2019 32nd IEEE International System-on-Chip Conference (SOCC) 978-1-7281-3483-3/20/$31.00 ©2020 IEEE 10.1109/SOCC46988.2019.1570548017

A Smart Single-Sensor Device for Instantaneously Monitoring Lower Limb Exercises

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***Abstract*—Studies have shown that stair exercises can enhance the strength of lower limbs for patients with limb disorders. However, there are only few systems that can monitor the lower limb exercises in the medical institutes. To analyze the lower limb exercises instantaneously, we propose a smart single-sensor wearable device, S^3-*Sock*, equipped on shoes. The sock can monitor and measure the stride count, step height, and the distance of step trajectory about lower limb exercises. The experimental results demonstrate that the proposed system is reliable under different lower limb exercises. The averages of absolute mean errors of stride count in stair-climbing and walking are about 2.00% and 0.88%, respectively. The averages of absolute mean errors of step height are about 5.12% and 8.23% in step-by-step and step-over-step stair climbing, respectively.**

I. Introduction

Stair climbing and walking are common lower limb exercises, and play major roles in daily activities. However, they might be challenges to the specific patients, especially the ones who suffer from lower limb disorders. These patients usually conduct rehabilitation programs for improving the strength of their lower limbs.

According to the study [7], it has revealed that the rehabilitations with step exercises or stair exercises both enhance the strength of patients' lower limbs significantly. Additionally, the study has shown that the effects of the step exercise with steppers, which requires bulky equipments, are similar to that of stair exercise. Since conducting rehabilitation with stair exercise is more accessible for patients at home, stair exercise can be a proper substitute for rehabilitation with steppers. However, without steppers, how to monitor and record the rehabilitation activities instantaneously at home is a concerned problem.

In an entire treatment procedure, a number of issues, such as the insufficiencies of physical therapists, the heavy workload of the repeatable therapeutic exercise, and ineffectiveness of self-rehabilitation, need to be resolved from the clinical practice to the self-rehabilitation. In the earlier days, most of the related studies focused on the issues in the clinical practice. For example, in these works [3] [14], the authors proposed mechanical systems to assist patients in self-rehabilitation. These systems stimulate patients to control their lower limb muscles for elevating the effectiveness of rehabilitation and reducing the workload of the physical therapists in medical institutes. For the patients who need to conduct self-rehabilitations at home, however, the required equipments are usually high-cost and non-portable. When different sensors such as pressure sensors, G sensors, accelerometer sensors or gyroscope sensors, embedded in wearable devices become pervasive, researchers used them in motion sensing devices [5], navigation systems [8], and biometric data collection systems [13] due to their high portability and convenience. To improve the effectiveness in clinical practice, several studies also proposed methods of using sensors to detect gait event or to analyze the gait patterns of specific diseases [6]. Compared with these studies focusing on the improvement in clinical practice, there are only few studies related to the rehabilitation at home.

Recently, the study [4] proposed a wearable sensor-based approach that can analyze and classify motions using multiple wearable sensors. However, the approach can only reveal the motion types, but cannot provide precise data for patients conducting self-rehabilitation at home. In the study in [12], the authors proposed a novel pedestrian navigation method that integrated the information of barometer and 9-axis MEMS-IMU. Although the work demonstrated a high accuracy in the recognition of walking and stair-climbing activities, it is inconvenient to patients due to the requirement of wearing many devices.

Therefore, in this work, we propose a smart single-sensor wearable device, ***S^3-Sock***, which is convenient to patients with stroke, Parkinson's disease, diabetes [2], or knee-replacement [1], to monitor and record their lower limb exercises instantaneously.

