Unsupervised segmentation of heel-strike IMU data using rapid cluster estimation of wavelet features

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***Abstract*—When undertaking gait-analysis, one of the most important factors to consider is heel-strike (HS). Signals from a waist worn Inertial Measurement Unit (IMU) provides sufficient accelerometric and gyroscopic information for estimating gait parameter and identifying HS events. In this paper we propose a novel adaptive, unsupervised, and parameter-free identification method for detection of HS events during gait episodes. Our proposed method allows the device to learn and adapt to the profile of the user without the need of supervision. The algorithm is completely parameter-free and requires no prior fine tuning. Autocorrelation features (ACF) of both antero-posterior acceleration (a_{AP}) and medio-lateral acceleration (a_{ML}) are used to determine cadence episodes. The Discrete Wavelet Transform (DWT) features of signal peaks during cadence are extracted and clustered using Swarm Rapid Centroid Estimation (Swarm RCE). Left HS (LHS), Right HS (RHS), and movement artifacts are clustered based on intra-cluster correlation. Initial pilot testing of the system on 8 subjects show promising results up to 84.3%±9.2% and 86.7%±6.9% average accuracy with 86.8%±9.2% and 88.9%±7.1% average precision for the segmentation of LHS and RHS respectively.**

I. INTRODUCTION

The analysis of gait parameters is beneficial for assessing treatment effectiveness, quality of mobility and general health [1], [2]. Information about gait parameters provides important diagnostics for balance, functional ability, risk of falls [1].

The current methods for assessing gait parameters are mostly laboratory-based. They are expensive and not practical for application in daily life [3]. Force platforms, as the gold standard, can be used to precisely record the ground reaction forces exerted by the feet during the gait cycle [4]. Other popular methods use lower-limb sensors [5], pressure insoles [6], or stereo-photogrammetric cameras [7].

A waist-worn Inertial Measurement Unit (IMU) is a low-cost solution for extracting gait parameters [1]–[3], [8]. An IMU consists of an accelerometer and a gyroscope. Using a single waist-worn accelerometer, Moe-Nilssen and Tura estimate gait regularity from the autocorrelation function (ACF) pattern of the mediolateral (ML) and anteroposterior (AP) acceleration [1], [3]. Using similar setup, Bugané extracts the gait parameters by identifying important gait events including heel-strikes (HS) and toe-offs (TO) based on peak detection and thresholding of the AP and ML acceleration [8]. Similarly, Köse use the stationary wavelet transform and peak detection to extract HS & TO events using a single IMU worn on the lateral side of the pelvis to finally calculate bilateral step length estimate [2].

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The above methods tend to perform poorly in real-world situations where the data is noisy, where gait patterns vary in real-time, and where there is a degree of drift in the placement of the sensors. To reliably identify HS using an IMU, the system should be able to distinguish movement artifacts from HS acceleration patterns. In this paper we propose a parameter-free HS and stride pattern clustering. The proposed protocol allows the system to adapt to the user gait pattern over time.

Section II gives an overview of the hardware and software. Section III describes the feature extraction methods. Section IV explains the feature clustering results. Section V describes the experimental settings, results and analysis. Finally Section VI provides the conclusion and future directions.

II. OVERVIEW

A. Hardware and Software

We use the Shimmer MEMS kinematic module with a Wireless 9DoF Kinematic daughterboard IMU. The base package of Shimmer contains a Freescale MMA7361 tri-axial accelerometer. The daughterboard provides a Honeywell HMC5843 magnetometer, and an InvenSense500 gyroscope [9]. The sensor is attached to a belt and positioned on the right side of the ML axis, similarly to the setup of Köse [2]. The device has been calibrated such that the positive x-axis points downwards towards the gravity vector, positive y-axis points forward towards AP vector, and positive z-axis points sideways towards ML vector. The IMU is sampled at $50Hz$. Prototyping is done using Matlab.

B. Algorithm

A gait sequence is detected using the frequency profile of both Vertical acceleration (a_V) and ML acceleration (a_{ML}) [1]. A peak detection algorithm is applied to the cadence signal, particularly the a_V segment, to extract HS, TO, and movement artifacts. On each peak location, gyroscopic and accelerometric wavelet features are calculated.

