Classification of Gait Quality for Biofeedback to Improve Heel-to-toe Gait*

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***Abstract*— A feature of healthy gait is a clearly defined heel strike upon initial contact of the foot with the ground. However, a common consequence of ageing is deterioration of the heel first nature of gait towards a shuffling gait (flat foot at contact). Physiotherapy can be effective in correcting this but is costly and labour intensive. Gait rehabilitation could be accelerated with home exercise, guided by a biofeedback device that distinguishes between heel first and shuffling gait.**

This paper describes an algorithm that distinguishes between heel-to-toe gait and shuffling gait on the basis of angular velocity of the foot, using an inertial measurement unit. Measurements were made of normal and abnormal gait and used to develop an algorithm that distinguishes between good and bad steps.

Results demonstrate very good algorithm performance, with a classification accuracy at the accuracy-optimal threshold of 92.7% when compared with physiotherapist labels. The sensitivity and specificity at this threshold are 84.4% and 97.5% respectively. These performance metrics suggest that this algorithm is usable in a biofeedback device.

I. INTRODUCTION

Kinematic measures of gait are highly variable from person to person, but a common aspect in healthy individuals is a heel-to-toe gait in which the heel strikes the ground before the forefoot [1]. In fact, while the generally accepted gait cycle definition begins with initial contact (IC), many sources use the terms initial contact and heel strike (or heel contact) synonymously for healthy subjects. However, there is a tendency for gait to deteriorate with age, resulting in a shuffling gait in which the initial contact occurs with a flat foot [2]. Other changes include a broader stepping base, increased time in double support, a less vigorous push off and a shorter stride length [1].

Gait deterioration is highly prevalent in older adults. A population study of adults aged over 70 showed a gait disorder incidence rate of 35% [3]. Gait disturbances in old age can stem from a range of sources, including sensory deficits [4], neurodegenerative disorders such as Parkinsonism [5] and ataxia [6], and anxiety (fear of falling) [7]. Loss of healthy gait leads to a higher risk of falling. A study of 3628 falls in elderly individuals found gait/balance disorders to be the second most frequent cause behind 'environment-related' causes [8]. Another study of patients who had suffered from falls found gait disturbances to be responsible in 55% of cases [9]. Irrespective of etiology, gait disorders generally present with a lack of heel-to-toe gait, and physical therapy is a common treatment. Conventional physical therapy involves exercises that emphasize the importance of heel strike. The training is repetitive to help retrain the subject's gait, and to build muscle strength. However, therapist time is limited and expensive, and while home exercise is useful, patients may practise improper gait unknowingly. Consequently the goal of this project is to develop a device to distinguish normal heel-to-toe gait from abnormal gait, and provide feedback about each step to the user in real time. This will be achieved based on measurements of gait kinematics with miniature accelerometers and gyroscopes.

Accelerometers have been widely used for activity monitoring and fall detection. A triaxial accelerometer has been used to distinguish walking events from non-walking in PD patients and healthy controls [10], while a fall detection algorithm has been implemented using the in-built accelerometers in smartphones [11]. Regarding specific gait events, a study successfully detected heel-strike and toe off events in healthy subjects [12]. While devices that can detect gait events have been developed, in most cases they do not operate in real-time, and the software that can operate in real time has been designed for healthy adults, where heel strike necessarily precedes forefoot strike. In this paper we present a real-time algorithm that distinguishes between heel-to-toe gait and shuffling gait using accelerometer/gyroscope data.

II. DATA ACQUISITION

A. Hardware

The Shimmer Motion Development Kit, produced by Shimmer Sensing, was used to acquire gait cycle kinematic data. The Shimmer Motion module contains an integrated 3 axis accelerometer (Freescale MMA7361), a 3 axis gyroscope (InvenSense 500 series MEMS Gyros), and a microcontroller (MSP430) with 8 channels of 12 bit A/D.

Fig. 1. Shimmer location, with coordinate system shown

The accelerometer range was set to $\pm 6g$, and the gyroscope range to $\pm 500 \deg / s$.

The Shimmer module was attached to the subject's right foot using the ankle strap supplied with the development kit. The device was oriented so that its z axis was approximately parallel with the axis of rotation of the ankle. Figure 1 shows the device's location and its local coordinate system.

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During experiments, the Shimmer device sampled six signals and streamed the data wirelessly to a PC running MATLAB. Signals included three channels acceleration (‘xAccel’, ‘yAccel’, ‘zAccel’) and three angular velocity (‘xGyro’, ‘yGyro’, ‘zGyro’).