We use this small device to record the stride count, step height, and distance of step trajectory of lower limb exercises. Meanwhile, these data are shown on a designed Android APP. The main contribution of this paper is to present the data analysis method with the ***S^3-Sock***. for achieving this objective,

II. Method

A. Stair gait phase segmentation

Traditionally, the gait phases of a stair cycle are defined with respect to the cyclic moving of the lower limbs, and divided into two phases, stance phase and swing phase. The stance phase consists of three sub-phases: weight acceptance, pull up, and forward continuance; while the swing phase consists of two sub-phases: foot clearance and foot placement. In

This work is supported in part by the Ministry of Science and Technology of Taiwan under MOST 106-2221-E-007-111-MY3, MOST-106-2314-B-007-005, MOST 106-2622-8-007-015-TA, MOST 107-2622-8-007-014-TA, MOST 107-2221-E-155-046, and MOST 108-2221-E-155-047.

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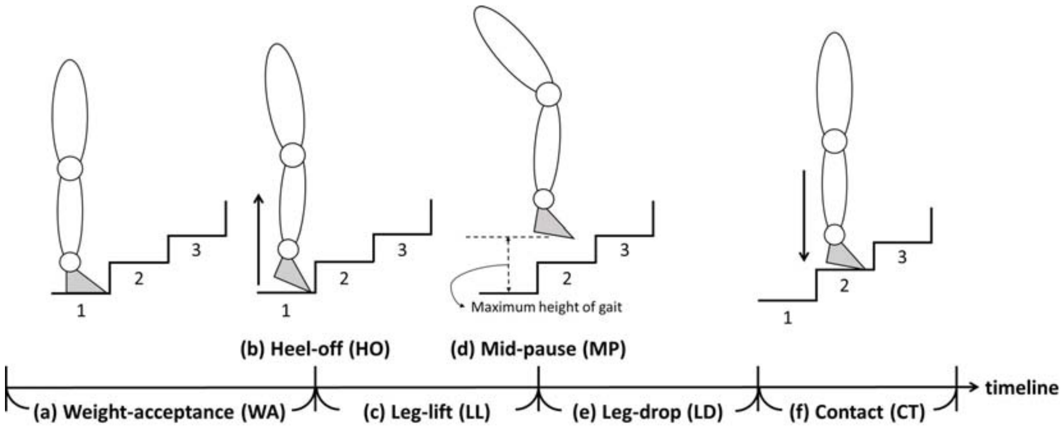


Fig. 1: Stair gait phase segmentation.

this work, we propose another gait phase segmentation based on the regular change of accelerometer value from a sensor equipped on foot during a stair cycle. As shown in Fig. 1, we divide a stair cycle into six phases, weight-acceptance (WA), heel-off (HO), leg-lift (LL), mid-pause (MP), leg-drop (LD), and contact (CT), where HO and MP phases are only small time points. This new stair gait phase segmentation is more suitable for measuring data about the lower limb exercises, which can be seen in the experimental results.

B. IMU-based device S^3-Sock

The S^3-***Sock*** is a wearable device, which contains a Gyro sensor [15] attached to a sock as shown in Fig. 2. The Gyro sensor consists of a 9-axis inertial measurement unit (IMU), a microcontroller (TI CC2640), a battery (3.7V, 85mAh), and a Micro USB connector for charging. The sensor is small and lightweight (38mm x 18mm x 11mm, 5g), and it can be attached to the sock tightly.

In the previous studies [8] [6], the authors adopted shoe-based wearable devices. However, it is difficult to fit all sizes of feet into one size of shoes. Since socks are flexible, they are well suitable for the foot length within the range of 22-28 cm. Hence, we integrated the Gyro sensor with a sock, which covers the first half of shoe. In fact, the sock is used as a flexible tight cover on the shoe. To increase the stability during exercises, we also placed two flats inside and outside the sock, respectively, as shown in Fig. 2.

