iGAIT: An interactive accelerometer based gait analysis system

Mingjing Yang, Huiru Zheng, Haiying Wang, Sally McClean, Dave Newell

School of Computing and Mathematics, University of Ulster, N. Ireland, UK
School of Computing and Information Engineering, University of Ulster, N. Ireland, UK
Anglo-European College of Chiropractic, 13-15 Parkwood Road, Bournemouth, Dorset BH5 2DF, UK

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ABSTRACT

This paper presents a software program (iGAIT) developed in MATLAB, for the analysis of gait patterns extracted from accelerometer recordings. iGAIT provides a user-friendly graphical interface to display and analyse gait acceleration data recorded by an accelerometer attached to the lower back of subjects. The core function of iGAIT is gait feature extraction, which can be used to derive 31 features from acceleration data, including 6 spatio-temporal features, 7 regularity and symmetry features, and 18 spectral features. Features extracted are summarised and displayed on screen, as well as an option to be stored in text files for further review or analysis if required. Another unique feature of iGAIT is that it provides interactive functionality allowing users to manually adjust the analysis process according to their requirements. The system has been tested under Windows XP, Vista and Window 7 using three different types of accelerometer data. It is designed for analysis of accelerometer data recorded with sample frequencies ranging from 5 Hz to 200 Hz.

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1. Introduction

Over the past decade, there have been considerable research efforts to employ accelerometers in healthcare. Some of the resulting applications use accelerometers to monitor daily activities and classify movements between patients and controls [1,2]. More recently, accelerometers have been widely used in gait pattern analysis [3–7] for different purposes including monitoring physical function of the elderly [2,8,9], prediction of fall risk [10,11], evaluation of the progress of neurodegenerative disease [12,13], and assessment of the outcome of therapy [14]. Accelerometer based gait data provide a novel way to measure gait patterns. Compared with traditional optical gait analysis systems, such as CODA (Codamotion, Charnwood Dynamics Ltd., Rothley, England) and Vicon MX (Vicon, Oxford, England), accelerometer-based approaches exhibit several advantages. For example, they are lower cost, portable, small in size, easy to operate and as a consequence, can be employed in real life environments to support rehabilitation [15] and physical activity monitoring [1].

Many types of accelerometers have been reported as being used in monitoring gait [1]. The simplest application of accelerometers is as a step counter; however it has been found that other gait parameters, such as cadence, speed, or symmetry, can be extracted from accelerometer data [16–20]. Turcot et al. [21] used two triaxial accelerometers (ADXL329) combined with gyroscopes and reflective marks to estimate the tibial and femoral linear accelerations. In total eight statistical parameters extracted from the acceleration data were used to discriminate between nine subjects with medial osteoarthritic knees and nine asymptomatic control subjects. Zhou et al. [14] used a system composed of five biaxial IDEEA accelerometers (MiniSun, CA, USA) mounted on the chest, thighs and feet to...
measure gait patterns of subjects following total hip arthroplasty. Several features related to speed, stride length, single limb support, cycle period and swing power were extracted as gait pattern indices. In the research conducted by Tura et al. [22], a MTx accelerometer (Xsens Technologies B.V.) was worn on the subjects’ thorax to assess gait symmetry and regularity of transfemoral amputees. DynaPort MiniMod (McRobert BV, The Hague, The Netherlands) has been employed to study the gait pattern in ageing people [9], youths [3], and children [7,23]. These accelerometer systems have their respective characteristics, for example different data formats, sampling frequency, number of accelerometers and placement position [1]. In this study we have used a single triaxial accelerometer attached to the lower back. The position is an approximation of the centre of mass (COM) of the body during walking and upright stances [24]. This placement is convenient and less intrusive for the subject compared with other positions, such as chest, neck, thigh and head. In addition, it has been shown that many key gait parameters, such as cadence, step length, speed, symmetry and regularity, can be obtained from such accelerometer data [3–7].

To the best of our knowledge, there is no publicly available software for the analysis of lower back acceleration data during walking. Most researchers use in-house software to analyse gait patterns from the acceleration data. Some accelerometer manufacturers provide gait data analysis software packages, which are designed to process information extracted from their own products. For example, McRobert BV provides a gait analysis service, but only to their registered customers who pay an annual fee. After users upload acceleration data, the service extracts the gait parameters, save the results in a PDF file and distributes it to the users [25]. Although this type of gait data analysis service is convenient it remains a ‘black box’ to the user, potentially limiting confidence in the analysis and the application of user specific needs, particularly when data are collected from subjects with abnormal gait patterns.

