane defined by $n$ and $t$ directions. The arrows indicate positive axes for the corresponding sensor measurements. L is the sensor-to-ankle distance. The world coordinate system is defined by the $x$ and $y$ axes, and the vertical axis $y$ extends in a direction parallel to gravity.

To eliminate the requirement of an off-line calibration, two new strategies were introduced to compensate the systematic error of speed under-estimation. First, the initial sensor velocity at the beginning of each stride cycle was taken into consideration. At the shank vertical event, although the shank angular velocity is minimal, it is not exactly zero (Fig. 2(b)). At the shank vertical event (when $\theta(0) = 0$), the initial sensor velocity is calculated as the product of the rotation radius and the rotation angular velocity,

$$v_t(0) = \omega(0) \cdot L \tag{1}$$

$$\begin{bmatrix} v_x(0) \\ v_y(0) \end{bmatrix} = \begin{bmatrix} \cos\theta(0) \\ -\sin\theta(0) \end{bmatrix} \cdot v_t(0) = \begin{bmatrix} v_t(0) \\ 0 \end{bmatrix}, \tag{2}$$

where $v_t(0)$ is the initial sensor velocity tangential to the shank. $v_x(0)$ and $v_y(0)$ are the initial sensor horizontal and vertical velocities in the global coordinate system, respectively. $L$ is the distance from the sensor to the ankle joint (Lateral malleolus), which is approximately half of the total shank length (Fig. 1). These initial conditions, $v_x(0)$ and $v_y(0)$, are added to the calculation of instantaneous sensor velocities,

$$\begin{aligned} v'_x(t) &= \int_0^t a_x(\tau)d\tau + v_x(0) \\ v'_y(t) &= \int_0^t a_y(\tau)d\tau + v_y(0), \end{aligned} \tag{3}$$

where $v'_x(t)$ and $v'_y(t)$ are the instantaneous horizontal and vertical velocities obtained from integrating the sensor accelerations. $a_x$ and $a_y$ are the horizontal and vertical accelerations in the global coordinate system, transformed from the sensor accelerations, $a_t$ and $a_n$ (Fig. 1).

Second, the shank angular velocity measurements at the end of a stride cycle were used to correct the walking speed estimation error caused by the acceleration bias. The accelerometer measurement bias is inevitable for low-cost IMU sensors [21], and the direct consequence is velocity drift, resulting from the integration of biased acceleration data over a period of time. To determine the constant accelerometer bias, it requires a known reference velocity at the end of the stride cycle, calculated as the product of angular velocity, $\omega(T)$ and the rotation radius, $L$,

$$\begin{aligned} v_{xref}(T) &= \omega(T) \cdot L \\ v_{yref}(T) &= 0. \end{aligned} \tag{4}$$

Here we considered using the CABCS model [22], where the sensor error was modeled as a constant acceleration bias in the sensor coordinate system. By comparing these reference velocities with the sensor velocities calculated from integrating accelerations (Eq. (3)), the accelerometer biases in their sensitivity axes, $a_{tbias}$ and $a_{nbias}$, were estimated. A detailed description can be found in Yang et al. [22].

With the estimated constant accelerometer bias, the velocity drifts were determined in a manner similar to the procedure shown in Eq. (3),

$$\begin{aligned} v_{xbias}(t) &= \int_0^t a_{xbias}(\tau)d\tau \\ v_{ybias}(t) &= \int_0^t a_{ybias}(\tau)d\tau, \end{aligned} \tag{5}$$

where $v_{xbias}(t)$ and $v_{ybias}(t)$ are the instantaneous horizontal and vertical velocity drifts due to the accelerometer measurement bias. $a_{xbias}$ and $a_{ybias}$ are the calculated horizontal and vertical acceleration bias in the global coordinate system, transformed from the accelerometer bias, $a_{tbias}$ and $a_{nbias}$.

The corrected instantaneous velocities were calculated by removing the velocity drifts from the original instantaneous velocities of (Eq. (3)),

$$\begin{aligned} v_x(t) &= v'_x(t) - v_{xbias} \\ v_y(t) &= v'_y(t) - v_{ybias}, \end{aligned} \tag{6}$$

where $v_x(t)$ and $v_y(t)$ are the corrected instantaneous sensor horizontal and vertical velocities in global coordinate system, respectively.

After calculating the corrected instantaneous sensor velocities through Eqs. (1)–(6), the average velocities in the horizontal and vertical direction were calculated over a given stride cycle as

$$\begin{aligned} \overline{v}_x &= \frac{1}{T} \cdot \int_0^T v_x(t)dt \\ \overline{v}_y &= \frac{1}{T} \cdot \int_0^T v_y(t)dt, \end{aligned} \tag{7}$$

where $\overline{v}_x$ and $\overline{v}_y$ are the average horizontal and vertical velocities over the corresponding stride cycle in (0, $T$], as defined by gait segmentation.

The walking speed over the stride was then calculated as $\overline{v} = \sqrt{\overline{v}_x^2 + \overline{v}_y^2}$. This calculation helped to reduce the walking speed estimation errors resulted from minor misalignment of the accelerometer normal and tangential axes with the shank longitudinal and fore-aft directions. Using the walking speed per stride $\overline{v}$, the