A Novel Technique for Gait Analysis using Two Waist Mounted Gyroscopes

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***Abstract*—Analysis of the human gait is used in many applications such as medicine, sports, indoor localization, and person identification. Several research studies focus on the use of MEMS inertial sensors for gait analysis and have shown promising results. Step detection and step length estimation are two basic and important gait analysis tasks. Although researchers have proposed many methods for step detection, all of them rely on experimental thresholds selected based on a limited number of subjects and walking conditions. Also, most of these methods do not distinguish walking from other activities; they can only recognize motion state from an idle state. On the other hand, step length estimation methods used in the literature either need constant calibration for each user, rely on impractical sensor placement, or both. In this paper, the human walking bipedal nature is employed for gait analysis using two waist mounted MEMS gyroscopes. This setup allows the step detection and discrimination from other non-bipedal activities without the need for magnitude thresholds. The hip rotation angle in the sagittal plane is also calculated that allowed us to estimate the step length without needing for constants calibration. By mounting an accelerometer on the center of the back of the waist, an auto-calibration method for the Weinberg equation's constant is developed. This method also improves the accuracy of the Weinberg equation for step length estimation.**

I. Introduction

Gait analysis is the identification, measurement, and evaluation of walking-related parameters. The analysis of the human gait can be used in a broad range of applications including sports, medical, and person identification applications. Step detection and step length estimation are two of the most important tasks of gait analysis. In fact, step detection is a prerequisite for the analysis of the other gait parameters including step length. The step length is strongly connected to the other gait parameters, as it is a final output of the muscles and joint activities during walking.

Several methods are used for gait analysis including clinical examination by a specialist, image processing, and floor sensors [1]. These methods need special setup and cannot be used for long-term analysis. Another method that does not suffer from these problems is the analysis of gait using wearable sensor systems. Wearable systems have brought the convenience of real-time gait analysis outside of laboratory conditions for a long-term, which can provide more useful information about persons' daily life, and have also enabled the use of gait analysis in new applications such as indoor localization. Wearable systems can still be used in laboratories as well, with the advantage of a lower cost analysis than the methods that require special setup.

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Microelectromechanical Systems (MEMS) technology enabled the miniaturization of inertial sensors including accelerometers and gyroscopes so they can be used in wearable systems. An accelerometer is a device used to measure linear acceleration and a gyroscope is a device used to measure angular velocity. MEMS inertial sensors became widely used in wearable systems for gait analysis due to their small size, lightweight, low cost, and low power consumption.

Researchers have proposed many methods for step detection with more than 99% accuracy in some cases [2]. All of these methods rely on experimental thresholds selected based on a limited number of subjects and walking conditions. Selecting and verifying an optimal threshold is a difficult task since it will vary according to a lot of factors such as users, footwear and the walking surface material [3]. Also, most of these methods do not distinguish walking from other activities, they can only recognize motion state from idle state [4]. The methods that can be used to distinguish walking from other activities, such as in [5], are based on machine learning techniques that need training and complex data labeling. On the other hand, step length estimation methods used in the literature either need calibration of constants for each user, rely on impractical sensor placement or both.

In this paper, a setup of two gyroscopes mounted on the lower left and right sides of the waist is used instead of a single inertial sensor for step detection and step length estimation. One of the gyroscopes is mounted as close as possible to the right upper hip bone while the other to the left upper hip bone. This setup provides data about the angular motion of the hips during walking and a fixed pattern between the two of them that can be exploited for step detection. This pattern is used to distinguish walking from other non-bipedal activities and reduces the rate of false steps detected without using magnitude thresholds. Using this setup, the hip rotation angle in the sagittal plane is also estimated and used to estimate the step length using only the effective leg length without using constants that need to be calibrated. The hip rotation angle is used with the vertical displacement of the body during walking to auto-calibrate the constant of the Weinberg step length estimation method that increases its accuracy and practicality. The body center-of-mass (CoM) vertical displacement during walking is estimated using a classical method by placing an accelerometer on the back center of the waist.

II. Background and Related works

Before estimating the step length, we need first to detect the step itself. We begin by reviewing some of the step detection methods, and then we review some of the step length estimation

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methods. Any step detection method can be paired with any step length estimation method as a part of a complete system.

