Validity and consistency of concurrent extraction of gait features using Inertial Measurement Units and Motion Capture System

Arif Reza Anwary, Hongnian Yu, Andrew Callaway, and Michael Vassallo

***Abstract*— Conditions causing gait abnormalities are very common and their treatment requires the detailed assessment of gait. Currently such assessments are carried out in gait laboratories and require the use of complex and expensive equipment. To increase availability and use at home and clinics, we design and develop an affordable, user friendly, wireless, portable automatic system to extract spatiotemporal features of gait that can be used indoors and outdoors. This study determines the concurrent validity of extracted gait features from Inertial Measurement Units (IMUs) against 'gold standard' Motion Capture System (MoCap) using a hybrid gait features extraction method. The analysis of the proposed method is based on minimum prominence and abrupt transition points in the IMU signals. It also compares the degree of agreement for mean spatiotemporal gait features. The concurrent data from synchronized IMUs and MoCap are collected from 18 subjects. We validate our proposed system using two experiments; 1) IMU and MoCap with self-selected (free) walking and 2) IMU and MoCap at various walking speeds. Interclass correlations, Lin's concordance correlation coefficients and Pearson's correlation coefficients (r) are applied to determine the correlation between extracted gait features from IMU and MoCap measurements. Bland-Altman plots are also generated to evaluate any unknown bias between the mean extracted features. The experiments show that spatiotemporal features of gait extracted from IMUs are highly valid. Our methods facilitate gait assessment in clinics and at home including the possibility of self-assessment.**

***Index Terms*— Inertial Measurement Unit (IMU); Accelerometer; Gyroscope; Feature Extraction; Wearable Sensors; Gait Analysis.**

I. INTRODUCTION

Gait disorders have multifactorial causes. Intrinsic causes include normal ageing, age related diseases, abnormal posture and ambulation as well as mental health disorders such as depression. Gait abnormalities are therefore common in clinical practice. The change in gait over time is a marker of prognosis in patients with Parkinson's disease, cerebrovascular accidents , amputees , stroke , osteoarthritis , spinal deformity, fractures, limb-length inequality and cerebral palsy [1, 2]. Gait analysis of elderly patients is used to determine falls risk [3] with a view of promoting prevention [4]. Gait can also predict physical and memory decline [5]. Human locomotion is analyzed using biometrics and biomedical engineering which opens several opportunities. The detection of abnormalities within an individual's gait also aids in the detection of poor quality of life, falls and increased mortality. These can lead to injury, disability and increased care costs. For these reasons, research in gait analysis is key, and has drawn interest from researchers across various disciplines.

Gait is often evaluated by physicians, therapists and researchers in artificial conditions using clinical tools that, despite validation, are often subjective and arbitrary and often lacking ecological validity. These tools are mostly based on visual observation by the therapist who then makes a subjective judgement based on their observations. Such tests include the 'get-up and go' test, six-minute walk test, Figure of 8 Walk Test, The Functional Gait Assessment, Groningen Meander Walking Test and Berg Balance Scale [6]. Scoring relies on clinical expertise, experience and judgement and abnormalities are identified in a dichotomous way (present or not). On the other hand laboratory based tests are more accurate and detailed and are able to analyse the various components of the gait cycle. Tools for assessment of gait such as 3D kinematic analysis using a motion capture system (based on stereo photogrammetry with multi numeric cameras allowing the 3D tracking of dedicated markers), ground reaction forces [7] and instrumented walkways [8] offer current "gold standards" of measurement in gait. These methods require technical or clinical staff trained to use such equipment. They are also time consuming and expensive, making them of little practical use for day to day use in clinics. Lower cost alternatives such as Microsoft Kinect [9] and camera [10] are appealing, but are limited in their use due to small capture volume, lack of privacy and because they only analyze a few gait parameters. There is therefore a need for an affordable, user-friendly, reliable, portable multi-sensor based gait analysis system that can capture data over a long time period and one that can be used both in clinics and at home. There are several wearable sensors used to analyze gait such as accelerometers, magnetometers, gyroscopes, goniometers, foot pressure sensors and

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inclinometers [11]. IMUs bring together several of these sensors and their use in clinical practice is increasing. They have several clinical applications including the monitoring of gait post operatively, measurement of gait symmetry, stride variability, analysis of gait in Parkinson's disease, human walking trajectory and falls risk characteristics [12]. IMU sensors increase the versatility and potential for new technological developments opening up possibilities for use at home and clinic. IMU sensors offer the freedom for the measurements to occur at home or within the community, outside of healthcare settings, offering greater ecological validity. Although techniques for IMU based analysis are being refined and are available [13], few studies have explored their use for gait analysis at home and in clinical areas. In addition, these studies do not describe a fully automatic system that is able to collect data from multiple sensors, extract features and provide quantitative measures from both limbs.

