Application of Hybrid Multi-Resolution Wavelet Decomposition Method in Detecting Human Walking Gait Events

Darwin Gouwanda, S. M. N. Arosha Senanayake
School of Engineering
Monash University Sunway Campus
Bandar Sunway, Malaysia
E-mail: darwin_gouwanda@ieee.org, senanayake.namal@eng.monash.edu.my

***Abstract*—Identifying walking gait events is important in gait analysis. In particular, heel-strike and toe-off are commonly used to define the stance phase and swing phase in normal human walking gait cycle. They are used to segment a stream of human motion data into discrete and meaningful sections that can be analyzed and compared with available literatures. This paper proposes multi-resolution wavelet decomposition to reveal relevant information. Subsequently, proposed method differentiates the signal twice to identify the heel-strike and toe-off events. With this information, various temporal gait parameters can be easily estimated, such as the duration of swing phase and stance phase, and the duration of initial double support and terminal double support. Experimental results on the temporal parameters are comparable to the available benchmark data with minimal discrepancies due to the anthropometric properties of the subjects and inconsistent walking speed.**

Keywords: Gait events detection, multi-resolution wavelet decomposition, inertial measurement unit

I. INTRODUCTION

Gait events detection is essential in the human motion analysis. The initial foot contact or heel-strike and end of foot contact or toe-off represent the start of stance and swing phase respectively [1]-[3], as shown in Fig. 1. These two events are widely used to measure and segment definable events or phases to aid the analysis of gait and the development of gait assisted devices, such as FES (Functional Electrical Stimulation) [4]-[7]. In several clinical situations, gait event detection is used to evaluate treatments for patients with pathological gait and celebral palsy [8]-[9], to assess functional performance of a patient after treatment or surgery such as hip and knee arthroplasty, to refine proper alignment and fit of external prosthesis or orthesis, and to assess fall risk of elderly persons [10].

Considering the importance of gait event detection in walking gait cycle, various tools and methodologies have been developed to identify these events and to extract various spatio-temporal parameters, such as stride time, stride length, step length and walking velocity. Winter, *et al.* developed microswitch shoes to detect walking gait events such as heel-strike, flat-foot, heel-rise, opposite heel-strike, and toe-off [12]. In similar approach, Vetlink, *et al.* developed orthopaedic shoes equipped with six degree of freedom force sensors to detect human walking gait events and extract various kinematic and kinetic parameters, such as ground reaction force and center of pressure [13]-[14]. Ghoussayni, *et al.* placed reflective markers on human feet to detect four major gait events in walking: heel-contact, heel-rise, toe-contact and toe-off. Besides that, force platform was utilized as well, to obtain the start and end of the contact phases [8]. Similarly, Zeni, *et al.* used 3D motion capture system to determine the gait events such as heel-strike and toe-off [15]. Saxe and Foulds placed two retro-reflective markers on human feet, placed on the heel and toe (fifth metatarsal) of the right foot, and two markers on the medial and lateral right ankle along the flexion/extension axis to detect different phases in human walking gait [16]. Catalfamo, *et al.* used F-Scan in-shoe measurement system to detect the initial contact and foot off in walking [1].

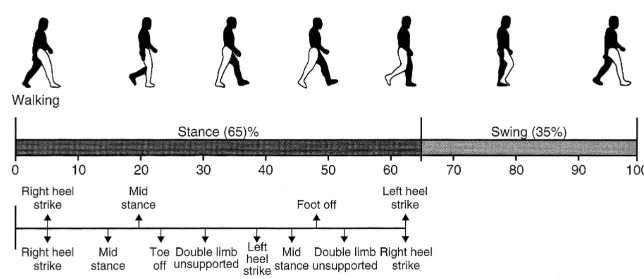

Figure 1. Human walking gait cycle [11]

In recent years, as rapid advancement of technology and science has caused significant impacts in biomechanics and biomedical engineering, researchers have shifted their research tools and methodologies, from conventional technologies such as marker based 3D motion capture system and footwear based system to more advanced technologies such as miniature accelerometer and gyroscope. These miniature sensors do have their merits, compared to the conventional ones. They are smaller, lighter and they do not encumber human motion. One of their most important features is their capability in capturing human motion outside the laboratory environment [17]-[19]. Mansfield and Lyons placed bi-axial accelerometer on the