A. Step Detection Methods

All of the step detection techniques that we have found in the literature use thresholds selected based on limited datasets and walking conditions to eliminate false positives. These thresholds can be magnitude thresholds or distance thresholds used to measure the similarity between waveforms.

The scheme in [6] searches for peaks and valleys in the waveform of the magnitude of 3-axis accelerometer, and to reduce false positives, thresholds are used to eliminate peaks which are too small in magnitude or time duration. The algorithm then makes use of the walking repetitive pattern to reduce false positive furthermore by calculating the dynamic time warping (DTW) distance between successive candidate steps and count them only if the distance is less than a given threshold.

In [2], the user's state is considered idle if the standard deviation of acceleration is less than a given threshold, otherwise the algorithm computes the signal auto-correlation for each lag within a predefined range, if the maximum auto-correlation is greater than a predefined threshold then the user state is considered walking and the period of walking is divided by the calculated step duration to count the number of steps.

The work in [7] detects steps by tracking the zero-crossings from negative to positive of the gyroscope data. To avoid false positives, a timeout for zero crossing detection and a calibrated threshold based on the slowest walk of each user are used.

These techniques do not distinguish walking from other activities that have the same frequency [4]. The authors of [5] have proposed a technique based on Adaptive Boosting machine learning algorithm to recognize walking from other activities as well as different types of walking like walking forward, backward, sidestepping, and stairs climbing. The algorithm uses 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer. The problem with this method is the need for complex training and data labeling for each activity.

B. Step Length Estimation Methods

The IMU sensors can suffer from different types of errors; one significant problem is the offset of the sensor signal known as the bias error. A common way to reduce the bias error is to calculate the average of the sensor's data values over a period of time in idle state and then subtract the calculated average from the data. However, this is not an easy task especially with accelerometer sensor since its vertical axis is affected by the gravity acceleration and the exact orientation of the sensor has to be known in order to determine the gravity acceleration component at each axis and calculate the bias that is independent of the sensor orientation. Moreover, this bias can change over time [8]. Due to the accelerometer bias, double integration of the forward accelerometer data cannot be used to obtain the walked distance since bias errors accumulate over time and lead to a quadratic drift from actual distance. Methods to estimate each individual step length are used to avoid error propagation over the entire traveled distance and hence reduce the drift error.

One method used for step length estimation is to restart the integration of a foot-mounted accelerometer at each foot stance where the foot velocity is known to be zero [9], this method is known as zero velocity update (ZUPT). The accelerometer data are first transformed from sensor frame to world frame using the rotation matrix obtained from the gyroscope data integration, and then the transformed accelerations are integrated to get the velocities between each two successive foot stances. The error in velocity is then estimated by calculating the mean velocity around the second stance event and then it's used to correct all velocities obtained in the entire step using weighted linear interpolation, then the velocities are integrated to get the step length. The main challenges of this method include extensive computations and non-practicality of mounting the sensor on the foot.

In [10], a gyroscope is mounted around the shank and the swing leg angle θ is obtained by direct integration of the gyroscope data in the sagittal plane for each step. The estimated step length is given by:

$$Step\ Length = 2\sin(\theta/2)$$

However, this method underestimates the step lengths for large steps, and needs calibration using a least squares fit between the calculated step lengths and the true step lengths.

Mounting the sensor on the waist is more practical and less intrusive than the foot and the shank. Multiple methods to calculate the step length by a sensor mounted on the waist are proposed in the literature. Walking steps can be modeled as an inverted pendulum, where the body rotates over the foot in contact with the ground [11]. Authors of [12] estimate the vertical displacement h of the hips resulting from the walking inverted pendulum model by double integrating the data of an accelerometer placed on the dorsal side of the trunk, and then they calculate the step length estimation using the following geometric relation:

$$Step\ Length = 2\sqrt{2lh - h^2}$$

where l is the effective leg length measured from the sensor to the ground. This method significantly underestimates the step length and has to be calibrated. The calibration can be done by multiplying the equation by a calibration constant.

