A gyroscope-based self-learning method improves reliability and accuracy of toe-off and heel-strike gait events detections

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Abstract

As people pay more attention to health problems, various gait monitoring methods have been proposed in the last decade. In gait detection, accurate determination of toe-off and heel-strike events is very important, because these events provide the fundamental walking informations. To find toe-off and heel-strike, gyroscope is one of the useful devices that has been widely studied, due to its portable, low-cost and practical characteristics. However, the methods in the past have either significant latency or comparative low detecting reliability. Therefore, this paper presents a novel gyroscope-based self-learning toe-off and heel-strike gait events detecting(SGED) method, with high reliability and low latency. The proposed algorithm, which combines the threshold filtering and self-correcting methods, has shown high detecting robustness. Its detecting reliability and latency at different walking speed were tested and compared with other three prior methods. It was observed that the proposed algorithm

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has reliabilities varied between 99.5% and 100% in detecting toe-off and heel-strike events, while the past methods' reliabilities sometimes drop to 90%. As for detecting latency, the proposed algorithm has the average value of 44.26ms, which is lower than two of the contrastive methods. The experimental results demonstrate that the proposed algorithm has a comprehensive better performance than prior methods on detecting toe-off and heel-strike events, and can thus provide more accurate information for studying walking gait.
Keywords:
Self-learning; Threshold; Toe-off; Heel-strike; Gait event detection

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1. Introduction

Human walking entails a significant amount of physiological informations, including body structure, behavior habits, and health condition. In the field of medical research, various aspects of walking information can be used to assist doctors find out early symptoms of underlying body diseases, such as deformity, muscular weakness or impaired control [1–3]. Due to these reasons, along with the development of electronics manufacturing, different kinds of intelligent wearing devices have been invented to monitor people's walking gait.

Traditionally, the movement of a leg in a gait cycle is divided into two phases: stance phase(STP), and swing phase(SWP) [1], as shown in Figure 1. When the leg movement enters one phase from another, a toe-off(TO) or a heel-strike(HS) occurs. Hence, the accurate detection of TO and HS can be used to calculate the duration of STP and SWP, as well as other walking informations, like the walking speed, etc. Therefore, accurately detecting the occurrence of TO and HS events is very important.

Up to now, many attempts have been made to detect TO and HS events [4]. Researchers have tried foot pressure sensing system [5, 6] and optical motion capture system [7, 8]. Although these systems provide rich and accurate gait

