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Real-world Gyroscope-based Gait Event Detection and Gait Feature Extraction

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***Abstract*—Falls in older adults are a major clinical problem often resulting in serious injury. The costly nature of clinic-based testing for the propensity of falling and a move towards home-based care and monitoring of older adults has led to research in wearable sensing technologies for identifying fall-related parameters from activities of daily living. This paper discusses the development of two algorithms for identifying periods of walking (gait events) and extracting characteristic patterns for each gait event (gait features) with a view to identifying the propensity to fall in older adults. In this paper, we present an evaluation of the algorithms involving a small real-world dataset collected from healthy adults in an uncontrolled environment. 92.5% of gait events were extracted from lower leg gyroscope data from 5 healthy adults (total duration of 33 hours) and over 95% of the gait characteristic points were identified in this data. A user interface to aid clinicians review gait features from walking events captured over multiple days is also proposed. The work presents initial steps in the development of a platform for monitoring patients within their daily routine in uncontrolled environments to inform clinical decision-making related to falls.**

Keywords-eHealth; Falls; Gait; Wearable Sensors.

I. INTRODUCTION

The global population is ageing - the proportion of the population over 60 years of age has risen from 8% in 1950 to 11% in 2009, and is expected to dramatically increase to 22% in 2050 [1]. This trend will place an enormous burden on healthcare systems and the instantiation of a proactive, preventative approach to delivering healthcare is gaining recognition. Falls are a major problem amongst the older adult population and can lead to injury, hospitalization, restricted mobility, and institutionalization [2]. Falls in older adults have been estimated to cost in the region of U.S. $20 billion per year [3]. The instrumentation of standard clinical tests has been shown to discriminate between fallers and non-fallers [4], [5]. However, as clinic-based testing is costly and often performed infrequently, research is beginning to focus on home and community-based technologies. Such technologies would provide insight into the variability in daily activities over extended periods. This paper focuses on the development of technology which translates the assessment of gait from a clinical to a home/community based setting.

Technologies for home-based gait monitoring can be divided into two categories: non-contact technologies and wearable sensors. Non-contact technologies range from image-based techniques (e.g. the Microsoft Kinect platform [6]) to sensorised floors (such as the GaitRite [7] walkway or The ELSI Underfloor Sensing Laminate by Marimils Oy [8]). Image-based systems have the limitation of not catering well with the changing orientation and/or position of the person or the inability to capture gait data for the entire day as the person moves between different locations. Additionally image-based systems have privacy concerns. While sensorised floor systems may provide a high level of detail, often these systems are expensive to deploy and require specialist expertise to install. Motion sensor based platforms, such as Passive Infra-Red (PIR) sensors, can capture variations in transition times between locations in an unobtrusive fashion, however the gait metrics derived for such systems are generally limited to gait speed measurements and their diurnal variations [9]. Wearable technologies are generally composed of inertial sensors (including accelerometers and/or gyroscopes) applied to various locations on the body (such as the waist or on the lower shanks). Wearable sensors have been shown to derive multiple gait parameters (such as stride length) from walking events (known as gait events) through identifying the repeating gait characteristic points of the gait cycle (such as initial contact point). In many cases wearable sensors have extracted the gait characteristic points using angular velocity (captured via a gyroscope) and/or linear acceleration data, from inertial sensors (often placed on the legs) [10], [11]. To date, a number of gait feature extraction algorithms have focused upon gyroscope data which quantifies rotation in multiple axes, and is therefore less dependent on the exact positioning of the sensor [12]. Wearable inertial technologies may provide a high utility (in terms of the number of gait features they can report), however they also require the conscious participation of the user (for example in applying the sensors daily). As such the successful instantiation of wearable sensors over extended term deployments may prove challenging. In contrast, wearable inertial sensors continuously extracting gait features can monitor and quantify longitudinal variability in gait, and this may provide a greater clinical insight into why falls occur than a single clinic-based falls assessment.