978-0-7695-3879-2/09 $26.00 © 2009 IEEE
DOI 10.1109/SoCPaR.2009.115

trunk of an individual to detect gait events in FES assisted walking [7]. Jasiewicz, *et al.* used accelerometer and gyroscope to detect the heel-strike and toe-off events in normal and spinal-cord injured individuals [20]. Tong and Granat used uni-axial gyroscopes and foot switches to develop a simple portable gait analysis system. This system is able to provide information on human lower extremity segment inclination range, cadence, number of steps and estimation of stride length and walking speed [21]. Using similar approach, Aminian *et al.* used miniature gyroscope and foot switches to extract spatio-temporal parameters of human walking gait such as stride length, stride time, gait cycle time, right and left stance [10].

In this paper, wireless inertial sensors are used to quantify human shank motion in walking. Most importantly, this paper proposes a simple and novel algorithm which is able to estimate various gait temporal parameters such as duration of one walking gait cycle, duration of the swing phase, duration of the stance phase, duration of the initial double support and duration of the terminal double support. This algorithm uses similar approach proposed by Aminian, *et al*, [10] in which the multi-resolution wavelet decomposition method is utilized to decompose the original signal captured by gyroscopes to reveal relevant information contained inside the signal. However, this paper does not threshold the signal to determine the local minima i.e. heel-strike and toe-off in a pre-determined interval. Alternatively, proposed method differentiates decomposed signal twice to identify the heel-strike and toe-off events in walking gait cycle. Furthermore, in order to evaluate its performance, a series of experiments are conducted on young and healthy experimental subjects.

II. INSTRUMENTATION – WIRELESS INERTIAL SENSOR

Lower limbs movements of the subject are captured using commercially available wireless inertial sensors, Wireless Inertia-Link. Single Inertia-Link system consists of one wireless tri-axial inertial sensor node and one USB wireless transmitter, as shown in Fig. 2 and Fig. 3 respectively. The Inertia-Link sensor node contains tri-axial accelerometer and tri-axial gyroscope that is capable of recording the acceleration and angular velocity of an object in a three-dimensional space. It produces discrete signal in form of $So_{(m)} = S_1, S_2, S_3 \ldots S_m$ where m is the total number of data samples collected in one experiment. Motion captured by the sensor node is transmitted to the computer in real time for visualization and further processes.

Figure 2. Wireless Inertia-Link sensor node [22]

It is important to note that even though Inertia-Link is able to capture the acceleration and angular velocity in three-dimensional space, only angular velocity of the shank along the Z axis is collected in each experiment, as illustrated in Fig. 4. The main reasons are that angular velocity of the human shanks can be directly captured by the inertial sensor without being affected by gravity or any linear acceleration and it contains timing information on heel-strike and toe-off events in the normal walking gait cycle, as discussed in [10], [14], [21].

Figure 3. Wireless Inertia-Link USB base station [22]

To ensure that the Inertia-Link sufficiently captures the shank motion, its sampling rate *(Ts)* is set to 200Hz.

III. EXPERIMENTAL SUBJECTS AND PROCEDURES

Nine young and healthy male subjects with no known gait abnormalities participated in this study. Subjects were briefed on the purpose of the experiment and procedures before they were asked to give their consents.

In this paper, each subject was required to walk on a 20 m pathway with two Wireless Inertia-Links attached to the right and left shank by means of rubber straps. While walking, movement of the subject shanks are captured and transmitted to the computer through the Inertia Link wireless USB base station in real time.