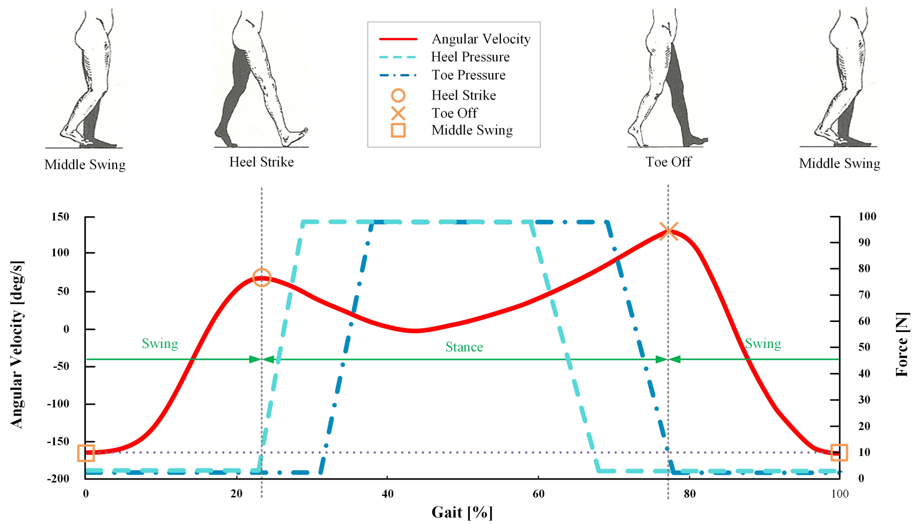

Figure 1: Typical angular velocity and foot pressure data curves in a gait cycle. One cycle of walking gait is divided into two phases: stance phase(STP) and swing phase(SWP). Toe-off(TO) and heel-strike(HS) events are between these two phases. The red solid line shows the typical angular velocity change at the bottom of the wearer's shank. The dark blue chain line and the light blue dash line illustrate the toe and the heel pressure variations. TO, HS, and middle-swing(MS) points are marked with different shaped orange markers. The gait begins with MS and the angular velocity increases until the HS happens. Then, the angular velocity decreases for a period of time and increases later. When TO is reached, the angular velocity drops again till next MS, which indicates the end of the step. The foot pressure sensor system works as a reference. The contact state is judged by the criteria which is 10% of the force sensor's upper limit.

informations, they have not been broadly used for their high price and overly complex usage method. Accelerometer [9–14] and gyroscope [15–25] become alternative choices, because both of them are small, portable, low-cost, and can be easily attached to the body at any place. However, the value of accelerometer is inevitably interfered by the gravitation, using gyroscope sensors tends to be a more convenient option. For example, Pappas et al. [15, 17] used a finite state machine algorithm on gyroscope to detect gait events. Aminian et al. [16] built a mobile gyroscope-based detecting system for spatiotemporal parameters estimation during walking and analyzed the recorded data using wavelet method. Catalfamo et al. [20, 22] combined several thresholds, time constraints, and the time-sequential characteristic of gait events to finish the detection.

From above mentioned methods, we can see that there are about three main limitations of the prior researches. First of all, most algorithms set constant thresholds or constraints based on the data from experiments [15–17, 20, 21, 23]. However, the parameters of walking are quite distinct among different people, and these algorithms might thus not work well for different subjects. Second, in gait detection, domain knowledge plays an important role in designing the algorithm. While previous researches that utilized the gait domain knowledge mainly focused on the time sequential characteristics [16, 19–23, 25], the quantity characteristics, including the gait events count and phase proportion, were always neglected. Third, some algorithms were only tested under subjects' preferred walking speeds [16, 20], while others were examined at pre-defined values [17, 18, 21, 23]. The reliabilities proposed in different papers were not experimented under the same condition and are therefore uncomparable.

In this paper, we introduce an adaptive gait events detecting method, which integrates threshold filtering and self-learning. The parameters in the algorithm are automatically adjusted according to different subjects. The quantity characteristics, as well as the temporal characteristics, of the gait domain knowledge are used. The detecting reliability and accuracy of the proposed method are verified by a reference foot pressure analyzing system, and the results show great improvements in detecting TO and HS gait events, comparing with other three pre-proposed algorithms [18, 21, 23].

2. Methods

2.1. Experimental instrumentation

In order to collect the angular velocity data at the shank, a gyroscope-based data acquisition platform was built. The system is consists of three parts: the gyroscope sensor module, the foot pressure sensor module, and the data acquisition system. Its framework is shown in Figure 2.