B. Experiments

Experiments were conducted to gather the data needed to develop a reliable algorithm. 7 subjects (mean age 32, 6 female) were recruited. 4 subjects were identified as having a healthy gait pattern, and 2 subjects were categorized as having a ’marginal’ gait, defined as gait that is not clinically characterized as pathological but may still be of concern during therapy. One subject had a true pathological gait, resulting from spastic diplegia stemming from cerebral palsy.

Each trial consisted of the subject walking on a treadmill at a comfortable, self-selected pace. The treadmill allowed ease of video analysis, while preserving foot/ankle kinematics when compared to overground walking [13]. After finding a preferred speed, data measurement was started. The 6 axis kinematic data was streamed from the wireless Shimmer device to a PC running MATLAB. A video of the experiment,taken from the side and synchronised with the Shimmer data stream, was recorded to allow each step to be classified by a physiotherapist. Each trial lasted 60 seconds.

For two subjects, both physiotherapists trained in gait therapy, trials were run for both normal gait and mimicked abnormal gait, including of elderly shuffling gait and pathological movements. With the mimicked abnormal gait trials included, a total of 11 trials were acquired comprising 396 steps.

C. Gold standard step labels

A physiotherapist analysed the video of each experiment, frame by frame, and assigned each step a rating of good, bad, or marginal. The main criteria used to determine quality of step was the angle of the foot on initial contact, a high angle from the horizontal (toes up) indicating a better step, and vice versa. Table I shows the distribution of good, marginal and bad steps that resulted.

TABLE I
BREAKDOWN OF STEP QUALITY OVER ALL TRIALS, AS CATEGORIZED BY THE PHYSIOTHERAPIST

Good steps	285
Marginal steps	30
Bad steps	81
Total	**396**

The same physiotherapist analyzed each video twice to obtain a measure of repeatability. The intra-rater agreement was found to be moderate (using Kappa’s reliability test yielded a rating of $\kappa = 75\%$). To account for human error in the rating process, the video was analysed further to measure the angle of the foot at ground contact at each step using a digital protractor. Figure 2 shows the measured angle distribution.

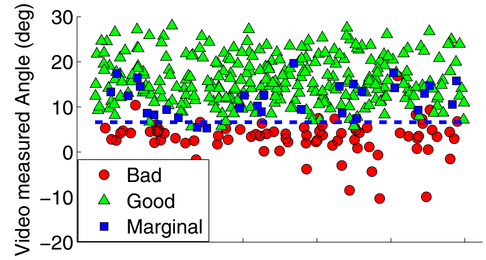

Fig. 2. Distribution of video measured angles, colour coded by physiotherapist rating. Points have been spread randomly in the x direction to provide greater visibility of scatter.

It is evident that the measured angle was greater for good steps than bad steps, however, there is some overlap with some bad steps having angles in the good range, and vice versa. The task here was to find the angle that best separates the two classes. For any given boundary, its suitability can be quantified by counting the number of steps that lie on the wrong side of the boundary. These steps are assumed to be incorrectly classified by the physiotherapist. The boundary which minimises this count, and hence is the optimal class boundary, is 6.6 degrees. All steps were then reclassified as either good or bad based on this boundary. Using this method, 42 steps were reclassified, including 30 marginal steps. Repeating this analysis yielded a κ rating of 87%, which indicates much better repeatability, with a boundary still in agreement with the physiotherapist.

III. FEATURE EXTRACTION ALGORITHM

A. Hypothesis

The algorithm was based on the hypothesis that the angular velocity of the foot about the z axis at initial contact (ω_{IC}^{z}) is a distinguishing feature between good and bad steps. The more negative the angular velocity (i.e. the toes rotate towards the ground), the better the quality of step.

B. Justification

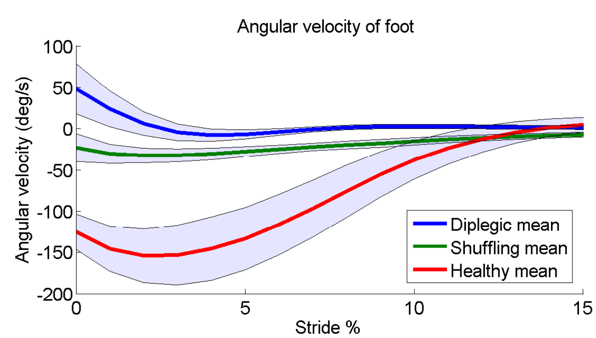

Fig. 3. Angular velocity of the foot. Positive velocity indicates toes moving upwards. 0% stride is initial contact, shaded zones are 1 standard deviation from the mean.