C. Subjects and procedures

In this study, 10 healthy volunteers (5 males and 5 females, 25.2$\pm$2.2 years old, and foot length = 29.3$\pm$7.5 cm) were recruited to participate in the experiments. As shown in Fig. 3, these participants were requested to wear their shoes, and then put the S^3-***Sock*** on the right shoe. Next, these participants conducted the assigned tasks with the S^3-***Sock*** in a fixed environment having stairs (12 stages, stage height range = [17.5 $\sim$ 18.5] cm, and total height = 2.16 m) and a straight hallway (total distance = 35.5 m).

In each trail, these participants were asked to keep being steady for 10 seconds (weight-acceptance, WA) first before conducting experiments. During this 10-second period, we collected raw data of accelerometer from the IMU, and processed them to obtain two parameters, RMS_{WA} and CV_{WA}, which will be used for analyzing the succeeding lower limb exercises.

In the next subsections, we will explain the simple moving average (SMA) algorithm, and the calculation of the parameters, RMS_{WA} and CV_{WA}. Then we present how to recognize a stride and divide the stair gait phases based on these parameters.

D. Raw data processing: simple moving average (SMA)

Noise may exist in sensors and affects the accuracy of measurement due to material aging or variation. We use the simple moving average (SMA) [10] algorithm to filter out the noise of a sensor to obtain a more smooth data profile without sacrificing the accuracy. The obtained new data are called *processed data* in the following explanation.

In each sampling (time) point, SMA algorithm uses its averaged neighboring raw data to represent the processed data. Specifically, with the neighboring interval of 5 in this work, the i^{th} processed data of acceleration in one dimension (d), denoted as $a_d^{SMA}(i)$, is expressed as EQ(1):

$$a_d^{SMA}(i) = (\sum_{j=i-2}^{i+2} a_d^{raw}(j)) \times \frac{1}{5} \tag{1}$$

where $a_d^{raw}(i)$ is the i^{th} raw data from the 3-axis accelerometer, and $d \in \{x, y, z\}$. Note that the first, second, second last, and last processed data use fewer raw data for average.

E. Parameter calculation for stair gait phase segmentation

In the previous study [11], the authors proposed methods of segmenting stair gait phases using fixed thresholds in acceleration. However, these fixed thresholds are not able to fit different participants. Hence, instead of fixed thresholds, we propose to use the relative thresholds for different participants based on the data we obtained at their indivial 10-second weight-acceptance phases.

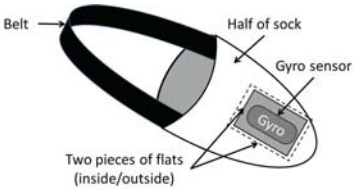


Fig. 2: The prototype of S^3-***Sock***.

Fig. 3: Wearing the S^3-***Sock*** on the right shoe.

In this subsection, before introducing the method of segmenting the gait phases in a stair cycle, let us review the proposed stair gait phase first. As shown in Fig. 1, the gait phases of a stair cycle is segmented with respect to the magnitude of variabilities in acceleration at the specific moments. Heel-off is the time point between weight-acceptance and leg-lift. Mid-pause is the tipping point between leg-lift and leg-drop, and it indicates the maximal height of a step. Contact is the period that the foot reaches to the stage, where the momentum decreases to zero.

Next, we introduce the calculation of RMS_{WA} and CV_{WA} parameters. At the weight-acceptance (WA) phase, the parameter RMS_{WA}, which represents the participant's steady state, is calculated as EQ(2) where n is the number of samplings at the WA phase and $RMS(i)$, which is the root-mean-square (RMS) value of the i^{th} processed data in acceleration, is calculated as EQ(3). $RMS(i)$ in acceleration can represent the degree of a subject's motion. Hence, we can calculate the RMS value for every processed data, and consider the value as one of the parameters for the segmentation of stair gait phases.

$$RMS_{WA} = \frac{1}{n}\sum_{i=1}^{n} RMS(i) \tag{2}$$

$$RMS(i) = \sqrt{\frac{a_x^{SMA}(i)^2 + a_y^{SMA}(i)^2 + a_z^{SMA}(i)^2}{3}} \tag{3}$$