In this paper, we present a computer aided gait assessment tool, iGAIT, for the analysis of gait data collected by an accelerometer. iGAIT is implemented in MATLAB and can be run in Windows XP, Vista and Windows 7. It provides an interactive and user friendly platform to visualise acceleration data. A total of four types of gait features: spatio-temporal, frequency domain, regularity and symmetry can be derived. The main advantage of iGAIT includes its capacity for analysing accelerometer data collected by accelerometer devices from different manufacturers, such as DynaPort MiniMod, smart mobile phones (such as HTC Touch Pro) with accelerometers and MTx (Xsens Technologies B.V.). Another unique feature is that it allows users to select specific gait cycles for further examination. The results (gait features extracted) can be saved as a text file that can be directly subjected to further analysis (statistical or machine learning). iGAIT is designed for the analysis of accelerometer data recorded with sample frequencies ranging from 5 Hz to 200 Hz, which is the most commonly used in gait analysis. In addition to the research lab, iGAIT can

![Fig. 1 – The graphical user interface of iGAIT.](image-url)
It allows users to load signals, plot signals, set parameters, manually select gait cycles, when necessary, and display gait features on screen.

2.2.1. Signal loading
The signal analysed by iGAIT should be collected by a triaxial accelerometer mounted on the upper body along the vertebral column, for example the lower back, neck and chest. The acceleration data are provided as a 3 dimensional numeric matrix saved in a MATLAB (MAT) file, a text file or a Microsoft Excel sheet. The first column is the acceleration in the vertical direction (VT), the second in the medial-lateral (ML) direction and the third in the anterior–posterior (AP) direction. The text file can be saved in a number of formats, including white-space delimited numbers, tab delimited numbers and comma delimited numbers. Hence, iGAIT is flexible enough to analyse gait data collected by a range of different accelerometers. After loading, the signals are displayed on the plot panel as shown in Fig. 1.

2.2.2. Parameters input
There are three parameters that are required to be set by the user, namely Sample Rate, Distance and Threshold as indicated in Fig. 1. In reported studies, accelerometers used in movement analysis have a wide range of sampling frequency (5–256 Hz) [1,20–22,32]. For example when they are used as step counters or for monitoring the daily energy expenditure, the selection of sampling frequency is not always critical, usually up to 10Hz [1]. On the other hand, when accelerometers are used in gait pattern analysis, they normally have higher sample rates often above 50Hz. To facilitate such analyses, iGAIT allows the user to set the sampling frequency as needed. By default, the sampling frequency is set at 10 ms (100 Hz).

In iGAIT, the average walking velocity is calculated by dividing walking distance by walking time. Since the distance information cannot be directly derived from the accelerometer, this must be inputted by the user.

To detect heel contacts, a threshold with a range of (0, 1) needs to be set. This threshold is defined as the ratio to the maximum value of the AP acceleration, for example 0.5 indicates the threshold is set at 50% of the maximum AP acceleration. Its default value is set to 0.4 as determined experimentally in this paper, where this value allowed correct detection of all gait events in control subjects. However, when a more irregular pattern is analysed, the threshold should be less than 0.4. The user can test different threshold values and find the best one according to the gait event detection results.

2.2.3. Selection of signal region of interest
An important feature of iGAIT is that it allows the user to select regions of interest for a given signal. This function is useful when the raw data contain redundant segments. For example, as shown in Fig. 3, the acceleration data collected by a mobile phone during walking normally include the phases before and after walking. Therefore, iGAIT allows user selection of data segments. This is also essential for some types of analysis where particular phases of walking attract more attention. For example, when analysing the gait patterns of
subjects with Parkinson’s disease, the steady walking phase is of more interest to clinicians and researchers [33,34]. When using iGAIT to analyse gait data of subjects with Parkinson’s disease, the beginning and the ending part of the walking data can be discarded so that only the region of interest is selected.

The selected signal is validated before frequency analysis. If the number of samples in the selected acceleration sequence is less than ten times the sampling frequency, which leads to a frequency resolution of less than 0.1 Hz, a message box will pop up to inform the user.

In an attempt to obtain a clear profile, after the selection of the signal region, only the signal from the VT and AP directions is displayed in the plot panel as shown in Fig. 3(b).