An extended model divides the step into two phases, single support and double support [13], where the step length part of the single support is estimated using the inverted pendulum model mentioned above without a calibration constant and the step length part of the double support is proportional to the foot size and then the step length is estimated by:

$$Step\ Length = 2\sqrt{2lh - h^2} + k \times F$$

where F is the foot size and k is a constant that needs to be calibrated for each user. Instead of double integrating the vertical accelerometer data, the following approximation equation, known as Weinberg method, is used in [14]:

$$Step\ length = k\sqrt[4]{(amax - amin)}$$

where $amax$ is the maximum vertical acceleration value during a single step, $amin$ is the minimum vertical acceleration value during the same step, and k is constant and need to be calibrated, this method is simple and does not need a lot of computations but needs to be calibrated for each user. Another method for step length estimation is based on the relationship between the step length and the step frequency [6]:

$$Step\ length = a \times f + b$$

where f is the step frequency, a and b are constants that have to be calibrated for each user.

III. System Architecture

A. System Overview

Our main gait analysis system components are depicted in Fig. 1. The system is based on two gyroscopes mounted on the lower waist using a belt, one gyroscope on the right side and the other on the left side. Data are collected from the gyroscopes over Bluetooth with a sampling rate of 50 samples/sec by the Data Collection module, and then filtered using a Moving Average Filter as a preprocessing for the Step Detection module. If a step is detected, its information is fetched along with the corresponding raw data by the Step Length Estimation module. The Step Length Estimation module can be paired with the vertical acceleration data collected from an accelerometer mounted on the center of the back of the belt near the CoM to auto-calibrate the constant of the Weinberg equation.

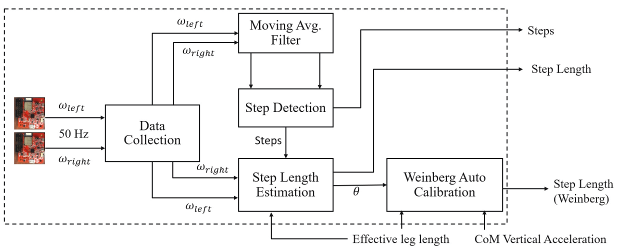

Fig. 1. Walking inverted pendulum model

B. Hardware

We use InvenSense CA-SDK board, which provides a Motion Processing Unit (MPU-9250), a Bluetooth module for wireless connectivity, and an MSP430 Microcontroller unit that provides an interface with the MPU-9250. The MPU-9250 combines a 3-axis gyroscope, 3-axis accelerometer and a 3-axis magnetometer in a small $3 \times 3 \times 1\ mm$ quad-flat no-leads (QFN) package. The gyroscope has a programmable full-scale range of $\pm$250, $\pm$500,$\pm$1000 and $\pm 2000°/sec$, an operating current of $3.2mA$ and a sleep mode current of $8\mu A$. The accelerometer has a programmable full-scale range of $\pm 2g$, $\pm 4g$, $\pm 8g$ and $\pm 16g$, an operating current of $450\mu A$ and a sleep mode current of $8\mu A$. In our algorithms and experiments, the lowest scale range of both the accelerometer and gyroscope is used.

C. Data Collection

Data are collected from the gyroscope axis perpendicular on the plane that divides the body into left and right parts (sagittal plane). The data are collected over Bluetooth and processed by a laptop. The MPU-9250 sampling rate is 50Hz. Although the programmability of the CA-SDK board allows the extraction of the timestamp, we do not use the board's timestamp for synchronization because of the clock drift. An alternative approach is to timestamp the data at the receiving device (laptop). The synchronization can be easily verified by attaching the boards to each other and move them randomly for a period of time then plot the signals to see whether they match each other or not.

D. Sensors Placements

Mounting the sensors on the waist offers ease of wearability since it can be done by the mean of a belt which can also facilitate the addition of more sensors. The hip can provide useful gait information because it represents the inverted pendulum mass in the stance phase and the point around which the leg rotates in the swing phase. In fact, forward progression cannot happen without the hip flexion [15]. To find the balance between wearability and accuracy, we attach the sensors to a Velcro belt using Velcro patches and position them as close as possible to the upper right and left hip bones. The sensors are positioned with the same orientation. Fig. 2 shows the placement of the right side sensor.