The HS features are clustered to 3 classes which are LHS, RHS, and outliers including TO events and movement artifacts. LHS and RHS patterns can be recognized based on the clustered wavelet features. Consecutive HS of the same foot with similar time difference with a_{ML} ACF peak is detected as a stride [1]. The user's bilateral stride profile can then be analyzed from the recognized signals.

III. FEATURE EXTRACTION

The signals measured from a waist-worn IMU provides rich information that can be used to estimate spatio-temporal gait parameters, gait events, and gait phases [1]–[3], [8], [10]. This section provide our proposed feature extraction method for our experimental configuration.

A. Cadence and Stride Rate Estimation using ACF

Moe-Nilssen proposes that gait parameters can be extracted by examining the ACF of vertical acceleration a_V and ML acceleration a_{ML} [1]. Cadence estimate is found by measuring the fundamental frequency of a_V ACF. Stride rate is found by performing similar calculations on a_{ML} signal.

We have previously used spectrogram analysis and image processing techniques to detect gait episodes with promising result [11]. We identify cadence as a tonal frequency over prolonged time period. Cadence frequency ranges between 0.6 to $2.5Hz$ (steps per seconds) or 36 to 150 steps per minute. In this work we simplify the prior algorithm to estimate cadence using informations from a_{AP} and a_{ML} signals.

A cadence can be estimated as follows: We take subsegments with interval of Δt from a_{AP} and a_{ML} signals. Both signals are filtered using a fourth order Butterworth filter with cutoff frequencies of 0.5 and $3Hz$. Fundamental frequencies f_{0AP} and f_{0ML} are approximated by calculating the spectral centroids from the resulting power spectra. The AP time-frequency continuity $f_{0AP}(\Delta t_{0AP})$ represents cadence, while the ML time-frequency continuity $f_{0ML}(\Delta t_{0ML})$ represents stride rate. A cadence estimate is valid at time $\Delta\tau : \Delta\tau \in \Delta t_{0AP} \cap \Delta t_{0ML}$ when the condition $f_{0AP}(\Delta\tau)/f_{0ML}(\Delta\tau) \approx 2 \pm 0.5$ is satisfied. The pseudocode is shown in Algorithm 1.

Algorithm 1 DetectCadence($a_{AP}(\Delta t)$, $a_{ML}(\Delta t)$)

[f_{0AP}, t_{0AP}]= get$f_0(a_{AP}(\Delta t))$;
[f_{0ML}, t_{0ML}] = get$f_0(a_{ML}(\Delta t))$;
if $f_{0AP}(\Delta\tau)/f_{0ML}(\Delta\tau) \approx 2 \pm .5 : \Delta\tau \in \Delta t_{0AP} \cap \Delta t_{0ML}$ **then**
    return true
else
    return false
end if

function f_0 = get$f_0(x(\Delta t))$
$\hat{x}(\Delta t)(k\Delta t)$ = BPF$(x(\Delta t),\ f_c = [0.5Hz, 3Hz])$
$P = |FFT(\hat{x}(\Delta t))|$ // N-point FFT
$f_0 = \sum_{n=0}^{N-1} f(n)P(n) / \sum_{n=0}^{N-1} x(n)$
$t_0 = \Delta t$
return [f_0, Δt_0]

B. HS Wavelet Features Extraction

The discrete wavelet transform (DWT) detects frequency localizations at specific times in a signal. A large value at a time-frequency localization indicates high similarity between the mother wavelet and the signal at the specified instant. This quality is especially useful for extracting instantaneous pattern and frequency changes such as ones imposed by HS and TO events [4].

HS events produces signals that are morphologically similar to the Debauchies 4-tap wavelet (db4). This can be seen by observing the peaks and valleys in the sensory signals around HS events. HS frequencies are localized around $6-8Hz$ frequency slot. For $f_s = 50Hz$, DWT at the 2nd level of decomposition effectively focuses on frequency localization around $6.25-12.5Hz$. We propose that using our configuration, 2nd level DWT is appropriate for detecting HS events.