2.2.4. Gait events detection
The first step of gait analysis is to detect heel contact events and to divide the acceleration signal into steps, which are defined as the interval between the heel contact of foot with the ground and the heel contact of the other foot. The heel contacts are detected by peaks preceding the sign change of AP acceleration [3]. In order to automatically detect a heel contact event, firstly, the AP acceleration is low pass filtered by the 4th order zero lag Butterworth filter whose cut frequency is set to 5 Hz. After that, transitional positions where AP acceleration changes from positive to negative can be identified. Finally the peaks of AP acceleration preceding the transitional positions, and greater than the product of a threshold and the maximum value of the AP acceleration are denoted as heel contact events, as shown in Fig. 4. In this example the default threshold value is set to 0.4; however iGAIT allows the user to select different threshold value. The proposed threshold based heel strike detection algorithm has been tested using the acceleration gait data collected from about 100 healthy subjects and 20 subjects with chronic pain.

In some cases, for example the acceleration data collected from subjects with chronic pain, the data are quite irregular [27–30]. In this case, where the program may have been unable to detect all heel strikes, iGAIT allows the user to add the omitted heel contact events or remove spurious heel contact events by using the mouse to select the related points on the acceleration plot.

2.2.5. Spatio-temporal features
After the detection of heel contacts, the number of steps is obtained by counting these contacts. Cadence is calculated using the number of steps divided by walking time; walking velocity is obtained from the walking distance divided by walking time. Mean step length is obtained from the walking distance divided by the number of steps. The root mean square (RMS) of acceleration indicates the intensity of motion. The RMS values of the three acceleration directions (VT, AP and ML) are calculated respectively using Eq. (1):

\[
\text{RMS}_{d} = \sqrt{\frac{\sum_{i=1}^{N} (x_{di} - \bar{x_{d}})^2}{N}}
\] (1)
where $x_i$ ($i = 1, 2, \ldots, N$; $d = \text{VT, AP, ML}$) is the acceleration in either the VT, AP or ML axis, $N$ is the length of the acceleration signal, $\bar{x}_d$ is the mean value of acceleration in any axis. In total, iGAIT extracts six spatio-temporal features from the acceleration data, namely, cadence, mean step length, velocity, RMSVT, RMSAP, and RMSML.

### 2.2.6. Spectral analysis

iGAIT also extracts six frequency domain features from each direction of the acceleration data, which measure both the amplitude and frequency of body movements. One of these frequency domain features is the integral of the power spectral density (IPSD), which was estimated by a periodogram using Eqs. (2) and (3).

$$
\text{PSD}(\omega) = \frac{1}{2\pi N} \left| \sum_{i=1}^{N} x_i e^{-j\omega d} \right|^2
$$

(2)

$$
\text{IPSD} = \int_0^\infty \text{PSD}(\omega) d\omega
$$

(3)

where $\omega$ ($0 \leq \omega \leq \pi$) is the angular frequency, $x_i$ ($i = 1, 2, \ldots, N$) is the acceleration in either the VT, AP or ML axis, and $N$ is the total number of acceleration samples. The frequency with the maximum value of PSD is the second frequency feature called main frequency. The other 4 frequency features (Fr1, Fr2, Fr3 and Fr4) are the frequencies when PSD is cumulated (CPSD), which is calculated by Eq. (4), for 50%, 75%, 90% and 99% of PSD, respectively. In total, iGAIT extracts eight frequency features from the acceleration data, namely, IPSD, main frequency, Fr1, Fr2, Fr3 and Fr4 in each of three directions (VT, ML and AP).

### 2.2.7. Computation of the regularity and symmetry parameters

The autocorrelation coefficient refers to the correlation of a time series with its own past or future values. iGAIT uses unbiased autocorrelation coefficients of acceleration data to scale the regularity and symmetry of gait [30]. The unbiased estimate of autocorrelation coefficients of acceleration data can be calculated by Eq. (5):

$$
f_c(t) = \frac{1}{N - |t|} \sum_{i=1}^{N-|t|} x_i x_{i+t}
$$

(5)
where \( x_i \) (\( i = 1, 2, \ldots, N \)) is the acceleration data, \( f_c(t) \) are autocorrelation coefficients. \( t \) is the time lag \( (t = -N, -N+1, \ldots, 0, 1, 2, \ldots, N) \). When the time lag \( t \) is equal to the periodicity of the acceleration \( x_i \), a peak will be found in the \( f_c(t) \) series.