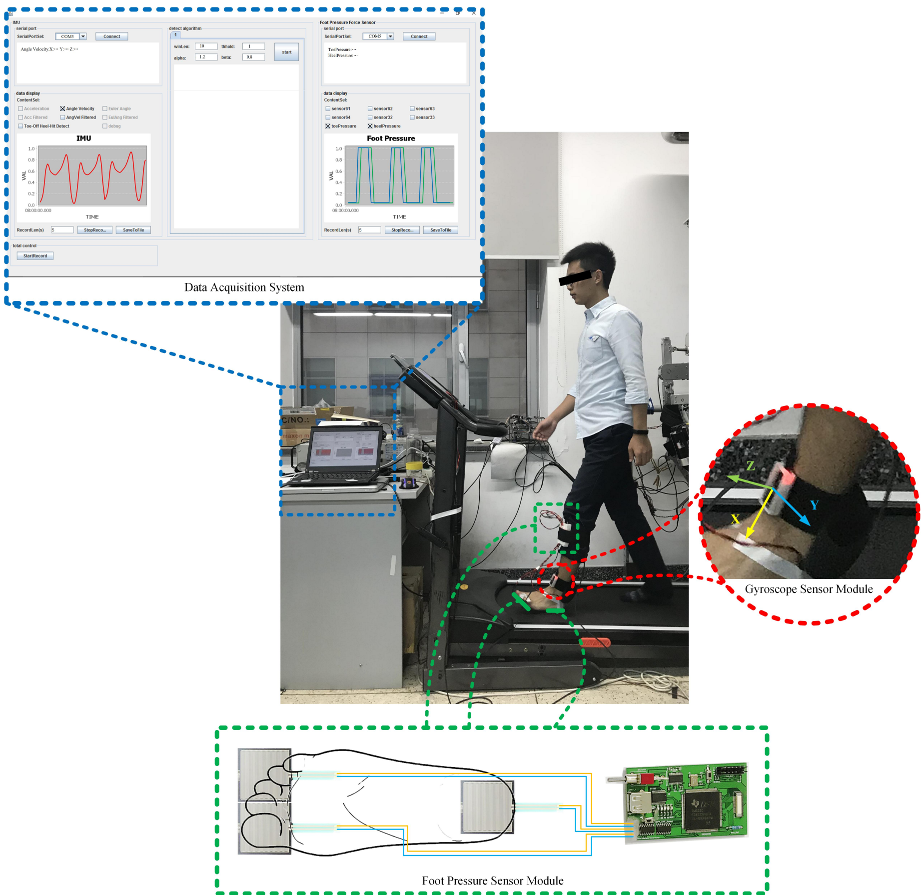

Figure 2: The instrumentation framework of the gait event detection system. The system mainly contains three parts: gyroscope sensor module, foot pressure sensor module, and data acquisition system. The gyroscope sensor module was attached to the bottom of the subjects' shank to collect the angular velocity at that position and its mounting direction is shown in the figure. Foot pressure sensor module was stuck to the sole to obtain force value at the toe and the heel. The data acquisition system was used for data sampling, displaying and analyzing.

The gyroscope sensor module we chose is HI219M, which is from Hipnuc Company[26]. The sensor module was was attached to an elastic belt, which was then fastened and secured at the bottom of the subject's shank. The belt was rotated to put the gyroscope sensor into the sagittal plane of the wearer's leg, as shown in Figure 2. Angular velocity data were transmitted to the host computer through serial port communication and the transmitting frequency was set to 100Hz.

For collecting the foot pressure information, especially those at the toe and the heel, we used three pieces of slim force sensor unit, from Interlink Electronics[27]. The paste positions of these units are shown in Figure 2. The size of the unit is 50mm×50mm and the measurement range of each sensor is among 0-100N. The force sensor system is working as a reference for detecting TO and HS.

A data acquisition software was developed to receive, display and analyze data from gyroscope and force sensors. It contains serial port control, data presentation, and detecting algorithm on-line implementation functions. Its code is open source and can be downloaded at [28].

2.2. Self-learning toe-off and heel-strike gait event detection(SGED) algorithm

2.2.1. Toe-off and heel-strike detection

Figure 1 shows the typical angular velocity variation at the bottom of the shank and the pressure change at the toe and the heel in a gait cycle. Toe-off(HS), heel-strike(HS) and middle-swing(MS) events are marked. From the chart, it can be seen that TO and HS points have the local maximum angular velocities, while MS points have the local minimum values. If a gait cycle is defined to start from MS, it will then go through HS and TO, and ends up with another MS. Accordingly, we proposed the self-learning toe-off and heel-strike gait event detection(SGED) algorithm. The procedure of SGED is described in a flowchart, as shown in Figure 3.