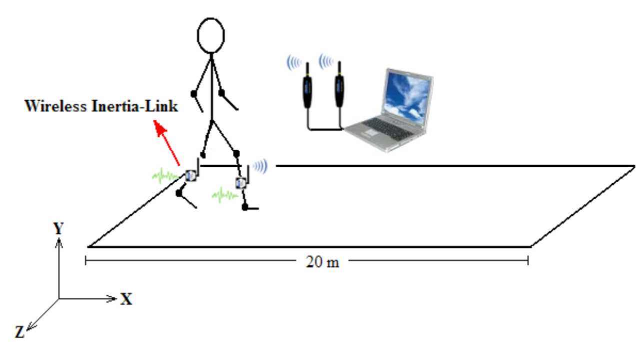

Figure 4. Walking experimental setup

IV. HYBRID MULTI-RESOLUTION WAVELET DECOMPOSITION METHOD

The application of wavelet transform analysis in science and engineering began to take off in the early of the 1990s, with a rapid growth in the numbers of researchers turning their attention to wavelet analysis during the decade. Wavelets are widely used in various fields, ranging from engineering, medicine, finance, geophysics to astronomy [23]. In general, wavelet transform consists of Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). This paper uses DWT to perform multi-resolution wavelet decomposition [24] to identify the toe-off and heel-strike events in walking. Code is written using Matlab version 7.5 to implement the hybrid multi-resolution wavelet decomposition method.

In multi-resolution wavelet decomposition, the original signal (*So*) passes through low-pass filter and high-pass filter. As a result, it is split into two components: the low frequency component, which is called the approximation signal (A_1) and the high frequency component which is called the detail signal (D_1). This decomposition method is repeated n times with each successive approximation signal being decomposed to produce next approximation signal (A_n) and detail signal (D_n) [24] as illustrated in Fig. 5.

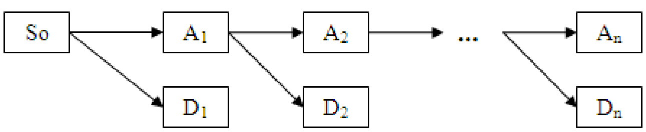

Figure 5. Multi-resolution Wavelet Decomposition

$$So = A_n + D_1 + D_2 + \ldots + D_n \qquad (1)$$

For clarity and simplicity, only one segment of the original signal, which is collected from human shank during walking, is considered here, as shown in Fig. 6. The segmented signal contains two peaks and two valleys, which both peaks approximately correspond to the time of mid-swing in walking gait cycle, first valley corresponds to the heel-strike and second valley corresponds to the toe-off [10], [18],[20]. It is important to mention that this algorithm can be applied to both shanks and to the complete data collected in one experiment.

Several assumptions are made to estimate the heel-strike and toe-off events in walking. The first assumption is that the heel-strike and toe-off occur between two successive mid-swings in the normal human walking gait cycle. The second assumption is that angular velocity of the shank during heel-strike and toe-off is less than 0 rad/s. Lastly, a threshold value of 2 rad/s is chosen to identify two mid-swings in each walking gait cycle.

In order to extract relevant information regarding the heel-strike and toe-off events, the original discrete signal is decomposed twice using symmlet2 wavelet transform. As a result, this method produces three major components: 2nd level approximation signal (A_2), 2nd level detail signal (D_2) and 1st level detail signal (D_1).

$$So_{(m)} = A_{2(m)} + D_{2(m)} + D_{1(m)} \qquad (2)$$

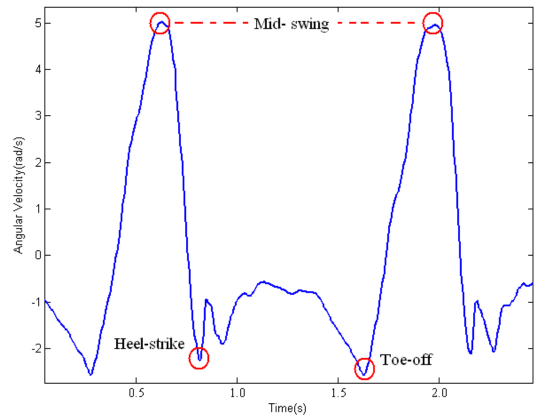

Figure 6. Shank angular velocity with heel-strike, toe-off and mid swing events in walking gait

In subsequent processes, only $A_{2(m)}$ is taken into consideration because $A_{2(m)}$ does not contain high frequency components and it retains low frequency component, which has less noise compared to the original signal. Most importantly, it amplifies the original signal and preserves three major features that are necessary for next processes: heel-strike, toe-off and mid-swings, as shown in Fig. 7.