The autocorrelation coefficients are divided by \( f_c(0) \) in Eq. (6), so that the autocorrelation coefficient is equal to 1 when \( t = 0 \).

\[
NFC(t) = \frac{f_c(t)}{f_c(0)} \tag{6}
\]

Here \( NFC(t) \) is the normalised autocorrelation coefficient, and \( f_c(t) \) are autocorrelation coefficients. \( t \) is the time lag \( (t = -N, -N+1, \ldots, 0, 1, 2, \ldots, N) \).

The peak value \( a_1 = NFC(t_1) \), which is found at the \( t_1 \) lag time to be a step period, indicates the step regularity in a direction. The peak value \( a_2 = NFC(t_2) \), which was found at the \( t_2 \) lag time to be a stride period, indicates the stride regularity in a direction. The variance of the stride regularity and step regularity \( D = |a_2 - a_1| \), can be used as an indicator to measure gait symmetry. A smaller value of \( D \) indicates a more symmetric gait. A larger value of \( D \) indicates a more asymmetric gait.

In total, iGAIT extracts seven regularity and symmetry features from the acceleration data, namely, Step regularity VT, Stride regularity VT, Symmetry VT, Step regularity AP, Stride regularity AP, and Symmetry AP and Stride regularity ML.

2.2.8. Results display and saving

All of the four types of features (31 in total) extracted from the acceleration data can be saved in a text file, which can be used in further study such as statistical analysis and machine learning analysis. Eighteen out of thirty one features are also displayed on the screen in the results panel (Fig. 4).

2.3. System specification

The iGAIT system was compiled as a standalone Windows application. iGAIT can run without the Matlab complete installation and requires 400 MB of free hard disk space to install Matlab Compiler Runtime, which is provided with iGAIT. The program needs 120 M memory (RAM) and has been tested under Windows XP, Vista and Windows 7 with a 2 GHz processor and display resolution set to 1024 x 768.

3. Sample runs

iGAIT was used to analyse the gait pattern of 15 control subjects (6 males and 9 females). A smart mobile phone (HTC Touch HD), in which a tri-axial accelerometer is embedded, was attached to the back of participants by belts. In each trial, participants walked 25 m along a hallway at their preferred walking speed.

The sampling frequency of the accelerometer was 25 Hz, which is the highest sampling frequency provided by the HTC smart mobile phone. All the raw data were stored in a memory card in the mobile phone as text files. The n-by-3 text array contained the three axes of acceleration data, left to right: VT acceleration; ML acceleration and AP acceleration, respectively.

Fig. 5 – The autocorrelation coefficients of acceleration curves in three directions, the X axis is time lag (s); the Y axis is the normalised autocorrelation coefficients; green star denotes the step regularity index, red star denotes the stride regularity index. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Firstly, the acceleration data were imported into iGAIT using the ‘Load Signal’ function and all of the three acceleration dimensions were displayed on the plot panel as shown in Fig. 1. Because the raw data included the data collected before and after walking, redundant data were eliminated. This was achieved by clicking the ‘Region Select’ button (second step), and using the cursor to locate the start and end points which enclosed the acceleration data. These data were then used in the following analysis.

Thirdly, the sampling frequency was set as 25 Hz (sample interval 40 ms), the walking distance was set as 25 m, and the default threshold value (0.4) was used.

When the ‘Gait Detect’ button was clicked, ‘heel contact’ points were marked in the AP acceleration plot as black triangles. If, through visual inspection, it was apparent that some of these events had been missed they were entered manually by using the ‘+’ button. On the other hand the ‘−’ button was used to remove incorrectly identified events.

The fifth step was to click the ‘Analyse’ button, whereby the gait features extraction function was called. The autocorrelation coefficient curves of the three direction acceleration data were displayed in a new window. The local maximum autocorrelation coefficients values around the step time and stride time were automatically marked as a green star and a red star, respectively, on the curves (Fig. 5). In some cases, the local maximum value cannot be automatically found. In this instance the mouse can be used to locate the position. In total, 31 features were extracted and 18 out of 31 features were presented on the screen (Fig. 4). The last step was to save the features. The program generated a text file as shown in Fig. 6, which included all the features calculated by the program.