At the beginning of SGED, we assume that a data stream of angular velocity has been received from the gyroscope sensor and is ready to be inputted into the detecting system. The inputted data, which were sampled directly from sensors, contains lots of noises, and are thus called Raw Angular Velocity Data. A data

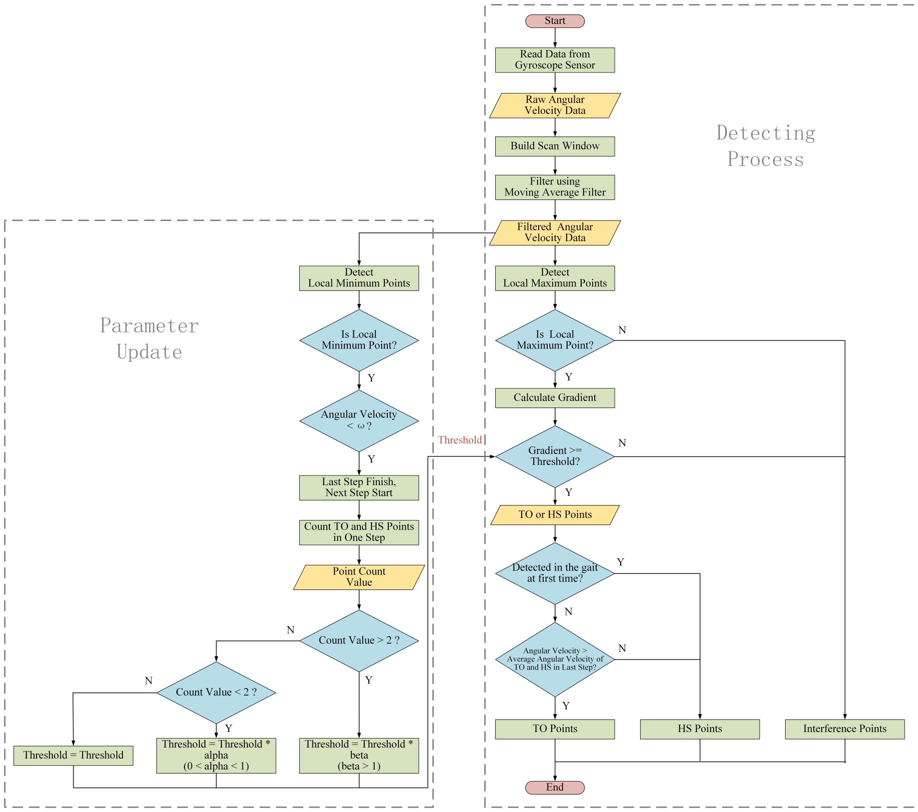

Figure 3: The process of Self-learning Toe-off and Heel-strike Gait Event Detection (SGED). The whole procedure is divided into two correlated parts: Detection Process and Parameter Update. The detecting process is to find out TO and HS events using several constraints, including local maximum value and a gradient threshold. Parameter Update takes the responsibility of updating the threshold in the SGED to the optimal value. The SGED begins with a stream of gyroscope data, called Raw Angular Velocity Rata, which is read from the gyroscope sensor module. This data stream is inputted into a customized scan window and filtered using the Moving Average Filter at first. The local maximum requirement and the gradient threshold are used to find out toe-off(TO) and heel-strike(HS) points. The detected sequence and the angular velocity limit are implemented to distinguish between TO and HS. At the end of each stride, the SGED will do the gradient threshold updating. The TO and HS points detected in the last step will be used as the judging rule for threshold upgrade. The updated threshold will later be used in the TO and HS detecting process in the next step.

scan window will be built and the Moving Average Filter is employed to reduce noises. Filtered data will then be scanned using the Find Local Maximum Values algorithm, described in Algorithm 1. If the middle point of the data buffer has the local peak value, the 'gradient' at that position will be calculated. Yet, the gradient described is defined as the change speed of the angular velocity on both sides of the middle points of the scan window. The pseudo-code of gradient's calculation is depicted in Algorithm 2. Later, a threshold is introduced to rule out those local peaks caused by disturbances and the rest are regarded as TO or HS points. The last step is to distinguish these two types of points. Two criteria, the detected sequence and the angular velocity limit, are set up. Only those points, which are firstly detected after MS and have lower value than the average angular velocity of TO and HS in last step, will be classified as HS points. Otherwise, they will be accepted as TO points.

