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Seafarers Walking on an Unstable Platform: Comparisons of Time and Frequency Domain Analyses for Gait Event Detection

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Abstract

Wearable sensor-based gait analysis has been widely conducted to analyze various aspects of human ambulation abilities under the free-living condition. However, there have been few research efforts on using wearable sensors to analyze human walking on an unstable surface such as on a ship during a sea voyage. Since the motion of a ship on the unstable sea surface imposes significant differences in walking strategies, investigation is suggested to find better performing wearable sensor-based gait analysis algorithms on this unstable environment. This study aimed to compare two representative gait event algorithms including time domain and frequency domain analyses for detecting heel strike on an unstable platform. As results, although two methods did not miss any heel strike, the frequency domain analysis method perform better when comparing heel strike timing. The finding suggests that the frequency analysis is recommended to efficiently detect gait event in the unstable walking environment.

Index Terms: Frequency and time domain analysis, Gait event detection, Unstable surface, Wearable sensor

I. INTRODUCTION

Wearable inertial sensors have been predominantly applied to analyze various aspects of human ambulatory abilities under free-living conditions. Due to the capabilities of continuous and unobstructed monitoring of daily activities, the wearable gait analysis approach has been widely adopted in a number of fields such as biomechanics, rehabilitation, and sports medicine [1, 2]. Moreover, the development of inertial sensor-based gait recognition approaches emerged simultaneously with the dramatic evolution of ambient smart devices that have become a commercial and academic standard [3]. Multivariate human gait signals were collected by wearable sensors, and the signals were analyzed to provide the kinetic characteristics of human locomotion in daily life. In this manner, underlying gait characteristics that were difficult to directly observe could be discovered.

The majority of previous studies focused on stable walking such as level walking. Little information is available on gait mechanisms on unstable walking surfaces, including moving environments such as ships or trains. The motion of a ship on an unstable sea surface imposes significant differences in walking strategy [4]. A recent study by Walter et al. [5] investigated the effect of a ship's motion on human walking strategy and found that the magnitude of the ship's motion and walking performance were significantly related to the ship's directional motion.

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Chang et al. [6] also found that the number of steps per day and the strength of each step increased during a sea voyage compared to the measured data while the subjects were in a harbor. Although the findings of some previous studies improved the understanding of unstable walking in unstable environments, there has been a lack of attention on the development of systematic wearable systems to analyze human walking in an unstable setting such as on a ship while sailing. Thus, there has been a growing interest in developing an objective gait analysis method for subjects living in an unstable environment that makes physical work difficult. Also, the validation of a wearable sensor-based gait analysis approach under unstable environments is essential to promote the successful implementation and long-term use of wearable systems in unstable settings.

This study considered two representative gait event analyses method such as time domain and frequency domain analyses. The two methods have been dominantly applied to detect gait event in the free-living condition. Time domain analysis mainly deals with timings of signal peaks of initial contact and toe off activities [7–9]. Conversely, frequency domain analysis focuses on regularity of gait cycle by converting time series signal to frequency domain. Existing studies have shown that frequency domain analysis could be clinically relevant when investigating gait regularity patterns [10].

Therefore, this study aimed to compare two representative gait event algorithms including time domain and frequency domain analysis for detecting heel strike (HS) on an unstable platform. Acceleration data from a single chest-worn accelerometer have been applied to two methods. Since unstable gait required higher effort to maintain balance [4–6], the chest-worn sensor could provide better understanding of gait pattern in the unstable condition. However, HSs as a good indicator of gait event initiation can be directly measured by two ankle-worn accelerometers. Therefore, this study utilized the signal from ankle sensors as standard criteria of gait event timing. The number of steps and timing of gait events collected by the chest acceleration analysis algorithm were compared with the results obtained from the ankle acceleration-based gait detection algorithm in both stable and unstable walking conditions.