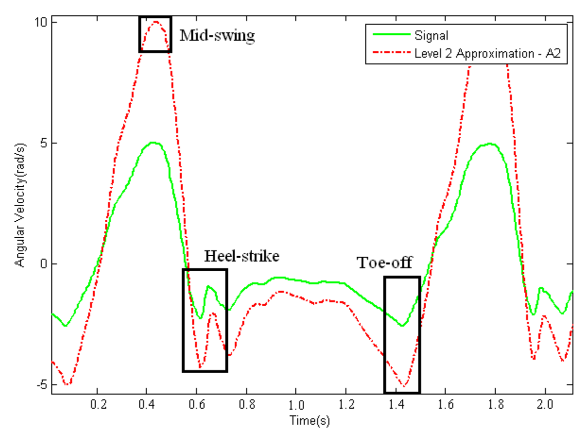

Figure 7. 2nd level approximation signal and original signal

In the next step, derivatives of $A_{2(m)}$ are calculated using finite difference equations to reveal relevant information regarding the location of peaks and valleys.

$$A_{2(m)}' = A_{2(m)} - A_{2(m-1)} / \Delta t \tag{3}$$

$$A_{2(m)}'' = A_{2(m)}' - A_{2(m-1)}' / \Delta t \tag{4}$$

$$\begin{aligned} \text{Where} \quad A_{2(m)}' &= 1^{st} \text{ derivative of } A_{2(m)} \\ A_{2(m)}'' &= 2^{nd} \text{ derivative of } A_{2(m)} \\ \Delta t &= 1/Ts = 0.005 \text{ s} \end{aligned}$$

As a result, $A_{2(m-1)}''$ produces sharp spikes, that have different amplitudes. Each spike corresponds to a change in the signal slope. Positive spike with high amplitude corresponds to the valleys in the approximation signal, $A_{2(m-1)}''$ while negative spike corresponds to the peaks in the approximation signal, $A_{2(m-1)}''$. For better illustration, refer to Fig. 8.

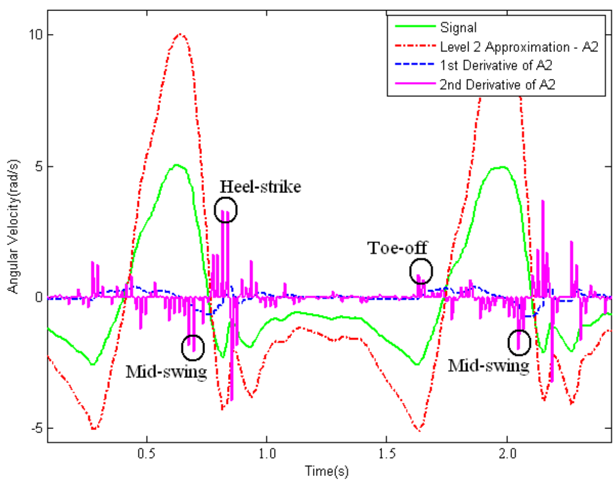

Figure 8. Identified heel-strike and toe-off in $A_{2(m)}''$ ($A_{2(m)}''$ is multiplied by 10 to improve signal visibility

Separating the positive spikes and negative spikes distinguishes the locations of peaks and valleys in the original signal and the approximation signal. To do so, the positives spikes ($A_{2(m)}'' > 0$) are placed in a 2D array, in which each row contains values of positive spikes that are close to each other. Subsequently, a local search is conducted in each row to identify the location of the maximum spike. This location eventually corresponds to the location of a valley in the original signal. Similarly, negative spikes are placed in a 2D array, in which each row contains values of negative spikes ($A_{2(m)}'' < 0$) that are close to each other. Thereafter, a local search is conducted in each row to identify the location of the minimum spike, which corresponds to a peak in the original signal.