Inertial sensor technologies have recently been investigated for their suitability for extended deployments in home and community settings [13]. While clinic-based data collection and analysis platforms are becoming more stable, significant

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challenges exist when moving towards the real-world [14]. For example, data collection in uncontrolled environments requires stable and extensively tested platforms requiring minimal user interaction, with the added complexity of data being transferred seamlessly to central servers. Analysis will likely be subsequently performed on the collected data with results made available for later examination by users, carers and/or clinicians. In the context of gait data, this challenge is made more difficult through the highly variable nature of real-world gait data; users may only walk for limited periods of time, those walking events may be short in duration, the environment may affect the nature of the gait cycle, and the persons own gait cycle may change throughout the day (perhaps across different environment, through tiredness, from diurnal variations and/or the effect of medications taken at different times throughout the day). Potential clinical benefits lie in bringing gait information together with contextual details, as demonstrated through associating images with gait data [13]. Furthermore, making this gait information accessible to clinicians through an interactive interface is crucial to the success of the system. This interactive tool must be easy to use, present meaningful data in a format that is easily interpretable and support the clinician in querying the data so as to inform an appropriate intervention.

This paper discusses the development of a platform which identifies gait events in continuous inertial data from wearable sensors, extracts gait features for each of these events, and presents this information to a clinician through a simple interface. A significant contribution of this work is that it pertains to the application of gait feature extraction on real-world data, and uses adaptive algorithms designed to allow for intra- and inter-individual variations. This system is evaluated using data collected from a healthy adult cohort. Future work will evaluate this system with an older adult cohort. This study design has been chosen in order to minimise any technical or user acceptance issues before involving a sensitive older adult cohort. The first algorithm analyses long duration (typically over 6 hours) gyroscope signals across 5 healthy adults, recorded in an uncontrolled environment during a routine day, to detect possible gait events. The second algorithm augments an adaptive gait feature extraction approach [11] to work on gait cycle signal shape, identifies the gait characteristic points and subsequently calculates commonly reported gait parameters. Results from an evaluation of the algorithms using data from healthy adults is presented along with a proposed user interface to feed back gait parameters for walking segments performed throughout the day to a falls specialist.

II. Background

In a recent review, Taraldsen et al. [15] surveyed a number of papers examining physical activity in older adults, all using accelerometers, over durations longer than 24 hours. Studies were broadly divided into two areas: Activity Counts (reporting energy expenditure and/or intensity of activity) and Activity Recognition (reporting stepping or walking events, posture, and/or transitions). It was noted that in order to compare across studies there is a need for a consensus in both activity monitoring protocols and also the variables (in this case, gait features) reported. As described briefly in Section I, both the technologies and methods by which gait features are derived varies widely. The diversity in gait feature extraction algorithms is evidenced in a systematic review using inertial sensors by Yang et al. [16]. Significant effort has been undertaken to validate these gait features using clinical gold standards. However, as gait monitoring moves from a stand-alone clinical snapshot (taken no more than once per year) to multi-day home-based gait monitoring, significant technical and person-centered challenges exist including the processing of continuous gait data, feeding back the gait information to clinicians and users, and the acceptability of the gait data collection system.

In terms of moving towards data collection in uncontrolled environments using inertial sensors, gyroscope-based features of gait cycles have been identified from walking data by comparing successive steps and extracting specific gait characteristic points [11], [17], [18]. Four of these characteristic points [19] (as illustrated in Figure 1) are relatively easy to identify:

1) Mid-Swing (MS) point: highest position of the leg during the gait cycle;
2) Initial-Contact (IC) point: initial contact of the foot with the floor;
3) Full-Contact (FC) point: full contact of all the surface of the foot and the floor;
4) Terminal-Contact (TC) point: terminal contact of the foot with the floor before the next step.

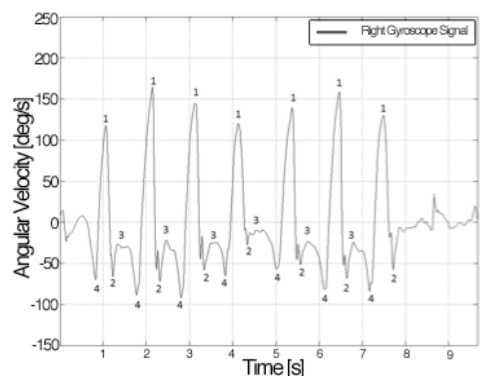

Figure 1: Example of gait gyroscope signal from the left shank over 7 gait cycles with annotated points 1) MS point; 2) IC point; 3) FC point; 4) TC point.