II. METHODS

A. Data Collection

In total, 36 healthy individuals between the ages of 22 and 36 years participated in the study. The descriptive characteristics of the participants areshown in Table 1. Before initiating the experimental protocol, participants filled out a health history form and signed an informed consent approved by the Institutional Review Board at the University of Nebraska Medical Center (IRB No. 273-16-EP). Thirteen of the 36 participants walked in a stable condition when the ship was in harbor. The remaining 23 participants walked in an unstable condition during a sea voyage. In both experiments, participants walked along a straight line on the main deck of the training ship of Mokpo National Maritime University at a self-selected speed.

Table 1. Descriptive characteristics of participants

	Harbor (n=13)	Sea (n=23)
Sex (female:male)	1:12	3:20
Age (yr)	24.2 ± 3.4	23.8 ± 2.7
BMI (kg/m^2)	24.1 ± 2.3	23.6 ± 2.6
Height (cm)	174.7 ± 6.4	174.3 ± 6.3
Weight (kg)	73.6 ± 8.8	72.0 ± 10.2

Values are presented as mean ± SD.

To collect acceleration data, participants wore three small and lightweight 3-axis accelerometers called Shimmer3 [11]. One sensor was attached to the chest and the others were attached to each ankle. Attachment of wearable sensors on lower limbs such as ankles and knee have been preferred to detect gait event in many studies [2, 3], and the attachments are proper to get lower limb motor control [12, 13]. Conversely, attachment of the sensors on the upper body such as chest and waist are preferred to investigate gait balance abilities such as posture control and upper body sway [14]. Since the unstable walking condition of this study requires more effort on balance control capability on waves, upper body attachment was selected in this study.

The acceleration ranges of the chest-worn and ankle-worn sensors were set to 4 g and 8 g, respectively. The accelerometers were fixed with an elastic band strap, and were sampled at 100 Hz. The accelerometers were synchronized at the beginning of the data collection.

B. Gait Recognition

The two methods have been implemented to recognize gait event. Fig. 1 illustrates a framework for time and frequency domain analyses to detect gait event by using data from chest-worn sensor. Validation of results from two methods performed using direct heel-strike measure from ankle-worn sensors.

In time domain analysis, three types of gait recognition methods including a zero-velocity update, a correlation-calculation method, and a peak detection method have been used in the wearable sensor-based gait analysis approach [15, 16]. The peak detection method, which detects maximum peaks or minimum valleys of acceleration data using

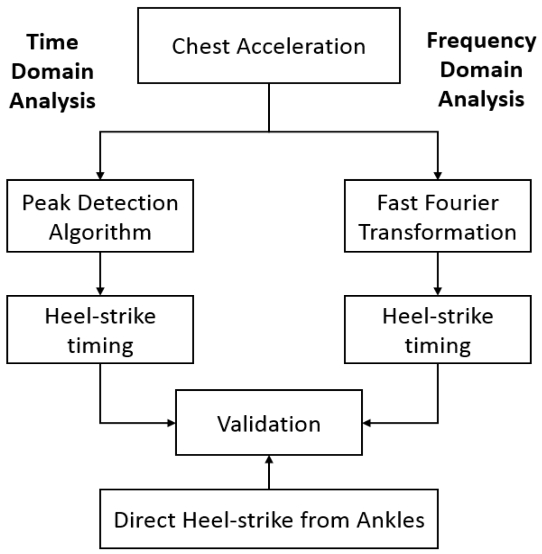

Fig. 1. A framework for time and frequency domain analyses to detect gait event by using data from chest-worn sensor; validation of results from two methods using direct heel-strike measure from ankle-worn sensors.

thresholds, was chosen in this study because the method requires minimum computation to recognize gait events. Since HS is the most important event for gait recognition, two thresholds including the minimum-peak height (or the maximum-valley height) and the minimum distance were used to analyze the collected raw acceleration data. For the acceleration data collected from the chest and left ankle sensors, the minimum-peak height was used to find peaks greater than the minimum-peak height that was the mean value of anterior accelerations. For the acceleration data from the right ankle sensor, on the other hand, the maximum-valley height was used to find valleys smaller than the maximum-valley height, since the sensor's orientation of the right ankle is opposite. The minimum distance was also used to find peaks or valleys where the distances between two peaks or two valleys were longer than the minimum distance. The recognized gait events from the two ankle sensors were used as important criteria of the gait event. The gait event results were then used to validate the chest sensor-based gait recognition outcomes.

