A Framework for Linking Gait Characteristics of Patients with Accelerations of the Waist

Tim Wark, *Member, IEEE*, Mohan Karunanithi, Wilbur Chan

***Abstract*— This paper describes a framework for the analysis of accelerometer data as part of research undertaken in preparation for a clinical trial involving ambulatory monitoring of elderly rehabilitation patients. In particular we examine the response of side-mounted accelerometers to various gait patterns and attempt to establish a relationship with a biomechanical model for human gait. We explore the use of a linear predictive (LP) model as a basis for identifying key harmonic frequencies in the accelerometer response signals and use these harmonics to relate measured data back to harmonic predictions from the biomechanical model.**

I. INTRODUCTION

Due to factors such as ageing populations and limited hospital resources, there is increasing pressure on healthcare systems to discharge patients in a timely fashion from secondary care facilities. As a result of factors such as these, there is an increasing emphasis on remote ways for monitoring patients who are at increased risks of events such as falls, syncope and cardiac arrhythmias [1], [2].

One of the areas that has thus received increasing attention over the past decade is that of ambulatory monitoring via accelerometers [2], [3], [4], [5]. As a result of this increasing usage, as well as recent advances in sensor and microprocessor technology, devices that can monitor human movement are becoming smaller, more sensitive and able to last from hours to days on a single charge.

A range of different problems have been considered in relation to ambulatory monitoring via accelerometers. The use of the discrete wavelet transform (DWT) has been investigated as a means of feature extraction to allow activity classification [5] into classes such as walking, running, sitting, etc. Similar work has been done using adaptive thresholding techniques [4], [6]. Another recent study has considered methods for assessing body sway and stability from raw accelerometer signals [7].

There has been limited work, however, in analysing the relationship between accelerometer response signals to human gait and a biomechanical gait model. A far more powerful analysis of accelerometer response signals can be conducted if the relationship between them and changes in the spatio-temporal state of human biomechanics is known.

T. Wark is with the e-Health Research Centre, CSIRO ICT Centre, Level 20, 300 Adelaide St, Brisbane QLD 4000, Australia `tim.wark@csiro.au`

M. Karunanithi is with the e-Health Research Centre, CSIRO ICT Centre, Level 20, 300 Adelaide St, Brisbane QLD 4000, Australia `mohan.karunanithi@csiro.au`

W. Chan is with the Division of Geriatric Medicine & Rehabilitation, The Prince Charles Hospital, Rode Road, Chermside QLD 4032, Australia `Wilbur_Chan@health.qld.gov.au`

Some related work has been undertaken in order to estimate changes in walking speed from trunk accelerations [3] . This biomechanical model assumed, however, that accelerometer devices could be mounted at the centre of mass (COM) of the subject, typically just anterior to the second sacral vertebra. A particular aspect of our clinical trial however, is that accelerometers must be mounted on the *side* of the patient at waist level. This restriction has been enforced by clinical investigators at the trial hospital in order to allow patient comfort and freedom of movement throughout the day and night as well as through an interest in monitoring stroke patients on their weaker side.

In this paper we present a framework for linking measured accelerometer signals with a biomechanical model for gait, where the assumption is made that accelerations in the waist are measured from the side. This model can then provide a solid basis for more extensive work in estimating and understanding gait characteristics from measured waist accelerations.

II. BIOMECHANICAL GAIT MODEL

The biomechanics of human movement is a complex science and there is no limit to the complexity and number of model parameters which can describe every aspect of movement. The analysis of gait alone however, allows for far more simplified models with greatly reduced parameter sets.

One area that has seen much recent work in gait models is that of biometric gait analysis from video streams [8], [9], [10]. In these applications, biomechanical gait models are used to relate visual features extracted from video with rotations and translations of parts of the body, such the thigh or knee, over time.

Recent studies such as these have confirmed earlier observations that many aspects of gait movement are in fact sinusoidal in nature. This fact provides an important basis for the model presented in this paper.