The parameter CV_{WA} is the coefficient of variation (CV) at the WA phase, which expresses the variability of the RMS values at the participant's WA phase, and is calculated as EQ(4), where σ_{WA} is the standard deviation of RMS value at the WA phases, calculated as EQ(5), and n is the number of samplings at the WA phase.

$$CV_{WA} = \frac{\sigma_{WA}}{RMS_{WA}} \tag{4}$$

$$\sigma_{WA} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(RMS(i) - RMS_{WA})^2} \tag{5}$$

Similarly, we calculate CV for the i^{th} processed data in different gait phases, denoted as $CV(i)$, using the same idea. By comparing with the change of CV values, we can know the trend of the motion. Hence, CV is also considered as another parameter for the segmentation of stair gait phases.

As shown in Fig. 4, we use the double of RMS_{WA}, which is named RMS_{Active}, as the threshold separating the WA and heel-off (HO) phases. Since the value of RMS_{WA} is often small, using RMS_{Active} can avoid misjudging due to sensor noises. In our observation, the range of CV_{WA}, which is caused by sensor noises, is from 0.25 to 0.3. When the CV_{WA} of a participant is out of this range, we will adjust it into the one that is equal to the range boundary. For example, if the CV_{WA} of a participant is higher than 0.3, we set it as 0.3; if the CV_{WA} is lower than 0.25, we set it as 0.25.

F. Segmentation of a stair cycle and calculation of step height, and the distance of step trajectory

In this subsection, we will discuss the criteria of segmenting stair gait phases, and the calculation for the step height, and the distance of step trajectory. As mentioned, the accuracy of measurement may be affected by noise in sensors. To decrease

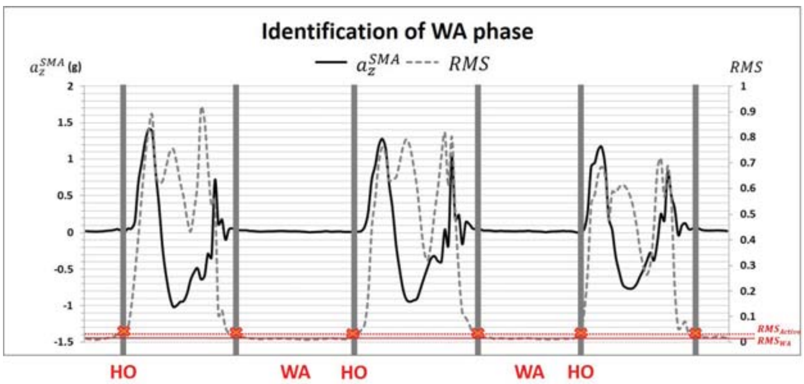
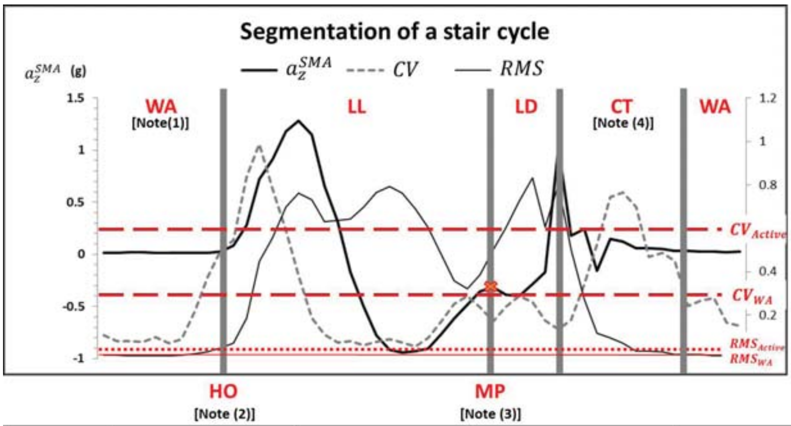


Fig. 4: Identification of WA phase by using RMS values from the accelerometer.