Algorithm 1 Find Local Maximum Values

Require:
Window length of data, $Array$;
Window length, $length$;
Ensure:
Peak check result,
0: is not peak,
1: is peak;
function IsPEAK($Array, length$)
    $result = 1$;
    if $length\%2 = 0$ **then**
        $middlePosition = length/2$;
    else
        $middlePosition = (length + 1)/2$;
    end if
    $maxValue = Array[middlePosition - 1]$
    for $i = 0$; $i < length$; $i++$ **do**
        if $maxValue < Array[i]$ **then**
            $result = 0$;
            break
        end if
    end for
    return $result$;
end function

2.2.2. Parameter optimization

In Algorithm 2, the inputted parameters include a variable, named threshold, which is used to separate TO and HS points from other interferences. It

Algorithm 2 Calculate Gradient and Filter with Threshold

Require:
Window length of data, $Array$;
Window length, $length$;
Threshold, $threshold$;
Ensure:
Toe-off or heel-strike points,
0: is not TOHS points,
1: is TOHS points;
function isTOHS($Array, length, threshold$)
    $result = 1$;
    if $length \% 2 = 0$ **then**
        $middlePosition = length/2$;
    else
        $middlePosition = (length + 1)/2$;
    end if
    $halfLength = middlePosition - 1$
    $foreGradient = (Array[middlePosition] - Array[middlePosition - halfLength])/halfLength$
    $backGradient = (Array[middlePosition] - Array[middlePosition + halfLength])/halfLength$
    $gradient = (foreGradient + backGradient)/2$
    if $gradient > threshold$ **then**
        $result = 1$;
    else
        $result = 0$;
    end if
    return $result$;
end function

is obvious that the value of threshold can dramatically influence the detecting performance. Therefore, choosing a proper threshold turns into the key of improving the detecting accuracy of the algorithm. Accordingly, we introduce the self-learning algorithm to do the optimization. There are three core elements in optimization algorithms: iteration time, iteration condition, and iterative method. The iteration time in SGED is set at the end of each step. The iteration condition is based on the number of TO and HS detected in the last step. If the number of TO and HS points filtered out in the gait cycle is bigger than 2, which indicates an impossible situation that more than one TO or HS happened, it means that the threshold set in the SGED process is too small, and vise versa. So, the iterative method, shown in formula (1), was put forward.

$$T(n+1) = \begin{cases} T(n) * \alpha & N_{TOHS} < 2 \\ T(n) & N_{TOHS} = 2 \\ T(n) * \beta & N_{TOHS} > 2 \end{cases} \tag{1}$$

$$0 < \alpha < 1 \quad ; \quad \beta > 1$$

T denotes the threshold. α and β represent threshold's learning rate. α is between 0 and 1, while β is bigger than 1. If the number of TO and HS points detected in the last step is smaller than 2, the threshold changes to a smaller value, and vice versa. If and only if TO and HS number equals to 2, the threshold is left as it is. In the study, α and β are configured 0.8 and 1.2, which have enough good performance.

2.3. Reference system

As for reference, the data from the foot pressure sensor module was used. In Figure 1, the force changes between the toe and the treadmill, and the heel and the treadmill are shown. It is noticeable that there are periods when the force values remain unchanged at 100N. This is because the force at that time exceeds the sensor's measuring range. However, as we only care about the attaching time points and the accurate force value doesn't matter a lot, we used the formula (2) to simplify the contact detecting results. The contact state(CS) was judged by a threshold that is 10% of the force sensor's upper limit. If the force values at the toe or the heel were greater than the limit, the contact would be considered to be on going and vice versa. Between these contact and non-contact region were accepted as TO and HS events.

$$CS(f_{toe}, f_{heel}) = \begin{cases} non-contacted & \begin{array}{l} f_{toe} < 10\% Max_f \\ and \\ f_{heel} < 10\% Max_f \end{array} \\ contacted & \begin{array}{l} f_{toe} >= 10\% Max_f \\ or \\ f_{heel} >= 10\% Max_f \end{array} \end{cases} \tag{2}$$