In order to further demonstrate the application of iGAIT, we applied the iGAIT to analyse the accelerometer data.
collected by an accelerometer (DynaPort MiniMod) from subjects with Complex Region Pain Syndrome (CRPS) and control subjects [30]. A total of 21 features including spatiotemporal, frequency, regularity and symmetry features were extracted by iGAIT and were used as input to Multilayer Perceptron-based classification models to discriminate the patients with CRPS from the control subjects. When using the top five features, i.e. Step Regularity VT, IPSD VT, RMS ML, IPSD AP and Stride Regularity VT, selected based on signal to noise ratio ranking criterion, the best classification accuracy (97.5%) was achieved. The comparison of the top five features between the control subjects and the subjects with CRPS in terms of their mean values and standard deviation is listed in Table 1. The reader is referred to [30] for a more detailed description of the application.

### 4. Discussion and summary

This paper presents an interactive, user friendly tool to support accelerometer based gait data analysis. It can plot acceleration data and allows the user to select portions of the data region directly from the plot. Users can also manually adjust detection of the gait events, which are under most circumstances automatically detected by iGAIT. In total, the tool can extract 31 gait features from accelerometer data. The results can be displayed on the screen and be saved for further statistical analysis. A key advantage of the tool is that it was not developed for specific accelerometer systems.

To date it has been tested on three types of accelerometers (DynaPort Minimod, Xsens MT9 and accelerometer embedded in HTC mobile) with different sampling frequencies (5–100 Hz).

Initially, iGAIT was designed for lower back acceleration data. However it is also suitable for data collected on the upper body along the vertebral column, for example the thorax, upper back, neck or occipital pole of the head. If an accelerometer is placed on one side of the upper body, most gait parameters are still reliably detected excluding the symmetry features and step regularity features. This is due to the placement being away from the middle axis of upper body, and results in the acceleration data referring to the right and left steps lacking consistency in all three directions. In many studies accelerometers attached to legs, feet and shoes are used to measure gait parameters as these sensor locations provide the strongest signals [34–36]. Gait events, such as heel strike and toe off, can be detected from such accelerometer data. Many parameters related to the lower limb movement can be obtained, for example, swing, single and double limb support. However movement of the trunk cannot be obtained from the lower-limb acceleration data, and multiple sensors have to be used on both sides of the lower limb to obtain gait symmetry features.

Currently the output files of iGait only include the input data file name, the feature names and the feature values. To avoid any confusion, a header will be added to the data and result files in future versions, which describes the data, such as, the sensor used, order of channels, sampling rates, sensor location, distance walked and user name.

In the future, iGAIT will be evaluated on a larger scale. For example, iGAIT is to be tested with acceleration data collected from subjects with different types of syndromes, such as back and neck pain, and pathologies such as Parkinson’s disease and stroke. Moreover iGAIT is to be tested with a wider range of accelerometer types.

The platform presented in this paper may be interpreted as a generic framework to facilitate the analysis of accelerometer-based gait data. The authors are interested in further assessing its practical utility through validation and integration with other research efforts. Therefore, different packages, including an open source version, will be available upon request from academic users.

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**Table 1 – The top five features with mean values, standard deviation and p values established by using independent unpaired t-test from both control subjects and CRPS subjects.**

<table>
<thead>
<tr>
<th>Feature</th>
<th>Control Mean</th>
<th>Control SD</th>
<th>CRPS Mean</th>
<th>CRPS SD</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step regularity VT</td>
<td>0.86</td>
<td>0.07</td>
<td>0.55</td>
<td>0.21</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>IPSD VT (g²)</td>
<td>0.52</td>
<td>0.29</td>
<td>0.14</td>
<td>0.14</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>RMS ML (g)</td>
<td>0.16</td>
<td>0.03</td>
<td>0.10</td>
<td>0.03</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>IPSD AP (g²)</td>
<td>0.39</td>
<td>0.27</td>
<td>0.09</td>
<td>0.02</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>Stride regularity VT</td>
<td>0.85</td>
<td>0.08</td>
<td>0.62</td>
<td>0.18</td>
<td>&lt;.01</td>
</tr>
</tbody>
</table>

**Fig. 6 – An example of output files generated by iGAIT.**
Conflict of interest statement

None of the authors had financial and personal relationships with other people or organisations that could inappropriately influence their work.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cmpb.2012.04.004.

References