A. Modeling Waist Movement on One Side

For reasons outlined in Section I, we are interested in modelling the way in which the waist, on one side, moves with respect to time during the gait cycle.

In work outlined in [11], the way in which the centre of mass (COM) moves during gait is modelled as two distinct phases of quasi-sinusoidal movement. We propose extending this model such that the waist movement on *one side* of the body can be represented by four main phases $\{\mathcal{A}, \mathcal{B}, \mathcal{C}, \mathcal{D}\}$ throughout the gait cycle. Assuming the gait cycle commences with the left foot forward, with the left waist being modelled, we can summarise these four phases as follows:

- $\mathcal{A}$: In this phase the left leg is the stance leg and the right leg is the swing leg. The right foot lifts off the ground as the right knee flexes, moving the gait cycle into a single-support phase. During this period the waist moves in a shallow arc, rising and then falling.
- $\mathcal{B}$: In this phase the right foot hits the ground so that for a short period the gait cycle undergoes double-support. In this period the left waist actually drops slightly.
- $\mathcal{C}$: In this phase the right leg now becomes the stance leg and the left leg the swing leg. The left foot now leaves the ground moving the gait cycle back into single-support.
- $\mathcal{D}$: In this final phase the left foot hits the ground, moving the cycle back to double-support. Unlike the previous phase of double-support, the left waist stays roughly level during this phase before the whole cycle repeats as the left leg switches back to being the stance leg.

An illustration of the parameters in this waist-movement gait model, for a given point on the left waist $\{w_{x,y,z}\}$, is shown in Figure 1. Here we define the length of a subject's leg as l_1, the average point-of-contact angle between the forward leg and the vertical as ϕ_s, and the distance between the left and right hips as l_2.

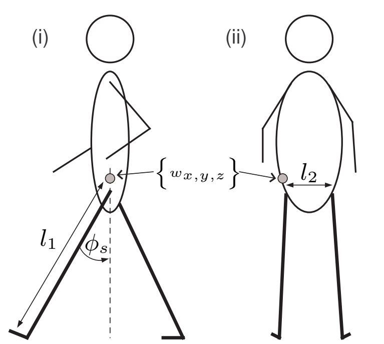

Fig. 1. Biomechanical model for inferring primary waist movements during gait when viewed from (i) the side, (ii) behind. Diagram illustrates the point when left foot first hits the ground.

For the purposes of this initial study we are particularly interested in the *vertical* waist movement during gait. Given the model parameters described, we can derive a model for vertical waist movement $w_y(t)$ during the four phases of gait cycle as:

$$w_y(t) = \begin{cases} l_1 \cos(\omega_1(t - \tau_A) - \phi_s) & : \quad t \in \mathcal{A} \\ m - l_2 \cos(\omega_2(t - \tau_B) - \phi_s) & : \quad t \in \mathcal{B} \\ l_1 \cos(\omega_1(t - \tau_C) - \phi_s) & : \quad t \in \mathcal{C} \\ l_1 \cos(\phi_s) & : \quad t \in \mathcal{D} \end{cases} \tag{1}$$

where $m = (l_1 + l_2)\cos\phi_s$, $\omega_1 = 2\phi_s/(\tau_B - \tau_A)$, $\omega_2 = 2\phi_s/(\tau_C - \tau_B)$.

We also define the relationship between leg length l_1, waist width l_2 and phase time boundaries $\tau_j, j \in \{\mathcal{A}, \mathcal{B}, \mathcal{C}, \mathcal{D}\}$ as:

$$\beta = \frac{l_2}{l_1} = \frac{\tau_C - \tau_B}{\tau_B - \tau_A} \tag{2}$$

where $\tau_C - \tau_A = T_0/2$.

This model response is shown for a single cycle of gait in Figure 2 where we have set $\phi_s = \pi/12$, $l_1 = 1$ and $\beta = 1/3$.