Based on assumptions mentioned earlier and the locations of peaks and valleys in the original signal, heel-strike and toe off events in human walking gait cycle can be easily detected. Heel-strike eventually corresponds to the first negative valley, while toe-off corresponds to the last negative valley which lies between two mid-swings, as shown in Fig. 9.

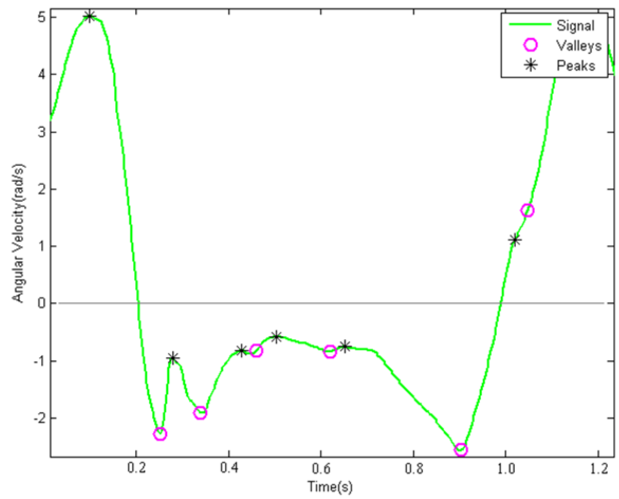

Figure 9. Identified peaks and valleys in the original signal

By identifying the right leg heel-strike (Ths_R), left leg heel-strike (Ths_L), right leg toe-off (Tto_R) and left leg toe-off (Tto_L) during walking, a series of temporal parameters for each gait cycle j can be easily calculated. These temporal parameters are:

- Stride time, *Tstride*
  $$Tstride(j) = Ths_R(j+1) - Ths_R(j) \tag{5}$$
- Duration of swing phase, *Tswing*
  $$Tswing(j) = Ths_R(j+1) - Tto_R(j) \tag{6}$$
- Duration of stance phase, *Tstance*
  $$Tstance(j) = Tstride_R(j) - Tswing_R(j) \tag{7}$$
- Duration of initial double support, *Tid*
  $$Tid = Tto_L(j) - Ths_R(j) \tag{8}$$
- Duration of terminal double support, *Ttd*
  $$Ttd = Tto_R(j+1) - Ths_L(j) \tag{9}$$
- Duration of double support, *Tds*
  $$Tds = Tid(j) + Ttd(j) \tag{10}$$

V. EXPERIMENTAL RESULTS

To examine its performance, hybrid multi-resolution wavelet decomposition method is applied to the normal human walking experimental data. Temporal parameters derived from these experiments are presented in Table I.

TABLE I. TEMPORAL PARAMETERS DERIVED FROM EXPERIMENTS

Subject	*Tstride(s)*	*Tstance(s)*	*Tswing(s)*	*Tid(s)*	*Ttd(s)*
A	1.3140	0.7615	0.5525	0.1365	0.1290
B	1.4865	0.8317	0.6548	0.1015	0.1100
C	1.3590	0.8100	0.5490	0.1227	0.1423
D	1.2057	0.6665	0.5392	0.0625	0.0640
E	1.3007	0.7776	0.5231	0.0668	0.1103
F	1.1875	0.6582	0.5293	0.0838	0.0773
G	1.3503	0.7880	0.5623	0.1157	0.1350
H	1.2103	0.6822	0.5281	0.0807	0.0612
I	1.2655	0.7593	0.5062	0.0617	0.1340