Figure 3 shows the mean angular velocities over the first 15% of the gait cycle for three subjects with different qualities of gait. This was determined by segmenting the angular velocity record into distinct cycles based on time of initial contact, and calculating the ensemble average. It is evident that the angular velocity at contact was large and negative for a healthy patient. This value was close to zero (flat foot initial contact) for the shuffling gait, while the diplegic gait subject had a positive velocity indicating that the toes struck first). This supports the hypothesis for ω_{IC}^z.

C. Algorithm

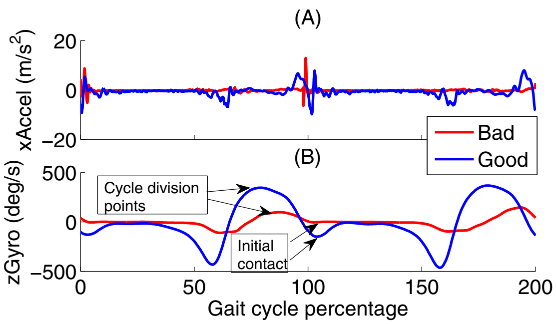

Fig. 4. Two sample gait cycles for a good step case and a bad step case. (A) xAccel (acceleration in the vertical direction) and (B) filtered zGyro (angular velocity in sagittal plane).

Figure 4 shows representative gait cycles for a good step and a bad step. For both, there is a high frequency spike in the xAccel channel at initial contact, accompanied by a local minimum in zGyro. This minimum is the angular velocity of the foot at impact, and is the feature to be extracted. The problem is to determine when initial contact occurs.

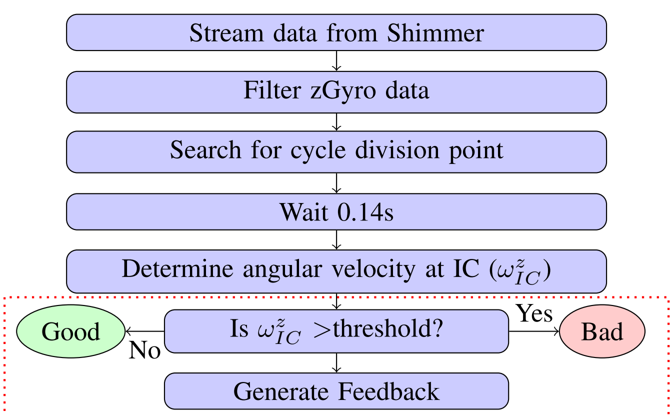

Fig. 5. Algorithm flow chart, showing feature extraction of ω_{IC}^z. The dashed box shows the feedback mechanism, although this is not implemented during the feature extraction, it gives an example of how feedback can be determined once a threshold is determined.

Figure 5 shows the algorithm developed to extract the angular velocity at initial contact. It proceeds as follows:

1) Filter the zGyro channel with a low pass equiripple FIR filter of order 20, with a pass band of 5Hz and stop band of 10Hz.
2) Determine the cycle division point, the boundary between two consecutive cycles, which is the peak angular velocity during the stride phase. This is determined by finding the first local maxima of zGyro that is greater than 50 deg/s.
3) Find a local minimum in zGyro that is greater than 250 deg/s and occurs at least 140ms after the cycle division point. This is ω_{IC}^z.
4) If no minima is found within 940ms, restart the search for a cycle division point (step 1).
5) Otherwise restart the search for a new cycle division starting 390ms after ω_{IC}^z.

D. Classification

Support vector machines were used for classification. The modified gold standard described in Section II-C was used for the training set, and classification performance was determined using 2-fold cross validation. SVM was implemented using MATLAB's inbuilt `SVMTRAIN` and `SVMCLASSIFY`, with the training data normalised to a mean zero, maximum 1 range. A box constraint of 1 was used.

IV. RESULTS

Figure 6 shows the grouping of training points for ω_{IC}^z, together with the boundary chosen for maximum accuracy. The two classes were well separated, however some points were misclassified.