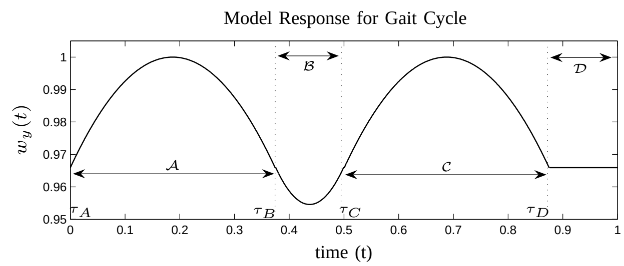

Fig. 2. Example gait model for vertical displacement of waist on a single side during four phases of gait $\{\mathcal{A}, \mathcal{B}, \mathcal{C}, \mathcal{D}\}$. Cycle period is normalised to $T_0 = 1$ where $T_0 = 2\pi/\omega_0$.

B. *Use of Fourier series to determine theoretical Gait Harmonics*

A Fourier series (FS) can be used to represent a periodic function as a sum of sin and cosine basis functions. Given that gait is clearly periodic in nature, we can thus represent the waist movement function $w_y(t)$ of period T_0 as:

$$\hat{w_y}(t) = \frac{1}{2}a_0 + \sum_{n=1}^{\infty} (a_n \cos n\omega_0 t + b_n \sin n\omega_0 t) \tag{3}$$

where $\omega_0 = 2\pi/T_0$ and a_n and b_n are the FS coefficients derived as:

$$a_n = \frac{2}{T}\int_0^{T_0} w_y(t)\cos(n\omega_0 t)dt$$
$$b_n = \frac{2}{T}\int_0^{T_0} w_y(t)\sin(n\omega_0 t)dt \tag{4}$$

Evaluating Equation 3 we can derive an approximation $\hat{w_y}(t)$ for the gait cycle response that is continuous over the cycle interval. An example of this approximation is shown in Figure 3 for a FS of order 10.

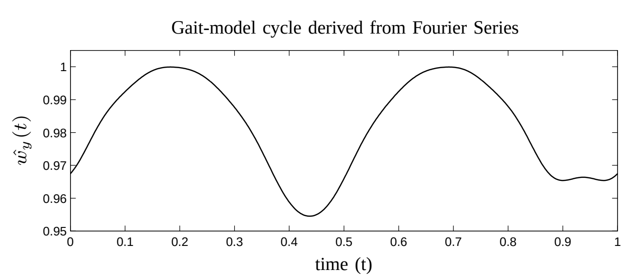

Fig. 3. Fourier series approximation (N=10) to vertical waist movement during gait cycle.

Given the FS for the gait cycle, we can then estimate the magnitude of the discrete frequency spectrum for gait from the FS coefficients a_n, b_n as:

$$|X(j\omega)| = 2\pi \sum_{n=1}^{\infty} \delta(\omega - n\omega_0)\sqrt{a_n^2 + b_n^2} \qquad (5)$$

Using Equation 5 we can thus calculate the theoretical intensities for the fundamental frequency ω_0 and n^{th} harmonics $n\omega_0$. These are shown in Figure 4 for the fundamental and first four harmonic frequencies.

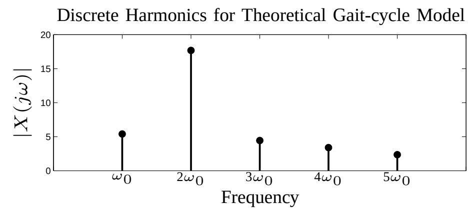

Fig. 4. Relative magnitudes for theoretical fundamental and harmonic frequency components during gait cycle.

III. Relationship between gait model and accelerometer outputs

The goal of the work presented in this paper is to be able to determine the relationship between the response signals from a waist mounted accelerometer and a simple biomechanical model for gait. We propose that by finding key harmonic frequencies from the measured data, we have a means to relate this data back to the harmonic predictions from the gait model.