Over recent years, several algorithms have been described for the identification of these characteristic points [11], [20], [21]. In particular Sabatini et al [20] adopted an approach using empirically-defined signal values during experiments. However, it was found that this was too dependent on specific measurements, and not always feasible in everyday-life context across varying environments and people. Subsequently, Lee et al [21] adopted an approach focussing on finding patterns within the gait signal and demonstrated this using a quasi real-time analysis system. The system produced a high accuracy and a small delay in detection of gait events. Greene et al [11] used an adaptive approach to initially identify the MS points and to subsequently identify the remaining gait characteristic points (IC, FC, and TC). This approach allowed for varying heights in the MS point which occur both between successive gait cycles and also across different individuals. Subsequently local minima and maxima were determined through firstly ensuring they were of a certain range and subsequently finding the peak and trough points.

After the characteristic gait points are found, a number of gait features can then be derived. While the number of gait parameters that may be extracted from the gait cycle is large (for example, 130 variables were identified from falls risk assessments using inertial sensors [22]), often only a subset of these are commonly reported in the literature. These include:

- Cadence: number of steps per minute.
- Stride time: the time from IC of one foot to IC of the next foot.
- Coefficient of Variation (CV) of stride time: ratio of stride time standard deviation and stride time mean.
- Stride length: distance covered between the TC and IC points of the same foot.
- CV stride length: ratio of stride length standard deviation and stride length mean.
- Stride velocity: stride length divided by stride time.
- CV stride velocity: ratio of stride velocity standard deviation over stride velocity mean.

As outlined above, significant work has been undertaken in the extraction of gait features from inertial data from wearable sensors in clinic-based environments. However, limited research has taken place in catering for the additional challenges in moving towards gait assessment from uncontrolled real-world environments (such as the home and community).

III. METHODS

The gait of 5 healthy participants (3M, 2F, mean age: 30 years old) has been measured using the SHIMMER wireless sensor platform [23] placed on participants lower shanks using an elasticated bandage. All participants worked in a research environment mainly performing desk-based research and were asked to continue performing their normal daily activities. The participants were instructed to wear the sensors for as long as was comfortable. The sensors were removed at the end of the working day corresponding to a mean duration of 6.6 hours of data. Shimmer data were synchronized manually after data collection. Accelerometer and gyroscope signals were recorded at a sampling rate of 51.2 Hz and stored locally on an SD card. The gyroscope data was low-pass filtered with a cut-off frequency at 20Hz using a 5^{th} order Butterworth filter. Gyroscope signals were post-processed off-line using the MATLAB®platform [24].

IV. REAL-WORLD GAIT FEATURE EXTRACTION

Two novel algorithms are presented in this section. The first algorithm identifies periods (or frames) of inertial sensor data where a gait event has likely occurred. Subsequently, for each frame of data, a second algorithm is applied which extracts multiple gait features.

A. Identification of Gait Events

Each frame of gait data is found by identifying a recurrent signal peak corresponding to the MS point occurring over multiple gait cycles. Below, the steps of the algorithm are described in detail. Figure 2 shows multiple gait events identified from continuous gyroscope data.

Step I - LP Filter: The signals are low pass filtered with a zero-phase 5th order Butterworth filter with a 3Hz cut off frequency.

Step II - Calculate the adaptive threshold: An adaptive threshold is used to identify the MS point candidates in the left and right gyroscope signals. Firstly peaks are found using the derivative of the signal. The adaptive threshold is defined as an average of heights, in degrees/sec, of the top ten peaks and scaled by 0.2. A minimum value of 40 degrees/sec is taken.