Fig. 2. Right sensor placement

IV. Step Detection

A. Step Detection Algorithm

Our algorithm is based on the detection of the swing phase. A peak detection technique is used, where the peak corresponds to the mid-swing. Instead of rejecting false steps using a magnitude threshold, the pattern that exists between the rotations of the two hips and the repetition of this pattern across subsequent steps are employed.

During the swing phase, the hip rotates in the sagittal plane towards the trunk; this rotation is called hip flexion. On the other hand, during the stance phase, the hip rotates apart from the trunk in the sagittal plane; this is called hip extension. Since the swing phase of a foot happens during the single support period while the other foot is in its stance phase, the angular motion of a hip during its swing phase will be in the opposite direction of the angular motion of the other hip. This pattern of opposite directions can be captured by our gyroscopes' setup. Consequently, we should expect that gyroscope data corresponding to the swinging foot be $+ve$ since the hip is rotating counterclockwise. Similarly, the gyroscope data corresponding to the stance foot should be $-ve$ since the hip is rotating clockwise in the stance phase. After several walking trials, we observed that sometimes the stance leg gyroscope produces $+ve$ fluctuations in the early stance phase, and the pattern of opposite signs always hold starting from the mid-stance point as illustrated in Fig. 3. Since the swing leg is modeled as a pendulum, where the mid-stance is the equilibrium position, the mid-stance point can be identified as the point with the maximum angular velocity ($+ve$ peak) of the swing leg.

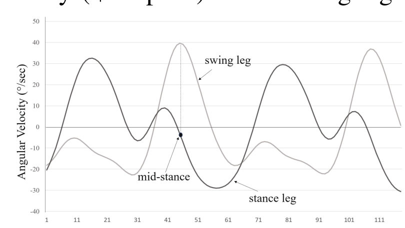

Fig. 3. Plot of two hips mounted gyroscopes filtered data during walking

During the gait cycle, the swing phase of a foot is succeeded by the swing phase of the other foot. After the last step is taken by a foot, the other foot will swing to reach the last position of the gait. So, to consider that a gyroscope peak corresponds to a gait swing and hence detect a step, it has to be preceded and succeeded by a peak of the other gyroscope, and all of the three peaks have to satisfy the rotation pattern described earlier. This pattern repetition has to happen within the walking steps expected frequency, so the time between each two subsequent peaks has to be less than a time threshold Δt_{max} and less than another time threshold Δt_{min}, where Δt_{max} and Δt_{min} are selected according to [16].

Our algorithm works as follows:

- Data is filtered using a centered moving average filter of window size 15.
- Eliminate hills which overlap with a positive value in the region between the peak and the end point.
- If a hill of a sensor readings signal occurs between two hills of the other sensor readings signal and the time between its zero crossing and the zero crossings of each of the other hills is less than a time threshold t_{max} and greater than a time threshold t_{min}, it will be counted as a step, t_{max} and t_{min} are chosen according to [8].
- If the first hill of the other sensor is not already counted as a step, which can only happen for the first step, it will be counted as well.

V. Step Length Estimation

The gyroscopes are used to estimate the rotation angle of the hips in stance phase. Integration of the gyroscope data for the short time period of the stance phase will reduce the drift error significantly and stops it from growing throughout the entire gait. Since the gyroscope signal can experience fluctuation during the early stance, we integrate the gyroscope data during only late stance. The symmetry of the inverted pendulum model allows us to do so, and this also offers the advantage of reducing the integration time that will reduce the drift even more. Using simple geometry and since the triangle formed by the leg at mid-stance and the same leg at the end of its stance phase in Fig. 4 is almost an isosceles triangle, the following derivation can be used to estimate the step length SL:

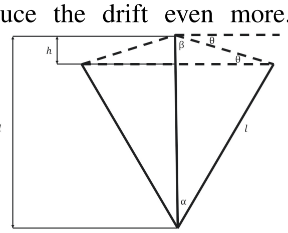

Fig. 4. Walking inverted pendulum model angles

$$\beta = 90 - \theta \tag{1}$$
$$\alpha = 180 - 2\beta \tag{2}$$
$$s\alpha = 2\theta \tag{3}$$
$$SL = 2l\sin(2\theta) \tag{4}$$

where θ is the angle obtained by direct integration of the gyroscope and l is the effective leg length measured from the sensor to the ground.