The challenges arising from diagnosis and management of gait abnormalities and their consequences result in a national imperative to address this. This study adds to our previous work [14] that investigated gait asymmetry based on normal walking but without different walking speeds or determining the level of agreement from statistical analysis. We design and implement a novel hybrid validation to automatically analyze gait by identifying and extracting specific components of gait. We use IMUs and Motion Capture System (MoCap) data with Treadmill to increase the reliability and validity of gait features. Based on our proposed method, we develop a data collection system based on the simultaneous collection of 14 important gait features from both legs separately. Using a multisensory based IMU system, we aim for this system to be low cost to increase its availability and affordability.

The main contributions of this paper are: 1) propose a novel hybrid adaptive gait events detection approach based on combining local minimal prominence characteristics and abrupt transition in the signals using a low-cost IMUs based gait analysis system, 2) ascertain the ability to extract gait features from the parallel use of IMU and MoCap, 3) determine the levels of agreement for average spatiotemporal gait features using the proposed approach with the criterion measure than the established MoCap, and 4) conduct synchronous IMUs data collection from both legs using our dedicated and sophisticated smartphone application from 18 subjects. We perform two experiments to validate our method; 1) IMU and MoCap with self-selected (free) walking and 2) IMU and MoCap at various walking paces.

II. METHODS

A. Sensor selection and data acquisition

An IMU incorporates an accelerometer and a gyroscope that respectively measure acceleration and angular rotation of an object. The measurement of human locomotion is very variable with individuals walking at different speeds. The device must be capable of capturing such variability and requires a high bandwidth that is capable of measuring low to high acceleration changes. To achieve our aims we look to use a commercially available affordable IMU sensor. It should provide wireless Bluetooth facility, long battery life, the ability to simultaneously synchronize multiple data points. Preferably such a sensor would have some track record of use in clinical settings such as rehabilitation or sports and research. The equipment is required to have a long battery life to enable its use to measure gait parameters over a prolonged period. In choosing our sensor we look towards other characteristics such as pressure, water and temperature resistance.

To meet our aims and develop our processing algorithm, we choose the sensors with the criteria: (a) capable of providing interpretable information of different stages of the gait cycle; (b) easily available, low cost, user friendly, portable, wireless and with low power consumption; (c) fulfil criteria for privacy and patient and public acceptability; (d) the compatibility of the sensors should allow use on existing sensor boards or systems or allow easy development for integration; (e) capable of allowing fusion and concurrent data collection.

Several wearable sensors are validated for use in gait analysis [15]. We choose the MetaWearCPro [16] sensor as it meets all the criteria mentioned above. It uses accelerometer and gyroscope collected data. The range of the accelerometer is set at $\pm$ 8 ms^{-2} and the range of the gyroscope is $\pm$ 500 $degs^{-1}$, with sampling at a rate of 50Hz. The sensor is active when connected to an android device via Bluetooth but is in sleep mode when disconnected. Battery usage is high when active but low in sleep mode. An application is developed for smartphones to collect real time synchronous data from IMUs[14]. An HTC M9 mobile phone is used to connect the IMUs. We previously identified metatarsal foot locations for optimal data collection and extraction [17]. Two IMU sensors are located at these positions for both feet with a view of collecting accelerometer and gyroscope data.