Step III - Group MS peaks to identify gait event: All peaks above the adaptive threshold are found. Gait events are grouped together as one event as long as two MS peak points are not more than 4 seconds apart. Additionally, each gait event must last a minimum of 15 seconds. This duration has been chosen to ensure that only events where steady state walking occurs are examined.

Step IV - Ensure left and right occurrence of gait events: Identified gait events are compared between both signals and MS peaks must occur consecutively.

B. Extraction of Gait Features from Gait Events: Framing algorithm

The extraction of gait characteristic points from the gyroscope data was performed using a modified version of the approach used by Greene et al [11], as per Figure 3. Initially, an adaptive threshold, proposed by Greene et al. [11] over the entire gait event is found (step II) and used to identify MS points (step III). Subsequently, a novel technique taking advantage of the shape of the gait cycle signal, has been adopted to identify the other gait characteristic points as shown in Figure 4 (A). In order to find the IC, FC and TC points, the signal is windowed between consecutive MS points (step III). The first local minimum is defined as the IC point, subsequently a local maximum is defined as the FC point, and lastly another local minimum is defined as the TC point (step IV). Figure 4 shows an example of the gyroscope signal and characteristic points during the final phases of the algorithm.

Step I - LP Filter: A 5th order Butterworth low-pass filter with cut-off frequency 5Hz is applied to the gyroscope data to remove noise components.

Step II - Calculating the adaptive threshold: The adaptive threshold is defined as per Greene et al [11] and is calculated as:

$$th = 0.8\frac{1}{N}\sum_{i=1}^{N}(\omega_{ML_i} > \overline{\omega_{ML}}) \tag{1}$$

Where $\overline{\omega_{ML}}$ is the mean of the medio-lateral (ML) angular velocity signal and N is the number of samples occurring above the mean.

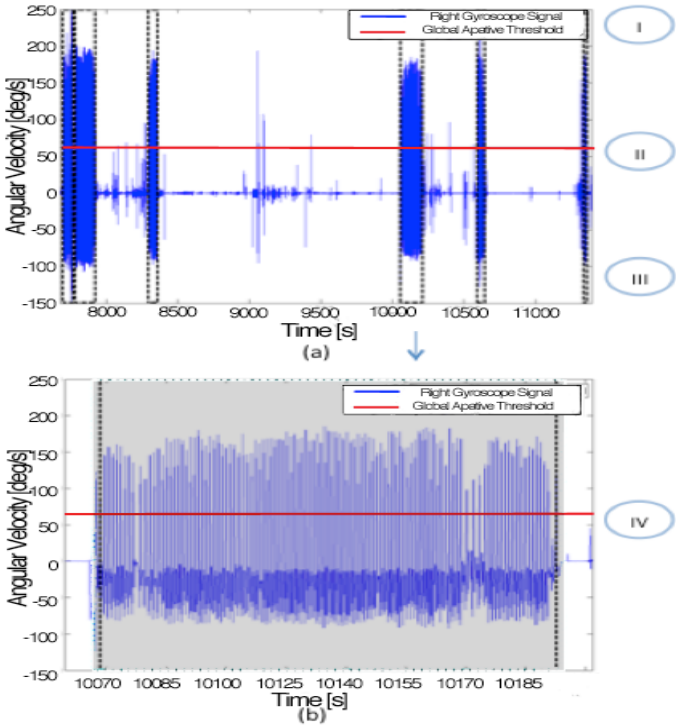

Figure 2: Example of right gyroscope signal processing through the described algorithm where the Roman Numberals in the circles refer to the steps of the algorithm. Part (a) is the gyroscope signal filtered at 3Hz. Each identified gait event is outlined by dotted rectangles. Part (b) shows the gyroscope signal for the gait event occurring between 10060 and 10210 seconds. The black dotted rectangle delineates the entire gait event identified. The shaded rectangle (slightly larger than the black dotted rectangle) shows the edges of the gait event as identified by the gait feature extraction algorithm.

Step III - Identifying the MS points: MS points are defined to occur above the threshold and the peak of the signal above the threshold are identified as candidate MS points. Candidate points occurring after 0.5 seconds are excluded.