To compare the experimental results with available benchmark, relative stance (*Stance*), relative swing (*Swing*), relative initial double support (*IDS*) and relative terminal double support (*TDS*) are calculated using following equations:

$$Stance(\%) = Tstance(j)/\ Tstride(j) \ x\ 100\% \tag{11}$$

$$Swing(\%) = Tswing(j)/\ Tstride(j) \ x\ 100\% \tag{12}$$

$$IDS(\%) = Tid(j)/\ Tstride(j) \ x\ 100\% \tag{13}$$

$$TDS(\%) = Ttd(j)/\ Tstride(j) \ x\ 100\% \tag{14}$$

In their works, Sammarco, Whittler and Perry [11], [25], [26] stated that stance phase lasts approximately 60% - 65% of the walking gait cycle, swing phase lasts approximately 35% - 40% of the walking gait cycle and double support phase lasts approximately 10% of the walking gait cycle, as illustrated in Fig. 1. From the Table II, it can be clearly observed that all parameters agree with the benchmark, with acceptable discrepancies. These discrepancies can be explained by the anthropometric properties of the subject and inconsistent walking speed. Differences in time duration of all four phases are mainly caused by difference in subject's body height, length of his shanks and thighs. Additionally, inconsistent walking speed may cause these discrepancies as well. As the walking speed increases, swing phase will become proportionately longer, stance phase and double support phase will become shorter,. This effect can be observed in subject D who has longer swing phase and shorter stance phase and double support phases compared to the other subjects, as presented in Table II.

VI. DISCUSSION

In this paper, two wireless inertial sensors are attached on the right and left shanks of the subjects to identify heel-strike and toe-off events in a normal walking gait cycle. By enabling the wireless transmission between the sensors and the base stations, this system can be used in any indoor and outdoor environment, which in turn provides information that is more likely to reflect the actual human walking gait.

TABLE II. RELATIVE TEMPORAL PARAMETERS

Subject	*Stance(%)*	*Swing(%)*	*IDS(%)*	*TDS(%)*
A	57.95	42.05	10.39	9.82
B	55.95	44.05	6.83	7.40
C	59.60	40.40	9.03	10.47
D	55.28	44.72	5.18	5.31
E	59.78	40.22	5.14	8.48
F	55.43	44.57	7.06	6.51
G	58.36	41.64	8.57	10.00
H	56.37	43.63	6.67	5.06
I	60.00	40.00	4.88	10.59

Furthermore, a hybrid multi-resolution wavelet is proposed to identify heel-strike and toe-off from shank angular velocity in walking gait cycle. Even though, it uses similar approach proposed in [10] to decompose the original signal using multi-resolution wavelet, it does not threshold the signal to find the local minima in the certain fixed intervals of the signal. Instead, proposed method uses symlet2 to decompose the original signal twice to reveal the relevant information contained in the signal and differentiates the signal twice to generate multiple spikes, which provides the location of the heel-strike and toe-off in walking.

One of the merits of the proposed method is that it uses only two decomposition levels compared to ten decomposition levels as proposed in [10]. As a result, it reduces complexity and computational time significantly. Furthermore, this method does not find local minima (heel-strike and toe-off events) in pre-determined intervals. The proposed method defines two mid-swings in the normal walking as its references where a series of local maxima and local minima is identified. From this series, the first local minima which have value less than zero will be the heel-strike and the last local minima which have value less than zero will be the toe-off. By not assuming the pre-determined interval to identify the local minima, the proposed method may perform better in detecting the heel-strike and toe-off event in abnormal walking gait, which may have longer or shorter stance phase and swing phase.

From the experimental results, it can be observed that the values of the parameters measured by the wireless inertial sensor are in good agreement with existing benchmark. However slight differences exist due to the anthropometry properties of the subjects and their inconsistent walking speed.

VII. CONCLUSION

Even though, heel-strike and toe-off detection may seem to be trivial, it has wide applications, ranging from rehabilitation, evaluation of pathological gait, fall risk assessment, to the design and development of gait assisted devices, as described in various literatures.

In this paper, two wireless inertial sensors are attached on the right and left shanks to gather information regarding the occurrences of different gait events in walking. To achieve this, the proposed method uses simple multi-resolution wavelet decomposition to extract the relevant information and differentiates the signal twice to obtain the heel-strike and toe-off events in normal walking gait cycle.

The experimental result shows that hybrid multi-resolution wavelet decomposition method is remarkably satisfactory. It has shown to be a practical gait analysis tool in various applications. In the future, larger pool of experimental subjects, which includes subjects with normal and abnormal walking gaits, will be considered to evaluate its accuracy and reliability.

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