A. Obtaining Accelerometer Gait Data

As part of obtaining ground-truth data before commencing our clinical trial, we obtained accelerometer data from 10 subjects between the ages of 20 and 60. All subjects wore a small, two-axis accelerometer, which was worn at waist height in a flexible elastic belt. As with the requirements for the clinical trial, the device was worn to the side in the sagittal plane such that one axis measured along the vertical axis and the other along the anterior/posterior axis.

Subjects we asked to walk for several minutes in periods of normal, fast and slow/stilted walking. For the purposes of analysis in this paper, the boundaries between the different classes of gait (normal, fast, slow) were extracted manually for each subject's data.

B. Linear Predictive Model

In order to extract key harmonic information from the accelerometer signals, we propose the use of a LP model. Linear prediction works on the assumption that the future value of a signal can be predicted from a linear function of previous samples. This can be represented mathematically for sample n of signal x as:

$$\hat{x}[n] = G + \sum_{k=1}^{p} c_k x[n-k] \qquad (6)$$

where c_k is the k^{th} predictor coefficient, p is the number of previous samples used in the prediction, and G is an arbitrary gain factor. The predictor coefficients are estimated from the input signal, in our case, by a standard recursive procedure known as *Levinson-Durbin* recursion.

Taking the standard Z-transform, we can then express the spectral shaping filter $H(z)$ for this system as:

$$H(z) = \frac{G}{1 - \sum_{p=1}^{k} c_k z^{-k}} \qquad (7)$$

where z is defined as $e^{j\omega T}$ for frequency ω and sampling frequency $1/T$. Thus the frequency response for a given input signal can be estimated from the linear prediction coefficients for that signal.

C. Deriving Harmonic Frequencies from LP Spectrum

The LP spectrum is particularly attractive over the Discrete Fourier Transform (DFT) derived spectrum in that it can clearly highlight the key spectral components, or harmonics, of the input signal. This property of the LP spectrum is shown in Figure 5. Here the DC component of the signal is removed before LP coefficients are calculated.

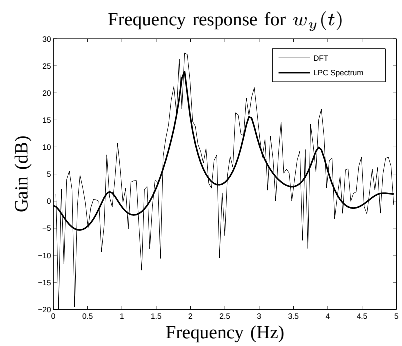

Fig. 5. Comparison of LPC and DFT spectrums for the vertical-axis accelerometer signal during typical gait.

In the graphs shown in Figure 6 we can clearly see the dominant harmonic representing the step frequency (i.e. two steps per gait cycle) at $2\omega_0$.

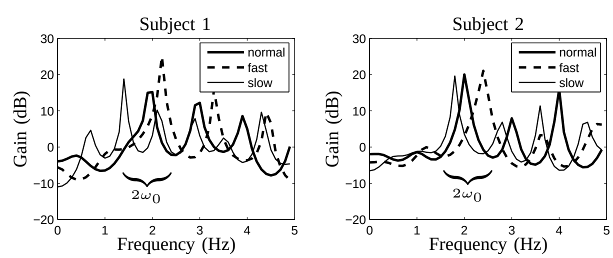

Fig. 6. Comparison of LP spectrum of $w_y(t)$ over various walking speeds (normal, fast, slow) from two different subjects. Locations for the dominant step frequencies can be seen clearly at approximately $2\omega_0$.