Step IV - Frame the signal between consecutive MS points: The 5Hz filtered signal is framed between 2 MS candidates and the highest peak in the frame is selected as FC candidate.

Step V - Identify IC and TC points: The minima occurring between the first MS point and the FC point is identified as the IC point and the minima occurring between the FC point and the second MS point is identified as the TC point. This process is repeated for each frame. For each point, a window of data occurring on the 20Hz signal 0.1 seconds either side of the point is extracted and each point is updated to occur at the local minimum within this window.

Step VI - Artefact rejection: If any artefacts, identified using the following list, were found, that data was removed from the calculation of gait cycle parameters.

- If the difference between IC and TC points is greater than 2 seconds.
- If the TC point is before the IC point.
- If the TC point is before the FC point.
- If the difference between two MS points is greater than 1.75 times the mean difference within that frame.

Step VII - Calculate gait parameters: A number of gait parameters have been derived from the gait characteristic points [11], [25] including walking time, number of steps, cadence, stride time, CV stride time, stride length, CV stride length, stride velocity, and CV stride velocity.

V. RESULTS

Tables 1 and 2 report results from the analysis of the daily monitoring of the 5 healthy participants involved in the study. Data was recorded for between 5.5 to 7.9 hours long (Table 1). In particular, participants 1 and 3 (with a length record of 5.6 and 6.5 hours respectively) had the highest number of gait events (27 and 25) and walking times (1413.8 seconds and 1214.29 seconds). Participants 2 and 5 (length record respectively 7.9 and 7.4 hours) had the lowest number of gait events (15 and 7) and walking times (650.89 seconds and 566.78 seconds).

To evaluate the accuracy of the algorithm for gait event identification, a manual analysis of signals was performed, thus providing a gold standard for evaluation. The algorithm correctly identified 92.5% of all gait events. Such a high accuracy is due of the adopted adaptive techniques that allow the algorithm to correctly analyse signals in different gait situations (e.g. different speed or walking time). Table 1 shows also that globally the minimum walking time was about 20 seconds (when walking periods less than 15 seconds were excluded) for all participants (except for participant 5 with 26.58 seconds), while the maximum registered walking time was longer, for example participants 5 (197.10 seconds), 1 (178.50 seconds) and 3 (154.90 seconds) and shorter for participants 2 and 4 (81.31 seconds and 90.88 seconds).

All gait derived parameters in Table 2 have been calculated taking advantage of the identified characteristic points through the Framing algorithm. The mean cadence was between 99.62 and 110.85 steps/min for participants 1,2,3 and 4. Participant 5 had the highest cadence with a value of 129.07 steps/min. Concerning the mean stride time, participant 3 had the highest average value (1.18 seconds) while the other participants were all around 1.10 seconds. The mean stride length was higher for participants 1 and 3 (1.20 and 1.21 metres), while participants 2 and 4 had the lowest values (1.01 and 1.02 metres). Finally, the mean stride velocity was around 1.10 m/s for all participants except participant 4 who had a value of 0.97 m/s. Concerning the coefficient of variations, the values were around 0.10% for the mean CV stride time and 0.5 for mean CV stride length and velocity.

Gait information produced by these algorithms can be overwhelming and difficult for clinicians to interpret due to the number of metrics reported, and their decontextualised nature. A prototype user interface is proposed in Figure 5 to allow clinicians user friendly access to information concerning daily gait patterns. Such an interface allows the clinician to interrogate gait data as required. General information concerning the selected day (walking time per day and total activity per

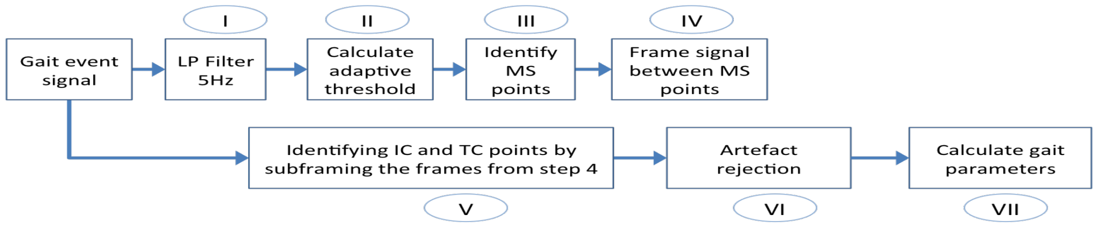

Figure 3: Framing algorithm.