The wavelet features that we use are: the 2nd level detail coefficients (d2) of a_{AP}, a_{ML}, a_V, ω_S, and ω_T; and the 2nd level approximation coefficients (a2) of ω_C. Each coefficient dimensionality is 11. The total dimension of a HS data is 66.

A particular subject's LHS and RHS pattern and their wavelet features are presented in Figure 1. The subject was walking with cadence of 111.9±7 steps/minute.

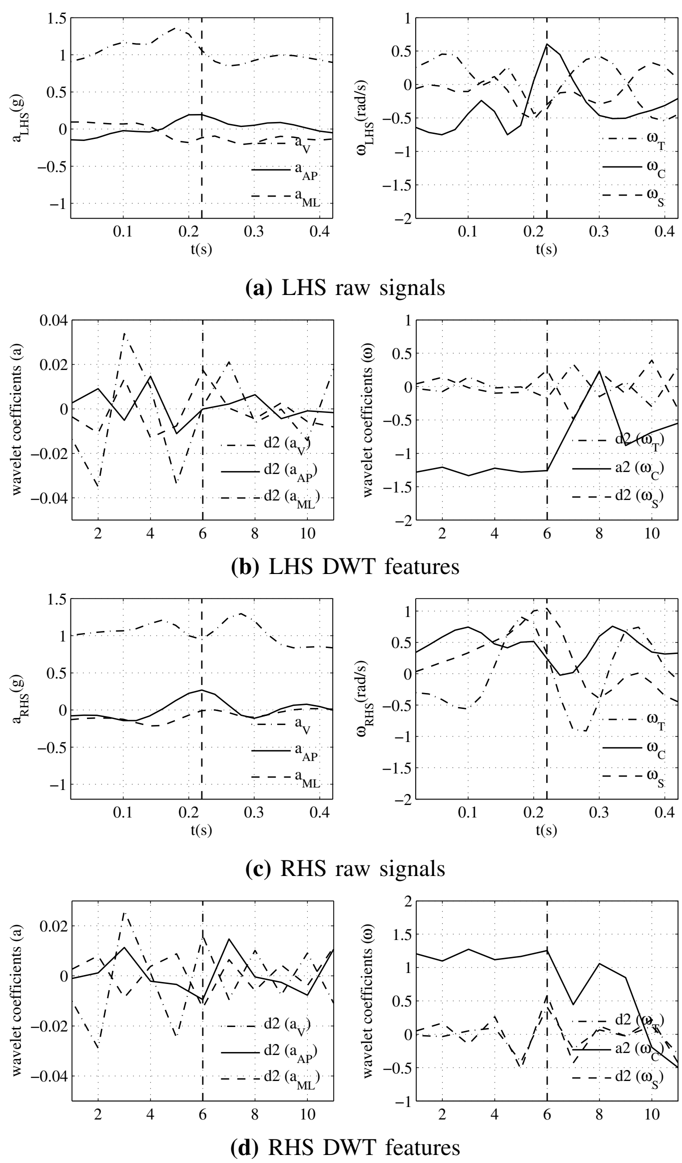


Figure 1: LHS and RHS pattern of subject 7 averaged over 273 RHS and 276 LHS events. Subject was walking with cadence of 111.9±7 steps/minute.

IV. Feature Clustering

The general template HS signals have been proposed in literatures [2], [8]. However, HS pattern of individuals change over time and are affected by clothes, footwear, walking surface, cadence, and emotional condition [12]. We propose that a data-driven approach using data clustering is appropriate for this particular task. The intention is to design a system that is able to adapt to pattern changes.

We have recently proposed a lightweight clustering algorithm using swarm-intelligence we term the Rapid Centroid Estimation (RCE) [13], [14]. We encourage interested readers to refer to [13] and [14] for further information.

A. HS Clustering

Using RCE, we cluster the wavelet features of the peaks to segment RHS, LHS and TO events. The cluster optimization function is the sum of intra-cluster correlation distance. Correlation distance is selected in order to preserve intra-cluster pattern similarity. A particular clustered data distribution is shown in Figure 2. We observed that choosing three clusters provides a representative model based on the visualization of the feature distribution.