Phase	[Note (1): WA]	[Note (2): HO]	[Note (3): MP]	[Note (4): CT]
Transition Threshold(s)	$CV(i) < CV_{WA}$ && $RMS(i) < RMS_{Active}$	$CV(i) > CV_{WA}$ && $RMS(i) > RMS_{Active}$	(1) $CV(i) < CV_{Active}$ && $a_z^{SMA}(i) < 0$	$a_z^{SMA}(i) > 0$
			(2) $a_z^{SMA}(i-1) < a_z^{SMA}(i)$, $a_z^{SMA}(i+1) < a_z^{SMA}(i)$	
		[Advanced] $CV(i) > CV_{Active}$	[Advanced] $CV(i) < CV_{WA}$	
Match Counter	5	5	5	1
Action	-	Reset V_z to 0	Reset V_z to 0	-

Fig. 5: The phase transition thresholds of a stair gait cycle.

the error in the integration of acceleration values, the zero velocity [9] is identified. Since we know the **zero velocity** occurs in the interval between the end of one stride and the beginning of the next stride, we reset the velocity to zero at this moment. The zero velocity detection was only used at the WA phase in the previous work [9]. However, we further apply it at the **mid-pause** phase, which can improve the accuracy of the integration of acceleration.

Next, we explain the criteria of the stair gait phase segmentation using the calculated parameters. Furthermore, we indicate the specific timing points for resetting velocity.

In this work, except for the contact (CT) phase, to transit from one gait phase to the next one, the thresholds of designed parameters have to be met for 5 times consecutively under the sampling frequency of 50 Hz. This consideration avoids the misjudgment due to noises in the sensor. When the thresholds are not met consecutively, we reset the counter. On the other hand, as shown in Note (2) and (3) of Fig. 5, when the parameters meet the **advanced thresholds**, which are much stricter than thresholds, we count it twice for judging the phase transition more accurately and effectively.

The left y-axis in Fig. 5 is the acceleration of processed data in the z-axis of sensor, and the right y-axis is the RMS and CV of processed data. When $CV(i)$ is lower than CV_{WA} and $RMS(i)$ is lower than RMS_{Active}, that means the subject is almost stable, the subject is identified at the WA phase.

When $CV(i)$ is higher than CV_{WA} and $RMS(i)$ is higher than RMS_{Active}, that implies the subject starts to move, the subject is identified at the HO phase as shown in Note (2) of Fig. 5. The velocity in the z-axis (V_z) is reset to zero at this phase.

When $CV(i)$ is lower than CV_{Active} at the leg-lift phase, which means that the leg approaches to pause and a local peak of negative z-axis acceleration value occurs, the mid-pause (MP) is identified as shown in Note (3) of Fig. 5. This is because the mid-puase is the tipping point between leg-lift and leg-drop, and the velocity approaches to zero at this phase. Hence, we also reset the velocity at this timing point. Note that the maximal step height also occurs at this phase.

When a positive acceleration occurs, that means the motion is affected by the reaction force due to the collision, the contact (CT) phase is identified as shown in Note (4) of Fig. 5. Note that the threshold here is required to meet for only once. Let us explain the reason that the acceleration becomes positive in the beginning of CT phase. The acceleration, a, can be expressed as EQ(6),

$$a = \frac{(V - V_0)}{\Delta t} \tag{6}$$

where V_0 is the initial velocity, V is the final velocity, and Δt is the time period. The velocity in the z-axis before the foot contacts the stage, V_0, is negative because the leg is dropping. At the moment contacting the stage, the velocity of foot V becomes zero. Since V is zero and V_0 is negative, the acceleration a is positive in the beginning of CT phase. Next, we discuss how to calculate the step height. First, we calculate