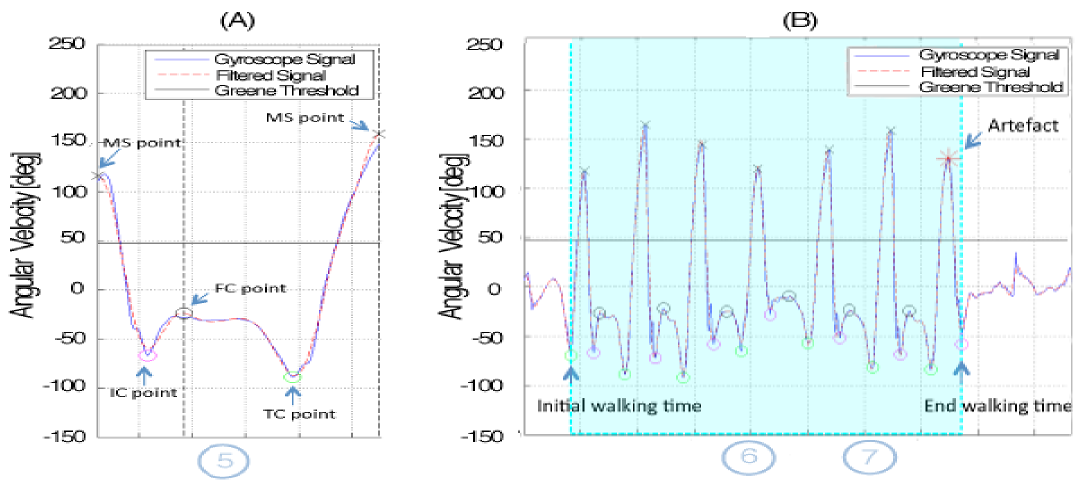

Figure 4: Example gyroscope signal for one gait event (A) and a number of consecutive gait events (B). In (A), a single gait event, between MS points, is shown along with IC, FC and TC points. In (B), the gait event under analysis (highlighted with a transparent blue shading) is shown along with an artefact (identified as no future IC, FC or TC points are found). The numbers in circles refer to steps in the Framing algorithm from Figure 3.

TABLE I: Results from the gait experiments.

Subject ID	Total record time [hours]	# of identified gait events	correctly identified events (number of missed)	Total walking time [s]	Min walking time [s]	Max walking time [s]	Min # of steps	Max # of steps
1	5.6	27	90 % (3)	1413.8	19.38	178.5	31	352
2	7.9	15	88.2% (2)	650.89	19.75	81.31	29	161
3	6.5	25	89.2% (3)	1214.29	19.67	154.9	33	253
4	5.8	19	95%(1)	679.06	18.55	90.88	25	171
5	7.4	7	100%	566.78	26.58	197.1	54	425

hour) or the previous week (activity over previous week) is presented on the upper panel. The middle panel provides the ability to select gait events which occurred throughout the day in order to provide gait information for that event. The calculated features for the selected gait event (as shown on the bottom right) and the corresponding gyroscope signal (bottom left) is also presented.

VI. Conclusions

This paper presents a platform that extracts gait information from gyroscope sensors placed on the lower shanks. The system automatically identifies gait events, extracts gait characteristic points for each event, and subsequently derives gait features. The identification algorithm accurately detected 92.5% of gait events from a day of gait data from 5 healthy adults (total duration of 33 hours). Upon a visual examination, the Framing algorithm successfully identified over 95% of the gait characteristic points using gyroscope data from the successive gait cycles within the gait events. A validation study using a larger and more varied cohort is required to evaluate the accuracy of the Framing algorithm. Further experiments with older people (mean age >60 yrs) will be beneficial for the project as studies reveal that one in three adults aged 65 and older fall each year. However this validation will be difficult as traditional approaches have been clinic-based, and this may not translate well for uncontrolled home and community environments. For example, the context of where the person is walking may be very important (e.g. is the surface uneven?) or other factors which may affect the biomechanics of walking (e.g. what type of shoes are being worn?). Additionally, longitudinal changes in gait may be more important, and as such technologies which provide a broad insight may be clinically useful (e.g. how has gait speed changed over the past year?).