The error accumulation is low in this method since we only need to integrate the gyroscope data for a short period of time and we need single integration to get the step length unlike the methods based on the double integration of the accelerometer data.

VI. Weinberg Method Auto-Calibration

The Weinberg method has a high accuracy compared the to other step length estimation methods [9], [17], that is confirmed by our experiments. The main disadvantage of the Weinberg method is the need for user calibration which is not user-friendly and prone to errors in the user's measurement of the distance. Moreover, we found that the calculated calibration constant does not always span different walking speeds, so an auto-calibration method can increase the accuracy and user-friendliness. The only way for calibration is the walking distance estimation, so another step length estimation method is needed to auto-calibrate the Weinberg method. The obvious option is to use a method with more or at least equal accuracy, which we did not find and if it exists we would not need the Weinberg method in the first place. The other option is to use a less accurate method. Step length estimation methods' accuracies vary between different steps. The method's accuracy refers here to its average accuracy since it is measured for the entire walking distance, so even if a method has low average accuracy, it may have some high accuracy estimated step lengths. So our problem now is how to detect a high accuracy estimated step length to use for calibration.

By looking at Fig. 4, we can conclude that since we can estimate the vertical displacement h using accelerometer integration, that step length can be estimated without knowing the effective leg length according to the following equation:

$$SL = 2 \times \frac{h}{tan(\theta)} \tag{5}$$

In fact, the effective leg length l can be estimated given these information using the following equation:

$$l = \frac{SL}{2 \times sin(2\theta)} \tag{6}$$

To estimate h, we attach a CA-SDK chip to the center of the back of the belt to be as close as possible to the CoM, which is the same recommended place for the Weinberg method. We use the method described in [12], which is double integration of the vertical acceleration and estimate h as the difference between the highest and lowest position during each step. But instead of using a high-pass filter to reduce the drift, we use the ZUPT method by restarting the integration at each foot's mid-stance.

Our experiments show that the average accuracy of this method is less than 80%, but for some of the steps, l is accurately estimated. Given the user input of his effective leg length, the step length SL is estimated using Equation 5, then l is estimated using Equation 6. If the accuracy of l is greater than a threshold $thresh$ it is used to estimate a new constant k_i using the following equation:

$$k_i = \frac{\sqrt[4]{a_{maxi} - a_{mini}}}{SL} \tag{7}$$

where i is the step number. Then the Weinberg constant K is calculated using a weighted averaging where the weight is the accuracy of l.

$$K = \frac{\sum_{i=1}^{n} k_i \times accuracy_i}{\sum_{i=1}^{n} accuracy_i} \tag{8}$$

where n is the number of steps and $accuracy_i$ is the leg length estimation accuracy of step i which will be set to 0 if less than the threshold $thresh$.

Two calibration constants are estimated using the above algorithm, one for slow and one for faster step speeds. A step is considered slow if its duration is less than or equal to 0.64 sec. This value is calculated by taking the mean of the slow gait to mean step frequencies of men and women aging from 10 to 79 years old in [16] and it is applicable to the slow walking speed of subjects in our experiments as well.

VII. Experiments and Results

Our experiments are divided into two categories: walking activity to calculate step detection and step length estimation accuracies, and no-walking activities to verify that our step detection algorithm can distinguish walking from other non-bipedal activities. Our ground truth for the step detection is the number of steps counted by an observer while the step length estimation ground truth is done by measuring the overall walked distance using a laser meter and then compare it to the overall distance calculated by summing the estimated step lengths.

Two male and one female subjects participated in our experiments. Their ages are 33, 36 and 34 years, their heights are 173, 179 and 169 cm and their effective leg lengths are 0.95, 1.01 and 0.89 cm respectively.