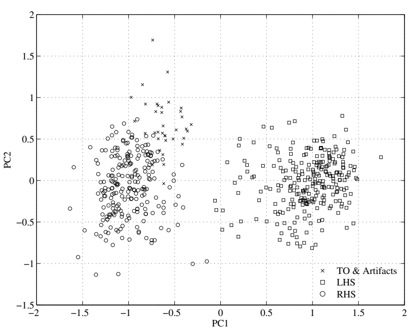


Figure 2: RCE clustering results of wavelet features.

B. Stride Profile

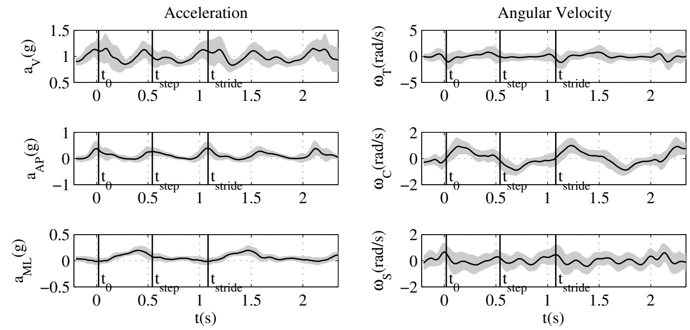
A stride is indicated by a consecutive HS of the same foot. A valid stride satisfies the following criteria:

1) The consecutive HS of the same foot have similar timing to the first ACF peak of a_{ML} and the second peak of a_{AP} and a_V.
2) The HS of the opposite foot have similar timing to the first peak of a_{AP} and a_V.

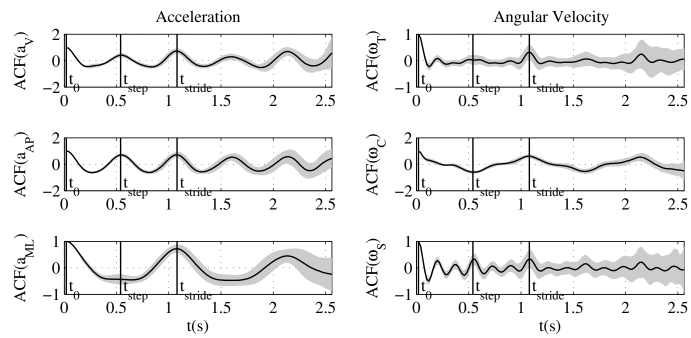
The stride profile of Subject 7 is presented in Figure 3a. The corresponding ACF profile is presented in Figure 3b.

V. Experimental Results and Discussion

We tested this method with 8 healthy subjects (5 male, 3 female) aged between 20 and 67 years old). A Shimmer 9DoF IMU was attached to the subject's waist at the right side of the ML axis. Each subject was told to walk for five minutes at a personally selected pace. The number of strides are counted. The experimental data collection is done in a house environment to simulate daily living condition.



(a) Right leg stride accelerometric and gyroscopic signal pattern.



(b) The corresponding ACF of Signals in Figure 3a

Figure 3: Right leg stride accelerometric and gyroscopic signal pattern of Subject 7 averaged over 238 successive strides.