It can be shown that we can calculate the harmonic frequencies from the LP spectrum by treating the LP coefficients c_k as coefficients of a polynomial of the form $c_0x^p + c_1x^{p-1} + \ldots + c_{p-1}x + c_p$ and finding the roots of this polynomial. For the complex root value r_i we can then calculate the harmonic frequency f_i from the angle of the root as:

$$f_i = \frac{\arg(r_i)F_s}{2\pi} \tag{8}$$

where F_s is the sampling frequency for the original data.

A comparison of the first four harmonic frequencies $\{f_1, f_2, f_3, f_4\}$ derived from the LP coefficients is shown in Figure 7 for the three classes of gait we measured. Based on the LP harmonics we see that excellent discrimination between the classes is exhibited.

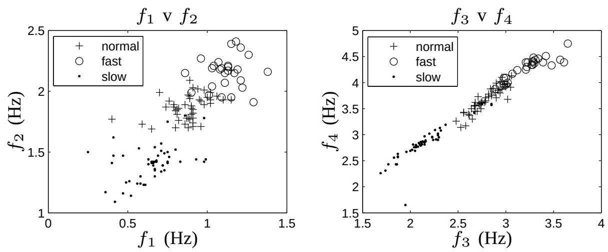

Fig. 7. Comparison of first four harmonic frequencies from 10 subjects walking at various speeds (normal, fast, slow). A 10sec sliding window was used to extract LP coefficients.

D. Comparing Theoretical and Measured Harmonics

In order to assess the suitability of the side-mounted (SM) gait model we proposed in Section II, we can compare the harmonic signature for the observed and predicted gait harmonics. It should be noted, that whilst the gait model predicts positional changes and the measured data indicates acceleration changes, the harmonics should still be the same in both domains.

This comparison is shown in Figure 8 for both our proposed side-mounted (SM) gait model as well as the centre of mass (COM) model as outlined in [3].

IV. Discussion and Future Work

From the comparison diagram in Figure 8 we can see that the harmonic signature from the measurement data, shown as a box-whisker plot, corresponds well with the predicted harmonics for the side-mounted gait model. This contrasts with the COM model, where the predicted harmonics clearly don't describe the observations which happen when a device is side-mounted.

As a result of this study, we believe that our current gait model provides a good representation of the type of asymmetrical accelerations which happen when a device is mounted to one side. We also believe that the use of the LP spectrum is a good technique for extracting key spectral information from measured acceleration data.

Ultimately the goal of our research will be to use the relationship between the measurement data LP coefficients c_k and the gait model FS coefficients a_n, b_n to estimate model parameters such as ϕ_s and β from the measured data. Future work will also investigate ways to extend the gait model to describe more closely the gait characteristics of elderly rehabilitation patients.

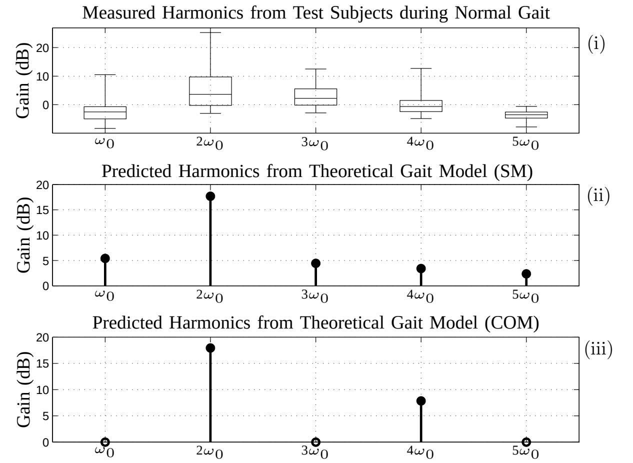

Fig. 8. (i) Box-whisker plot of measured harmonics from accelerometer data during normal walking, compared with (ii) predicted gait harmonics from gait model for side mounted (SM) device, and (iii) predicted harmonics for device worn at centre of mass (COM). *(Hollow circles represent values of -300dB, but were set to 0dB for clarity.)*

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