A. No-walking Activities

The subjects are instructed to do the following activities: rocking on a rocking chair, twirling on a rotating chair, transitioning between standing and sitting, and jumping in place. Each activity is repeated several consecutive times to ensure that a false step will not be detected due to an activity repetition. Fig. 5 shows the two gyroscopes signals of one subject doing the no-walking activities.

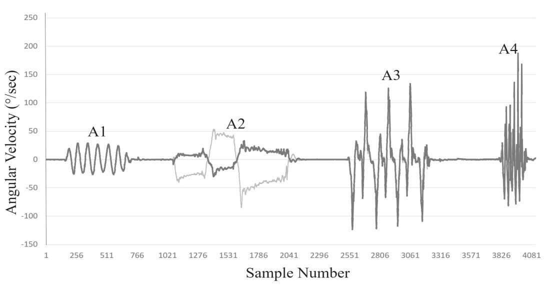

Fig. 5. Plot of two hips mounted gyroscopes filtered data during no-walking activities where A1 corresponds to the activity of rocking on a chair, A2 to twirling on a chair, A3 to transitioning between standing and sitting and A4 jumping in place

None of the activities exhibited the searched pattern between the gyroscopes signals of the two sensors, except for the twirling on a chair activity labeled by A2 in Fig. 5. However, this activity is not detected as a step because the time between the zero crossings is relatively large when compared to the maximum time between two consecutive steps, so the accuracy is 100% for these experiments.

B. Walking Activity

The subjects are asked to do three experiments, at their slow, regular and fast speeds. Each experiment is repeated 5 times to ensure results consistency for a total of 45 experiments runs. The subjects walk in a straight line for different distances ranging from 18 to 32 meters long for each experiment run. Fig. 6 shows the two gyroscopes signals of one subject walking at his regular speed.

C. Step Detection Results

The approximate mean accuracy of the step detection is 97.92% for low walking speed, 99.57% for regular walking speed and 99.26% for fast walking speed with total accuracy of 98.92%. Table I shows the sum of the steps taken by the

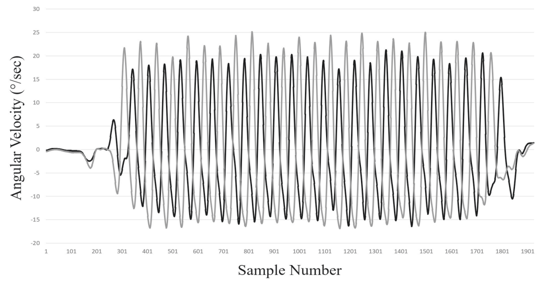

Fig. 6. Plot of two waist mounted gyroscopes filtered data during walking at regular speed.

three subjects, and the number of false $+ve$ and false $-ve$ of our step detection algorithm for each walking speed.

TABLE I
STEP DETECTION ERRORS

	Steps Count	False $+ve$	False $-ve$
Slow Walking Speed	715	1	11
Regular Walking Speed	553	2	1
Fast Walking Speed	493	4	0

D. Step Length Estimation Results

Four step length estimation methods are implemented to compare their accuracies:

1) The first method $M1$ is the CoM vertical acceleration integration based, we will refer to this method by the vertical displacement method:

$$SL_{M1} = K \times 2\sqrt{2lh - h^2}$$

K is calculated for each user based on a single walk at regular speed.

2) The second method $M2$ is our proposed method based on the estimation of the hip angle in sagittal plane:

$$SL_{M2} = 2l\sin(2\theta)$$

3) The third method $M3$ is the Weinberg method based on user calibration:

$$SL_{M3} = K_{user}\sqrt[4]{(a_{max} - a_{min})}$$

4) The fourth method $M4$ is the Weinberg method based on our new auto-calibration technique:

$$SL_{M4} = K_{auto}\sqrt[4]{(a_{max} - a_{min})}$$

Figures 7, 8, and 9 show the total estimated distances of all of the experiments as a percentage of the real distances at slow, regular and fast walking speeds respectively to show the average estimated step lengths as a percentage of the true step lengths.