Chest acceleration data were converted to a frequency domain representation using fast Fourier transform (FFT). The FFT converts a time domain acceleration signal into the frequency domain by representing the acceleration as a series of sinusoids. After being converted to the frequency domain, amplitude, power, and phase spectrums were created for each participants using a custom MATLAB environment (MathWorks Inc., Natick, MA, USA). The power spectrum revealed that vertical directional acceleration among three dimensional data was efficient to recognize gait events. For the vertical acceleration data, the majority of the signal energy was included in the two dominant frequencies (i.e., 1.8 Hz and 3.7 Hz) with significantly large amplitude. When we consider average step time between 0.5 and 0.7 seconds, frequency about 1.8 Hz could well represent gait event cycles. The number and timing of detected steps from the two methods have been analyzed.

III. RESULTS

Overall, two methods accurately detect HS in both stable and unstable conditions. The accuracies of detecting HSs in an unstable walking condition were comparable with the detection accuracies in a stable walking condition in a harbor. Fig. 2 presents raw acceleration data with gait detection results from two representative participants to explain the main differences between the harbor and sea experiments. The acceleration data from the harbor condition walking are shown in Fig. 2(a)–(c). The acceleration graphs from the stable condition showed regular patterns in terms of peak patterns. The unstable walking acceleration data are depicted in Fig. 2(d)–(f). As depicted in Fig. 2, significant agreement was observed in detecting HS events in both stable and unstable condition experiments. Outcomes of the FFT method were also compared to ankle-based direct HS measure (see Fig. 3). The number of steps recognized by FFT between the detected HS from the chest sensor and ankle sensors were consistent from both methods in unstable walking conditions on a ship.

Validation of results from two methods was conducted by comparing the number of computed HSs and timing of each steps. Directly measured HSs from ankle sensors used to determine agreement of two methods. Table 2 summarizes the comparison results. Although there was moderate ship motion during the sea condition experiments, the chest acceleration analysis method missed only one HS event over 60 HSs. The main difference of the sea walking gait patterns compared to the harbor walking gait events was the inconsistent step tempo. Although the average step times of the harbor and sea walking scenarios were similar (see Table 2), a wider variation of the gait tempo in the sea walking experiment was observed.

Moreover, the variation caused by the timing gap of the HS detection between the chest and ankle systems. The HS detection timing of the chest sensor in the sea walking was not aligned as accurately as that of the harbor HS detection. We concluded that this was caused by additional upper body movements to maintain stability during walking. It was found that strategies to maintain balanced and stable walking on an unstable surface inherently constrain the gait speed and energetic efficiency by adjusting the step tempo and step width [17, 18].