2.4. Analysis of reliability

The reliability of SGED was evaluated. The contact state judged from the reference system was used as the standard for identifying TO and HS (TOHS) events. If the point was of the same kind in the force-based contact classification and in SGED, the result would be thought as right diagnosis, marked as $Right_{TOHS}$. Otherwise, it would be considered as wrong classification. Moreover, there are two kinds of false classifications. One is the incorrect classification of the true TOHS events, $Wrong_{TOHS}$. Another one is the wrong sorting of the non-TOHS events, $Wrong_{nonTOHS}$. We use All_{TOHS} to represent the number of all real TO and HS time points in the data stream. The detecting system was assessed using the formula (3) to evaluate the reliability performance.

$$Rel = \frac{R_{TOHS}}{All_{TOHS} + W_{nonTOHS}} \times 100\% \tag{3}$$

Rel, which indicates the reliability, is between $0\% - 100\%$. 0% means the detecting method does not work at all. 100% suggests that the sorting algorithm works perfectly. Higher reliability value indicates a better performance of the algorithm.

2.5. Latency

The detecting latency was also tested. Among detecting methods, there are mainly three parts which contribute to the time latency. The first one is the detecting strategy itself. Some methods might import time latency if the detecting procedure was not properly designed. The second one is the calculation. Different detecting strategy leads to different computational complexity, which causes various time costs. The last one is the filtering process. Due to the diversity in noise sensitivity, different methods may choose different filters. The filter that has lower cut-off frequency will generate more smooth data curves, but will also create massive latency.

3. Results

3.1. Subjects

To test the detecting system's reliability and latency, SGED was examined by four subjects, two males and two females. All the subjects are 22-24 years old, with height from 165cm to 175cm, weight between 50kg and 65kg. Subjects had no previous history of lower limb injuries, surgeries on the lower limb, or rehabilitation programs.

3.2. Different speed walking tests

The SGED was implemented on different speed walking tests. The tests were divided into 5 groups: 0.56m/s (2km/h), 0.83m/s (3km/h), 1.11m/s (4km/h), 1.39m/s (5km/h) and 1.67m/s (6km/h). In each group, four subjects' angular velocity and foot pressure data were collected. Every experimental paradigm lasts 3 minutes and was tested three times. At the beginning of each paradigm, the subject was asked to spend 1 minute to get used to the treadmill walking belt's velocity. Then, data recording started, and lasted 2 minutes. After the sensors' data had been stored, subjects would take a short break and start the next trial. When all the tests were finished, recorded signals were inputted into the SGED system.

3.3. Reliability

The results of detecting reliability are drawn in histogram bar chart, as shown in Figure 4.

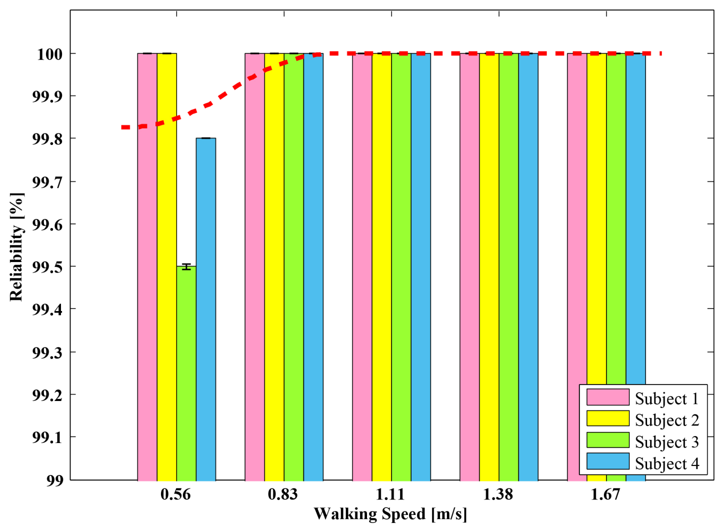

Figure 4: Reliabilities in different speed walking tests. The four different color bar indicates algorithm's detecting reliabilities of four subjects. The red dash line indicates the average reliability of these four values. It can be seen that under most circumstances, the algorithm has an average reliability greater than 99.5%. In normal walking speed situations, like 0.83m/s, 1.11m/s, and 1.38m/s, the mean reliability is nearly 100%. As for slow walking, like 0.56m/s, the reliability sometimes drops to 99.5%. However, for fast walking, like 1.67m/s, the algorithm can keep good performance.