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TABLE II: Derived parameters from the analysis.

Sub ID	Cadence (num steps per min)	Mean stride time [s]	Mean CV stride time [%]	Mean stride length [m]	Mean CV stride length [%]	Mean stride velocity [m per s]	Mean CV stride velocity [%]
1	104.43 ±12.43	1.14 ± 0.12	0.12 ± 0.06	1.20 ± 0.09	0.48 ± 0.07	1.09 ± 0.11	0.52 ± 0.12
2	104.92± 15.27	1.08 ± 0.14	0.11 ± 0.05	1.01 ± 0.07	0.49 ± 0.05	0.97 ± 0.13	0.51 ± 0.06
3	99.62 ± 7.06	1.18 ± 0.06	0.10 ± 0.04	1.21 ± 0.08	0.48 ± 0.05	1.04 ± 0.09	0.49 ± 0.05
4	110.85 ± 13.67	1.04 ± 0.19	0.12 ± 0.08	1.12 ± 0.09	0.48 ± 0.08	1.12 ± 0.15	0.50 ± 0.08
5	129.07 ± 13.22	1.10 ± 0.04	0.11 ± 0.03	1.02 ± 0.05	0.51 ± 0.04	1.12 ± 0.04	0.52 ± 0.04

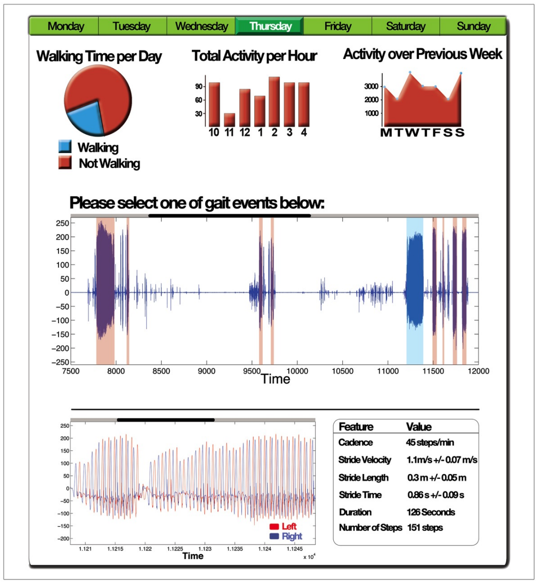

Figure 5: Clinician user interface for gait data

While the platform presented in this paper is applied to data from healthy adults, on-going work is investigating applying the methods to data collected in an older adult population where it can be reviewed (post data collection) by a clinical falls specialist. This system aims to present more contextualized gait information, collected in home and community settings, to support clinical decision making and inform falls interventions, as necessary. Significant challenges exist in the further development of this system including extracting gait features from individuals with an impaired gait.

We further plan to implement the proposed user interface in a web-based system (accessible via secure connection through laptop, tablet or smartphone) which could be accessed by both physicians and patients with the aim of leading to better self-management of the older population.

REFERENCES

[1] Affairs/Population U.N. E.&S., Division. World Population Prospects, 2009.

[2] M.E. Tinetti, "Preventing Falls in Elderly Persons," N. Engl. J. Med. vol. 348(1), pp. 4249, 2003.

[3] J.A. Stevens, P.S. Corso, E.A. Finkelstein, and T.R. Miller, "The costs of fatal and non-fatal falls among older adults," Inj. Prev., vol. 12(5), pp. 290295, 2006.

[4] E.P. Doheny, et al., "Falls classification using tri-axial accelerometers during the five-times-sit-to-stand test," Gait Posture, vol. 38(4), pp. 1021-1025, 2013 .