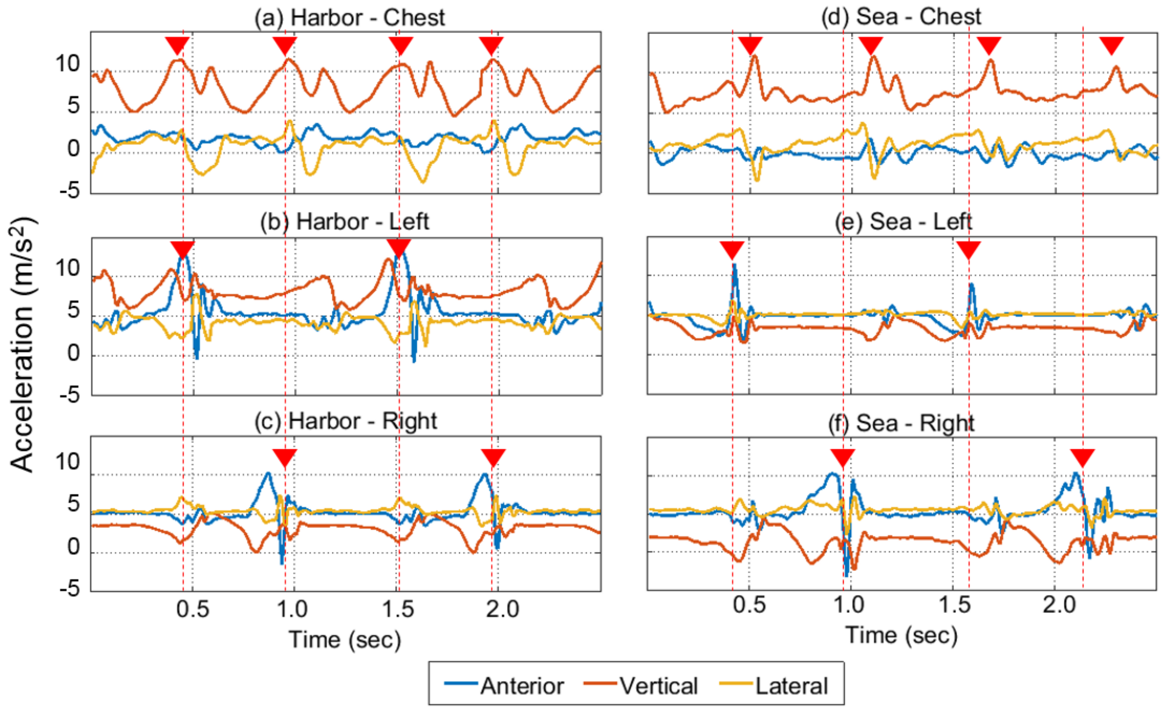

Fig. 2. Time domain analysis: acceleration patterns of two representative subjects. (a), (b), and (c) were acceleration data from the harbor. (d), (e), and (f) were acceleration data from sea experiments. Red triangles indicate recognized HS from raw acceleration data.