Algorithms' reliabilities between different detecting systems were compared. Prior detecting methods [18, 21, 23] and the SGED were all tested under the same condition, and Figure 5 shows the reliability comparison results.

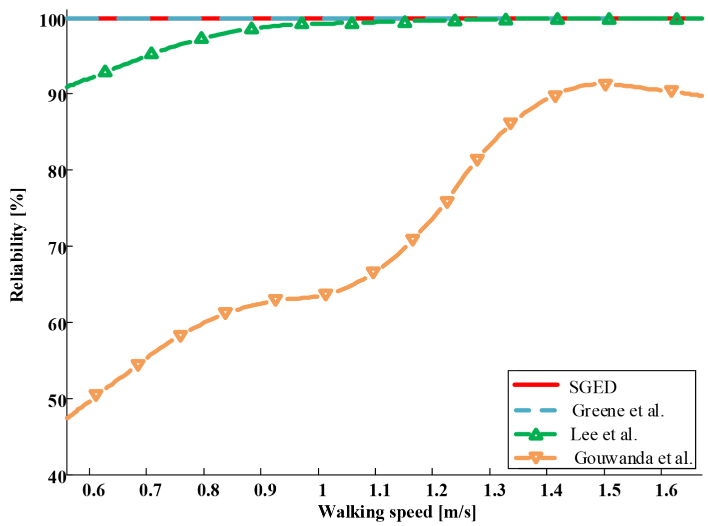

Figure 5: Reliability comparison between the proposed SGED method and other three detecting methods [18, 21, 23]. These algorithms were tested using the angular velocity data recorded at constant speed walking tests. The reliability variances are drawn. SGED and Greene et al.'s method[18] have nearly 100% detecting reliabilities all over the tests. The reliability of Lee et al.'s algorithm[21] is mostly 100%, except for the low speed walking. Gouwanda et al.'s algorithm[23] has comparative low reliabilities all over the tests.

3.4. Latency

Table 1 shows the latency comparison between the SGED and other three methods [18, 21, 23]. The comparison is made in three aspects as mentioned in Section 2.5. In the algorithm section, the latencies were measured by analyzing the detecting procedure of the methods. In the calculation section, all the methods were examined in Matlab with a computer equipped with i5-3210 CPU, 8GB RAM and 64bit Windows10. The time costs of detecting TO and HS in 6000 data points were tested, and the mean value at each point was recorded. In the filter section, time latencies were obtained by experiments.

4. Discussion

Among prior researches, three of the pre-proposed methods [18, 21, 23], which mainly focus on using thresholds and constraints to detect TO and HS,

Method	**Latency (ms)**		
	from algorithm	from calculation	from filter
SGED	0(0)	0.021(0.0002)	44.24(18.32)
Greene et al.	0(0)	0.002(0.0001)	90.97(16.93)
Lee et al.	0(0)	0.013(0.0009)	75.44(15.27)
Gouwanda et al.	10(0)	0.005(0.0002)	0 [no filter]

Note: Latencies are presented in form of "mean (variance)"

Table 1: Latency Comparison

are discussed. As the proposed SGED algorithm is also based on this detecting strategy, it is compared with these three methods.

In [18], Greene et al. presented an adaptive method to detect TO and HS time points. Greene et al.'s innovation was about using six thresholds, whose values were based on the maximum or the minimum angular velocity, to find out TO and HS events. However, the thresholds are constantly proportional to the walking angular velocity. While different people have different walking habits, their algorithm tends not to be suitable for everybody.

In [21], Lee et al. inventively created an idea of detecting TO and HS using MS. The method firstly detects MS points through positive local maximum value (The angular velocity data in their research is opposite to our experiment, due to the direct arrangement of the gyroscope sensor). Then, it looks backward and forward, to find local minimum values, which are considered to be TO and HS points. Nevertheless, Lee's method is very sensitive to noises. So, a Butterworth filter with a relatively low cut off frequency is needed, which leads to significant detecting latency.