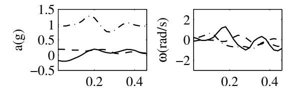
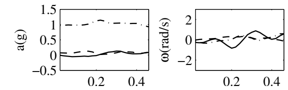
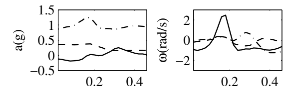
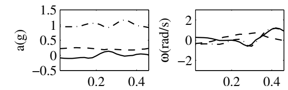
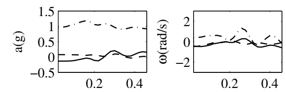
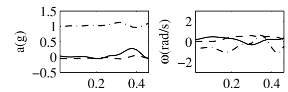
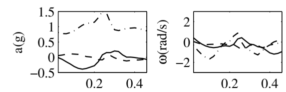
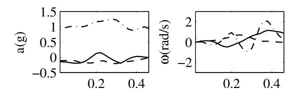
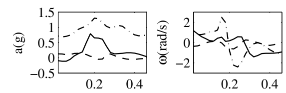
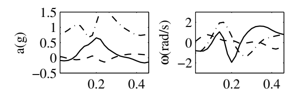
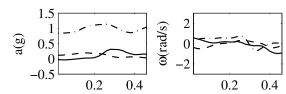
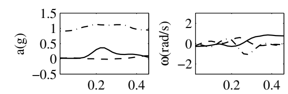
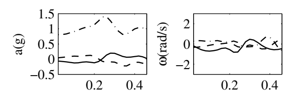
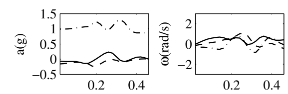
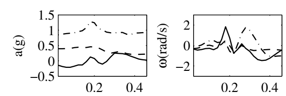
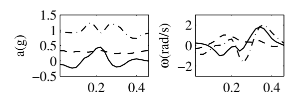
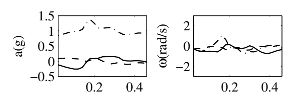
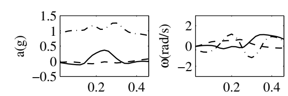
The gait parameters, including cadence and step symmetry, are calculated using Moe-Nilssen's method [1]. Accuracy is calculated by dividing HS positive detection rate by total number of steps. Precision is calculated by dividing HS true positive detection by the total number of true and false positives. The HS profile for each subject is obtained by averaging correct detections. The general HS profile for all subject is obtained by averaging each subject's HS profiles. Table I shows the experimental results.

Table I shows that our proposed method has on average 84.3%±9.2% and 86.7%±6.9% accuracy with 86.8%±9.2% and 88.9%±7.1% precision on LHS and RHS segmentation. The LHS and RHS profile of each user are also unique to each individual. The general HS profile shows similarity to the one proposed by Köse [2]. To our knowledge, we are the first to present reports regarding the precision of a HS segmentation method using a waist worn IMU.

VI. Conclusions and Future Directions

Identifying HS events is important for determining bilateral gait parameter. We have shown that using a waist-worn Inertial Measurement Unit (IMU) on the ML axis, gait parameters and gait events, especially LHS and RHS, can be estimated. We have proposed a simple, adaptive, and parameter-free method for HS segmentation. Our proposed method using ACF, Wavelet features and RCE yields promising results based on our experimental data. In the near future we plan to investigate variations of the method outlined in this paper.

TABLE I: Experimental summary of the proposed method on each subject

No.	Age	Gender	Cadence (steps/min)	Step Symmetry L / R	Accuracy/Precision LHS	RHS	HS Profile † LHS	RHS
1	65	M	103.2±7	47.5%±3% 55.2%±4%	71.4% / 74.3%	82.8% / 85.0%		
2	27	F	92.1±5	48.5%±2% 52.1%±6%	78.1% / 78.7%	77.8%/ 78.4%		
3	25	M	84.9±13	49.1%±3% 49.5%±4%	84.1% / 85.2%	85.9% / 88.5%		
4	67	M	112±13	56.1%±8% 49.4%±5%	90.2% / 95.7%	79.3% / 80.9%		
5	35	F	144.7±11	48.7%±5% 54.8%±4%	73.5% / 77.3%	92.1% / 93.8%		
6	36	M	108.8±7.5	50.2%±4% 51.0%±3%	88.5% / 91.1%	85.2% / 91.0%		
7	62	F	111.9±7	51.4%±3% 52.4%±4%	96.4% / 98.4%	96.7% / 98.5%		
8	20	M	120.5±7	49.8%±3% 51.3%±3%	92.6% / 93.8%	94.1% / 95.3%		
Summary	42.1±19.4		109.8±19	50.2%±4.4% 51.9%±4.09%	84.3% ± 9.2% / 86.8% ± 9.2%	86.7% ± 6.9% / 88.9% ± 7.1%		

† – . – : $a_V; \omega_T$ —— : $a_{AP}; \omega_C$ – – – : $a_{ML}; \omega_S$ x axis labels are $t(s)$

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