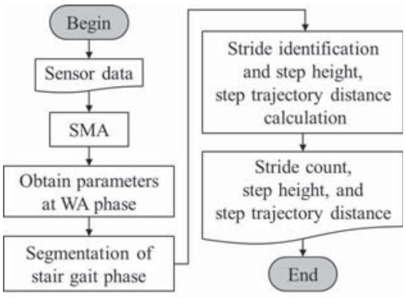


Fig. 6: The flowchart of our data analysis method.

the final velocity of *each* processed data, $V = V_0 + a\Delta(t)$. This final velocity V will become the initial velocity V_0 of the *next* processed data. Then we also use the velocity value to calculate the displacement, S, in the z-axis direction, as calculated in EQ(7),

$$S = V_0 \Delta t + \frac{1}{2} a (\Delta t)^2 \tag{7}$$

where V_0 is initial velocity of the processed data, a is acceleration of the processed data, and Δt is the time period between two consecutive processed data. Since the foot displacement from the HO phase to MP phase is in positive z-axis direction, and that from the MP phase to the beginning of CT phase (B.CT) is in negative z-axis direction, the net step height, S_{net}, is calculated as EQ(8),

$$S_{net} = \sum_{t=HO}^{MP} S_t - \sum_{t=MP}^{B.CT} \mid S_t \mid \tag{8}$$

where S_t is the displacement of two consecutive processed data. Note that the velocity at HO and MP phases will be reset to zero. In addition to the step height, we can also calculate the distance of step trajectory, $S_{traj.}$, as calculated in EQ(9), in one step, which is inspired from EQ(8). $S_{traj.}$ can be considered as one of indicators to the fitness level of a participant. For a participant with a larger $S_{traj.}$ during stair climbing, we generally believe that his/her health condition about the lower limbs is better. Furthermore, it can be an indicator to evaluate the improvement of rehabilitation for patients having lower limb disorders.

$$S_{traj.} = \sum_{t=HO}^{MP} S_t + \sum_{t=MP}^{B.CT} \mid S_t \mid \tag{9}$$

The flowchart of our data analysis method is shown in Fig. 6. For each trail, we process the raw data from the sensor equipped on the S^3-*Sock* with the SMA algorithm. Then we calculate parameters at the WA phase, RMS_{WA} and CV_{WA}. Next, we segment the stair gait phase based on the transition thresholds. We calculate the step height and the distance of step trajectory when the CT phase is identified. Finally, we report the total stride count, total step height, and total distance of step trajectory for lower limb exercises.

III. Experimental Results

In this section, we present the experimental results about the accuracy of the proposed method in three activities: single-step stair-climbing in the ways of step-by-step and step-over-step, and walking in a straight line. The measured results about the stride count and step height are summarized in TABLE I.

The participants were asked to conduct these activities for 10 times with the S^3-*Sock* on the right shoe. The experimental environment is with fixed stairs (12 stages, and total height = 2.16 m) and with a fixed hallway (total length = 35.5 m). Next, we present the experimental results in each activity.

A. Single-step stair-climbing in step-by-step

The experimental results are shown in Columns 2 to 4 of TABLE I. According to TABLE I, the average of absolute mean error in height is 5.12% and the average of absolute mean error in stride count is 2.58%. For most trails, the error in stride count is less than one. In general, the first and the last stride of one trail tend to unstable. Hence, the error of stride count that we obtained is reasonable.

B. Single-step stair-climbing in step-over-step

The experimental results are shown in Columns 5 to 7 of TABLE I. According to TABLE I, the average of absolute mean error in height is 8.23% and the average of absolute mean error in stride count is 2.00%.