[5] B.R. Greene, et al., "Quantitative falls risk assessment using the timed up and go test," IEEE Trans. BioMed. Eng., vol. 57(12), pp. 29182926, 2010.

[6] E. Stone and M. Skubic, "Unobtrusive, Continuous, In-Home Gait Measurement Using the Microsoft Kinect," IEEE Trans. BioMed. Eng., vol. 60(10), pp. 2925-2932, 2013.

[7] GAITRite Systems, http://www.gaitrite.com/, [retrieved: January, 2014].

[8] MariMils, http://www.marimils.com/, [retrieved: January, 2014].

[9] L. Walsh, B.R. Greene, A. Burns, and C. Ni Scanaill, "Ambient assessment of daily activity and gait velocity," Proc. 5th Int. Conf. Perv. Comp. Tech. for Healthcare (PervasiveHealth 2011), pp. 418-425, 2011.

[10] I. Tien, S.D. Glaser, R. Bajcsy, D.S. Goodin and M.J. Aminoff, "Results of using a wireless inertial measuring system to quantify gait motions in control subjects," IEEE Trans. Inf. Tech. Biomed., vol. 14(4), pp. 904915, 2010.

[11] B.R. Greene, et al., "Adaptive estimation of temporal gait parameters using body-worn gyroscopes," Proc. IEEE Eng. Med. Bio. Soc. (EMBC 2011), pp. 1296-1299, 2010.

[12] K. Tong K and M.H. Granat, "A practical gait analysis system using gyroscopes," Med. Educ. Phys., vol. 21(2), pp. 8794, 1999.

[13] A.F. Smeaton, J. Lanagan and B. Caulfield, "Combining wearable sensors for location-free monitoring of gait in older people," J. Ambient Intell. Smart Environ., vol. 4(4), pp. 335346, 2012.

[14] J. Doyle, C. Bailey, C. Ni Scanaill and F. van den Berg, "Lessons learned in deploying independent living technologies to older adults homes," Univ. Access Inf. Soc., 2013.

[15] K. Taraldsen, S.F.M. Chastin, I.I. Riphagen, B. Vereijken and J.L. Helbostad, "Physical activity monitoring by use of accelerometer-based body-worn sensors in older adults: A systematic literature review of current knowledge and applications," Maturitas, vol.71, pp. 13-19, 2012.

[16] S. Yang and Q. Li, "Inertial Sensor-based Methods in Walking Speed Estimation: A Systematic Review," Sensors, vol. 12, pp. 6102-6116, 2012.

[17] K. Aminian, B. Najafi, C. Bla, P.F. Leyvraz and P. Robert, "Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes," Int. J. Biomech., vol. 35(5), pp. 689699, 2002.

[18] K. Aminian, et al., "Evaluation of an ambulatory system for gait analysis in hip osteoarthritis and after total hip replacement," Gait Posture, vol. 20(1), pp. 102107, 2004.

[19] J. Perry, Gait Analysis: Normal and Pathological Function: Slack, 1992.

[20] A. Sabatini, C. Martelloni, S. Scapellato and F. Cavallo, "Assessment of walking features from foot inertial sensing," IEEE Trans. Biomed. Eng., vol. 52(3), pp. 486494, 2005.

[21] J. Lee and E. Park, "Quasi real-time gait event detection using shank-attached gyroscopes," Med. Bio. Eng. Comp., vol. 49(6), pp. 707712, 2011.

[22] J. Howcroft, J. Kofman and E.D. Lemaire, "Review of fall risk assessment in geriatric populations using inertial sensors," J. Neuro. Rehab., vol. 10:91, 2013.

[23] A. Burns, et al., "SHIMMER A Wireless Sensor Platform for Noninvasive Biomedical Research," IEEE Sensors J., vol. 10(9), pp. 1527-1534, 2010.

[24] MATLAB, http://www.mathworks.co.uk/, [retrieved: January, 2014].

[25] E.P. Doheny, T.G. Foran and B.R. Greene, "A single gyroscope method for spatial gait analysis," Proc. IEEE Eng. Med. Bio. Soc (EMBC 2010), pp. 1300-1303, 2010.

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