In [23], Gouwanda et al. innovatively proposed a real-time gait event detection method using constant temporal constraints and angular velocity thresholds to filter out MS, TO and HS points. Their innovation is mainly on reducing the detecting latency. However, their method is very sensitive to noises

From above, it can be seen that there is a common limitation in previous studies. The thresholds or constraints in the past studies are of constant values, which means that it may not be suitable for different subjects and may be sensitive to noises.

In the proposed SGED, the main idea for identifying TO and HS events is based on the fact that angular velocity and gradient variance at TO and HS are higher than other points. From the flow chart of SGED, it can be seen that a threshold is used to filter out TO and HS. Distinctively, the threshold in SGED will be refined in every step depending on the subjects and their walking speeds. The temporal and the quantity characteristics of the walking gait are all considered when updating the threshold's value. This indicates that the threshold is not set based on experience, but is dynamically varying due to the wearers.

To test the reliability of SGED, experiments on 4 subjects at 5 constant walking speeds, varying from 0.56m/s to 1.67m/s, were carried out. From the results, it can be seen that the algorithm's reliability is larger than 99.5% under most circumstances. In slow walking situation, the reliability drops a little. This is because when subjects walk slowly, the angular velocity at the bottom of their shank changes more smoothly, which makes it difficult for algorithms to detect TO and HS events.

Reliability comparison between SGED and [18, 21, 23] is shown in Figure 5. It can be seen that SGED is better than [21, 23] among 5 walking speeds, and is almost as good as [18]. The reliability performance of [23] is relatively worse than the results from their paper. This phenomenon primarily comes from the gyroscope's installation. In their experiment, the gyroscope was installed on a gait monitoring suit, which ensured its signal's stability. However, the gyroscope in our experiment is fastened to the subjects through an elastic belt. The sampled angular velocity data carry a lot of noises. Hence, the algorithm's detecting reliability drops dramatically.

In the latency comparison, we can see from the TABLE 1 that our algorithm have the smallest latency from filtering among those methods which use filters. [18] has the biggest filtering latency, because their algorithm is sensitive to noises, so they have to use a powerful filter, which promises their algorithm's reliability. In the calculation latency section, although our method may need the longest time, the time cost at each data point is less than 0.1ms. Such a small value is not worthy of mention comparing to time latency created by filtering. In the algorithm section, method in [23] has a constant latency of 10ms. This is because that when the method detects a peak value point, it will mark the next point as the TO or HS point. And in our experiment, the angular velocity data sampled from the gyroscope is at 100Hz. So, we thought there was a 10ms latency in [23].

In general, after comparing with other methods, the SGED method has shown relatively good performances on detecting reliability and latency. Moreover, we provide a new idea of solving the TO and HS detecting problem.

Besides, there are however some limitations with the proposed method. Firstly, the gyroscope sensor needs to be placed in the sagittal plane of the shank. As we only used one axis value of the gyroscope to measure the forward movement of the shank, the placement of the gyroscope sensor is limited. This problem may be solved by calculating the average value of the angular velocity of all the three axes of the gyroscope sensor.

Secondly, the detecting window length is now varying due to the walking speed, but what length will have the best detecting performance is still unknown. Better choice of the window length may solve the low discrimination at 0.56m/s. Therefore, more experiments and novel theory should be carried out for the decision of window length.

Finally, our results need to be confirmed with a larger population. Our experiments are done only on 4 subjects. To prove the high reliability of this detecting method, more people should be involved in such experiments.

5. Conclusion

This paper introduces a novel gyroscope-based self-learning gait event detecting method called SGED. The reliability, accuracy and latency of the method has been tested, and compared with other 3 pre-proposed detecting methods[18, 21, 23]. From the results, it is observed that this algorithm has good performances on detecting toe-off and heel-strike events at different walking speed.

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Conflict of interest

There are no conflict of interest.

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