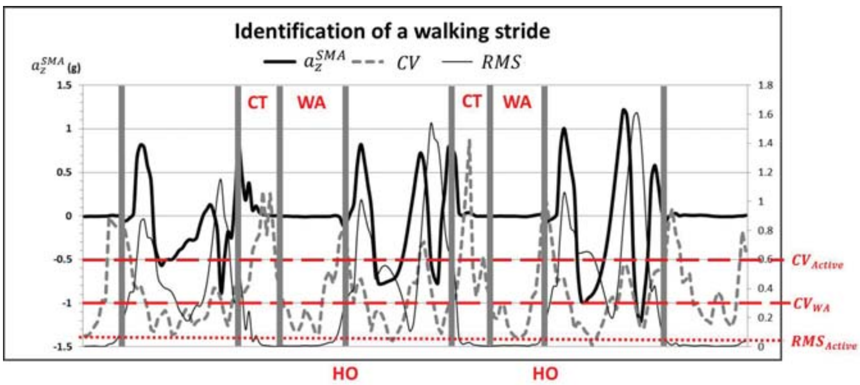


Fig. 7: Identification of a walking stride.

TABLE I: Experimental results.

Subject	**Stair-Climbing (Step-by-Step)**		**Stair-Climbing (Step-over-Step)**		**Walking**
	Absolute Mean Error in Height (%)	Absolute Mean Error in Stride Count	Absolute Mean Error in Height (%)	Absolute Mean Error in Stride Count	Absolute Mean Error in Stride Count
1	6.95	0.4 / 12 (real)	8.05	0.1 / 7 (real)	0.8 / 28 (real)
2	5.24	0.1 / 12 (real)	15.01	0.2 / 7 (real)	0.0 / 28 (real)
3	2.60	0.4 / 12 (real)	7.46	0.3 / 7 (real)	0.0 / 30 (real)
4	7.50	0.6 / 12 (real)	9.00	0.3 / 7 (real)	0.2 / 28 (real)
5	4.60	0.0 / 12 (real)	9.16	0.1 / 7 (real)	0.2 / 31 (real)
6	5.40	0.5 / 12 (real)	4.50	0.1 / 7 (real)	0.5 / 22 (real)
7	3.70	0.6 / 12 (real)	11.00	0.0 / 7 (real)	0.0 / 22 (real)
8	5.50	0.4 / 12 (real)	3.28	0.0 / 7 (real)	0.0 / 27 (real)
9	4.76	0.0 / 12 (real)	7.74	0.1 / 7 (real)	0.0 / 28 (real)
10	4.95	0.1 / 12 (real)	7.12	0.2 / 7 (real)	0.7 / 30 (real)
Average	5.12%	2.58%	8.23%	2.00%	0.88%

Single-step stair-climbing in the way of step-over-step is a normal way of stair-climbing for most people. Since its step height is larger than that of step-by-step stair climbing, the stride count can be calculated more accurately. However, its error in step height is larger than that of step-by-step stair climbing due to larger foot instability.

C. *Walking in a straight line*

We also modify the proposed method to measure the stride count in walking as shown in Fig. 7. Note that the segmentation of the walking gait phase is different from that of the stair gait phase. Since stair-climbing moves a foot vertically, the mid-pause phase can be easily determined between the leg-lift and leg-drop phases in the z-axis direction. However, walking is a horizontal movement in the xy-plane. The mid-pause phase is vague to be observed clearly in a walking gait. Hence, three phases, weight-acceptance (WA), heel-off (HO), and contact (CT), are only identified for this activity.

The experimental results are shown in the last column of TABLE I. The average of absolute mean error in stride count is 0.88%, which demonstrates the accuracy of the modified method.

IV. Conclusion

This paper presents an accelerometer-based wearable device, ***S^3-Sock***, for calculating stride count, step height, and the distance of step trajectory in various activities. The transition thresholds between two gait phases are determined with respect to the parameters at WA phase of each participant for improving the accuracy. The experimental results demonstrate that the accuracy of stride count in walking activity is 99%, and that in stair-climbing activities with step-by-step and step-over-step are about 97% and 98%, respectively. Furthermore, the accuracies of step height measurements with step-by-step and step-over-step are about 95% and 92%, respectively. Wearing this ***S^3-Sock***, the lower limb exercises can be monitored and recorded instantaneously.

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