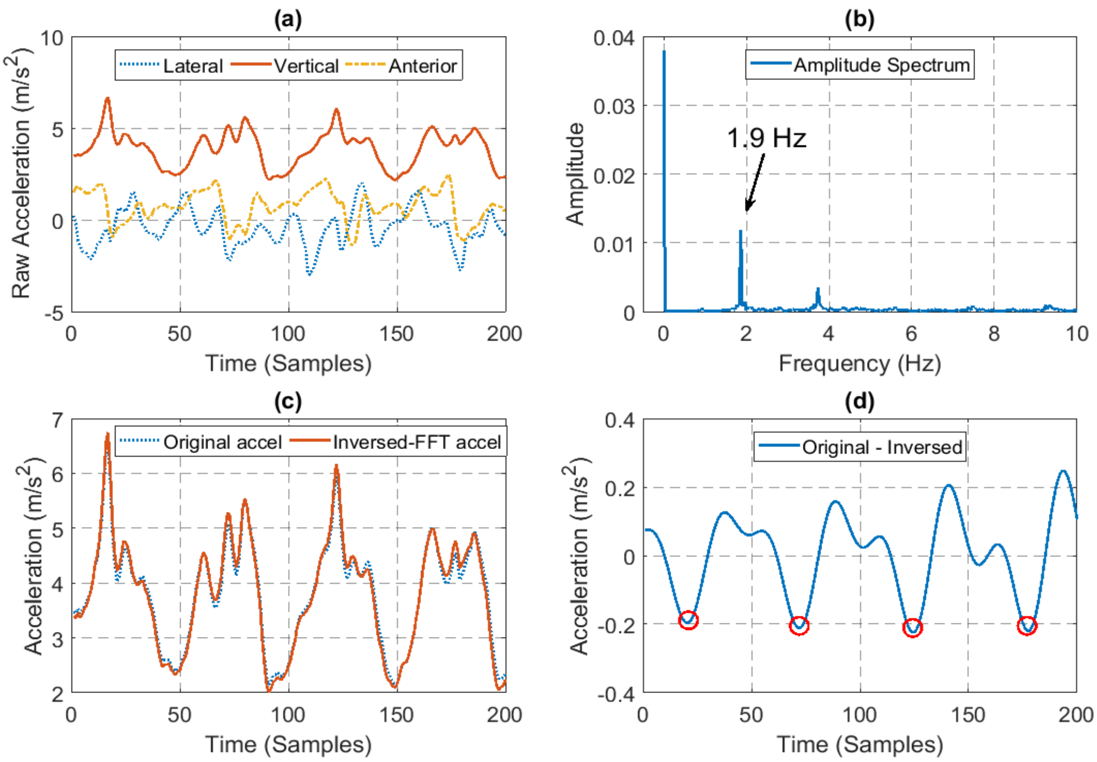

Fig. 3. Frequency domain analysis: (a) raw three dimensional acceleration data, (b) single-side amplitude spectrum of vertical acceleration, (c) original acceleration and 1.9 Hz removed acceleration data after inverse FFT, and (d) recognized peak indicating with red circles by calculating gap between original and inversed acceleration.

Table 2. Comparisons of results from two methods between the harbor and sea conditions

	Time domain analysis (peak detection algorithm)		Frequency domain analysis (fast Fourier transform algorithm)	
	Harbor	Sea	Harbor	Sea
Number of participants	13	23	13	23
Avg. step time by ankle sensors (s)	0.54 ± 0.08	0.55 ± 0.11	0.54 ± 0.03	0.55 ± 0.06
Directly measured steps by ankle sensors	60.00 ± 0.0	60.00 ± 0.00	60.00 ± 0.00	60.00 ± 0.00
Computed steps by a chest sensor	60.00 ± 0.0	59.90 ± 0.20	60.00 ± 0.00	60.00 ± 0.00
Delay time between two locations (s)	0.03 ± 0.09	0.05 ± 0.11	0.07 ± 0.02	0.06 ± 0.02

Values are presented as mean ± SD.

The number of recognized HSs from peak detection and FFT methods were almost perfect agreement (99.9%). However, FFT reliably capture HSs than peak detection method. In the last row of Table 2, time difference between ankle and chest data and standard deviation of the HS time difference are shown. FFT showed less fluctuation in HS recognition than peak detection method. This may be more irregular HS magnitude interfere to calculate a good threshold of the peak detection method. While FFT is able to the frequency of step cycles, so instant irregular HS magnitude does not results in crucial failure of HS detection.

Additionally, the mean of the gap differences in the harbor and the sea conditions was about 34 ms and 49 ms, respectively. For the mean gaps of the HS timing differences, the calculated values in the harbor and sea conditions were 6.3% and 9.1%, respectively. The differences between two sensor attachments were not significant, and therefore we can determine the effectiveness of the upper-based gait detection method. The standard deviation of the timing differences per each participant by using two different conditions was almost the same, and the similar variation in timing differences implies that the peak detection-based gait recognition has reasonable inter-subject reliability regardless of the differences in personal gait patterns.

IV. DISCUSSION AND CONCLUSIONS

In this paper, we compared two wearable sensor-based gait recognition methods in an unstable walking condition. The experimental results confirmed that frequency domain analysis (i.e., FFT algorithm) achieved more reliable heel strike detection accuracy than time domain analysis (i.e., peak detection algorithm). The finding suggests that the frequency analysis is recommended to efficiently detect gait event in the unstable walking environment. The key contribution of this study is to provide initial evidence for selecting appropriate gait event detection method in an unstable platform. Future work will include the investigation of gait characteristics in relation to gait adaptation to an unstable environment.

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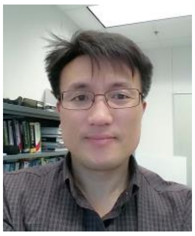

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