Table II shows the average accuracy of the four methods at slow, regular and fast walking speeds as well as their overall accuracies. Our proposed method has higher overall accuracy than the vertical displacement method, even though it does not require any constant calibration. Its lowest average accuracy happens at fast walking speed and it is higher than the overall lowest average accuracies of the vertical displacement and Weinberg methods. The user calibration constant of one of the users do not span his slow walking speeds for the Weinberg method, which decreases the slow walking speed average accuracy significantly. The Weinberg method using auto-calibrated constants has higher overall accuracy and it is the more stable method across different walking speeds as well.

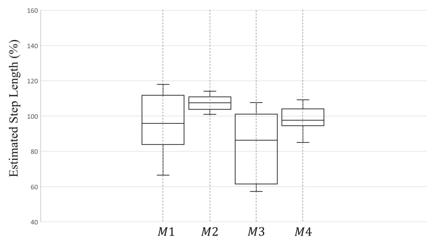

Fig. 7. Plot of the step lengths estimations as a percentage of the real steps lengths at slow walking speed

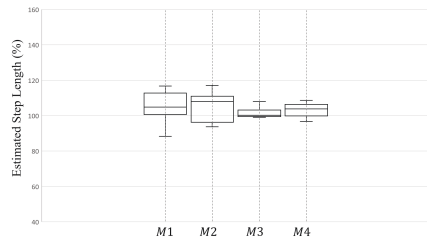

Fig. 8. Plot of the step lengths estimations as a percentage of the real steps lengths at regular walking speed

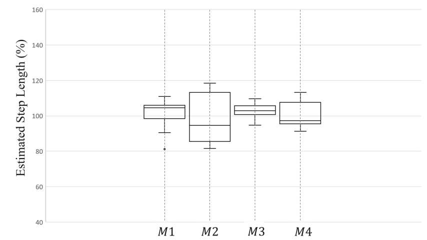

Fig. 9. Plot of the step lengths estimations as a percentage of the real steps lengths at fast walking speed

TABLE II
STEP LENGTH ESTIMATION ACCURACIES

	Vertical Displacement	Novel Method	Weinberg	Weinberg Auto
Slow Walking Speed	84.66%	92.53%	82.25%	94.94%
Regular Walking Speed	92.41%	92.34%	97.86%	95.57%
Fast Walking Speed	93.68%	88.18%	96.26%	94.02%
Overall	90.25%	91.02%	92.12%	94.85%

We expect its accuracy to increase even more in practice as the auto-calibration constants are expected to be enhanced with more walking steps. The vertical displacement and traditional Weinberg methods are expected to have lower accuracies in practice because of their constants calibration requirements.

VIII. CONCLUSION

In this paper, a new method for gait analysis is developed by mounting two gyroscopes, one on each side of the waist. This mounting position has been found to be practical and more convenient than other positions such as the feet, shanks or thighs. Using this setup, walking steps are accurately detected and discriminated from a lot of other non-bipedal activities without using magnitude thresholds or needing for training, which makes our algorithm more robust, easier to implement, and more practical than other step detection algorithms. Our step detection method is expected to accurately detect jogging and running steps, but more experiments are needed to evaluate its robustness in detecting these activities.

The hip rotation angle in the sagittal plane is also estimated based on the walking inverted pendulum model, which allows us to estimate the step length using only the user leg length without the need for per-user constant calibration unlike all other step length estimation methods that use inertial sensors mounted on the waist. This is also the first gyroscope based step length estimation that does not require further calibration algorithms, and the first waist-mounted gyroscope step length estimation method. Our step length estimation method is compared to two other methods that are based on waist-mounted accelerometer. Even though it does not need calibration constants, our method had a higher accuracy than one of the methods that need a per-user constant calibration and a comparable overall accuracy to the other method across different walking speeds.

The estimation of the hip rotation angle allows us to develop a method to auto-calibrate the Weinberg method's constant, which is one of the most accurate steps length estimation methods. Two constants are calculated; one for the slow and one for faster walking speeds, and these constants are to be continuously updated while the user is walking. The Weinberg method using the auto-calibrated constants has a higher accuracy than all of the other step length estimation methods used in our experiments including the Weinberg method that uses the user-calibration constant. It is also the most stable method across different walking speeds.

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