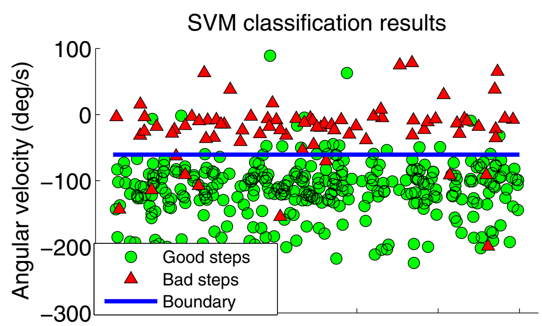

Fig. 6. 1d classification using ω_{IC}^z, with training points grouped by the gold standard rating. The points are spread randomly along the x axis for visibility. The boundary shown is the threshold for optimal accuracy as determined by SVM.

Figure 7 shows the corresponding ROC curve for the classification using this feature. ROC curves illustrate the trade-off between sensitivity (true positive rate, taking a bad step as a positive diagnosis) and specificity (true negative rate) as the threshold changes. The threshold shown in Figure 6 provides maximum accuracy. However, choosing a different boundary provides the ability to choose a different sensitivity/specificity balance. The area under the ROC curve provides a measure of sensitivity/specificity performance (with a perfect classifier having AUC = 1). The performance metrics for this classifier are given in Table II, which indicate very good classification performance.

V. DISCUSSION

Figure 7 shows the sensitivity/specificity performance of the algorithm. The specific operating point on this curve is

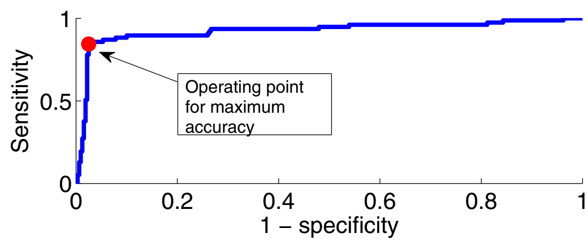

Fig. 7. ROC curve for feature ω^z_{IC}

TABLE II

CLASSIFIER PERFORMANCE FOR MAXIMUM ACCURACY THRESHOLD

Threshold	-60.65 deg/s
Accuracy	92.7%
Area under ROC curve	0.925
Sensitivity	84.4%
Specificity	97.5%

unclear at this stage, however the physiotherapist has suggested that sensitivity should be emphasised over specificity, with a minimum specificity of 75%. The sensitivity at 75% specificity is 89.6%, which indicates very good performance. As it stands, this algorithm is usable in a biofeedback device since it meets the physiotherapist's minimum requirements. However, this has only been tested in ideal conditions (supervised walking on a treadmill), and other factors need to be considered, such as uneven terrain and turning.

Orientation: One such factor is the orientation of the sensor on the foot. The preferred orientation would be to have the z axis aligned with the axis of rotation of the ankle. Any misalignment can be decomposed into rotations about the x, y, and z axes. Rotation about the z axis does not affect zGyro, hence the algorithm will be unaffected in this case. Rotation about the x axis would be uncommon because of the shape of the foot (the sensor would need to be placed near the toe or the heel for this to occur). Hence, the only axis which may introduce errors into the algorithm is the y axis. Errors may arise when the rotation of the foot, normally aligned with the z axis, is projected partially onto the other axes. These errors are not apparent in the experiments so far because care was taken to ensure optimal alignment, however in an unsupervised case alignment will be a problem.

One way to correct this would be to use a calibration period to determine the principal axis of rotation, and then use a change of basis to align the sensor data to this axis. Another method involves using the gravity acceleration vector to align the coordinate system. An investigation into this is underway.

Additional features: The SVM classifier permits additional features to be added to improve the performance. This was attempted, with the following features included:

1) Acceleration in vertical direction on initial contact
2) Time delay between peak velocity and initial contact

These features were selected because they appeared to vary with step quality, although by themselves they did not provide good classification. Hence they were considered as supplemental features. However, adding them to the existing angular velocity feature gave only a small increase in performance (accuracy 93.2%, area under ROC curve 0.934). Since these features barely added to performance they have been deemed superfluous.

Future Work: This study was a pilot effort intended to establish the feasibility of the biofeedback device. As such, both the sample size and nature of the subjects examined was determined by opportunity rather than by a strict design. . A more robust study using both with healthy subjects and those with clinical defined abnormal gaits will begin shortly. Secondly, a sensitivity analysis of the algorithm to changes in orientation will be conducted to determine whether the orientation is critical.

The algorithm is currently implemented in a MATLAB graphic user interface (in real time). This is currently running on a PC. Development of an Android UI for a smartphone is underway. Once this is complete, usability testing can be conducted, followed by a clinical trial, which will evaluate firstly the device performance, and also its ability to assist with gait rehabilitation.

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