B. Experimental protocol

Two experiments are conducted with institutional ethical approval. Each experiment measures gait with Experiment 1 measuring on a treadmill, Experiment 2 measuring on the ground free walking. Previous work demonstrates that there are differences in gait under these differing conditions [18]. There is therefore a need to ensure that the proposed algorithms can detect the same factors under all conditions they need to be used. For each experiment, each participant is provided with an information sheet and provided signed informed consent. Subjects are excluded if they have musculoskeletal conditions such as fracture or muscle injury, neurological illness, unable to exercise, major ligament injury within 3 months of the study, abnormal gait, recent surgery or impairment attributable to other causes by history or other medical diagnoses that have the potential of affecting the results of the study. Both experiments are conducted in a Gait Lab using a calibrated Qualysis [19] camera system. Lab based motion capture system and force plate are used to detect gait events [13], these studies use offline hand-craft feature engineering and do not describe a fully automatic system that is able to collect data from multiple sensors, extract features and provide quantitative measures from both limbs. This process is utilized here to demonstrate the validity of our system with two reflective markers positioned on the lateral malleolus and 5th metatarsal on each leg to identify heel strike and foot angle to horizontal. Concurrently, two IMUs are attached to the base of the first metatarsal of each foot for collecting data shown in Fig. 1(a).

1) Experiment 1

A convenience sample of 8 young subjects (7 males and 1 female, age 33.5 ± 5.06 years, weight 78.68 ± 16.51 kg, height 1.73 ± 0.6 m, BMI 26.14 ± 4.30 kg/m2) are recruited. Each subject walks on the treadmill at different speeds (0.6, 1.0, 1.4, 1.8, 2.0, 2.2 and 2.5 ms^{-1} respectively). Each subject performs a walk of 30 strides on the single belt treadmill (Woodway, model ELG). This experiment offers a more traditional laboratory based situation to demonstrate that the devices and algorithms perform well in each situation.

2) Experiment 2

A convenience sample of 20 young subjects (18 males, age 27.65 ± 5.18 years, weight 64.8 ± 7.4 kg, height 1.61 ± 0.15 m, BMI 25 ± 3.9 kg/m^2) are recruited. Each subject walks in a straight line for 10 m at a self-selected (free) walking pace, they then turn 180° and walk back 10 m to starting position (20 m total walking). This experiment offers a more natural, ecologically valid walking situation.

C. Adaptive gait features extraction

1) Concurrent IMUs and MoCap data collection

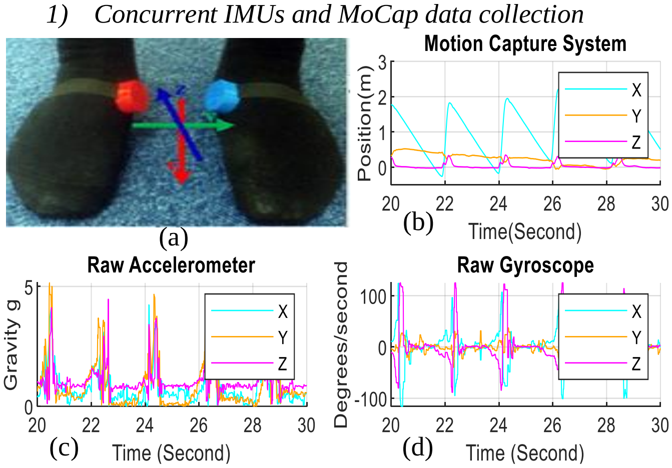


FIGURE 1. (a) Sensors placement in both metatarsal feet locations, (b) 3-D position from MoCap, (c) Raw accelerometer and (d) Raw gyroscope

Figure 1(b) shows 3D position output from Qualisys. The raw data accelerometer and gyroscope relating to subject 1 is presented in Figs 1(c) and 1(d).

2) Raw data processing

The IMU provides 3 axis acceleration from both accelerometer and gyroscope data. the Accelerometer measures user acceleration and gravitational acceleration towards earth. They are affected by altitude and impact, resulting in poor dynamic features. Gyroscope data have a low changing bias and are sensitive to temperature changes resulting in poor static features [20]. The 3-axis outputs from both sensors are combined to provide an absolute orientation vector as quaternion or Euler angles. The IMU combines the measurements from 3-axis accelerometer and 3-axis gyroscope sensors to provide an orientation vector as quaternion or Euler angles. The algorithm in [16] fuses the raw data performing an intelligent analysis to improve sensors' output and provide distortion-free and refined orientation vectors. The IMU input data consists of two components: forward acceleration and downward gravitational acceleration. There are several quaternions able to estimate the orientation from these data and we choose the Madgwick technique [21]. In this way the impact of gravity is removed and gravitational g is converted to user acceleration of movement (A_{xyz}) ms^{-2} by multiplying 9.81.

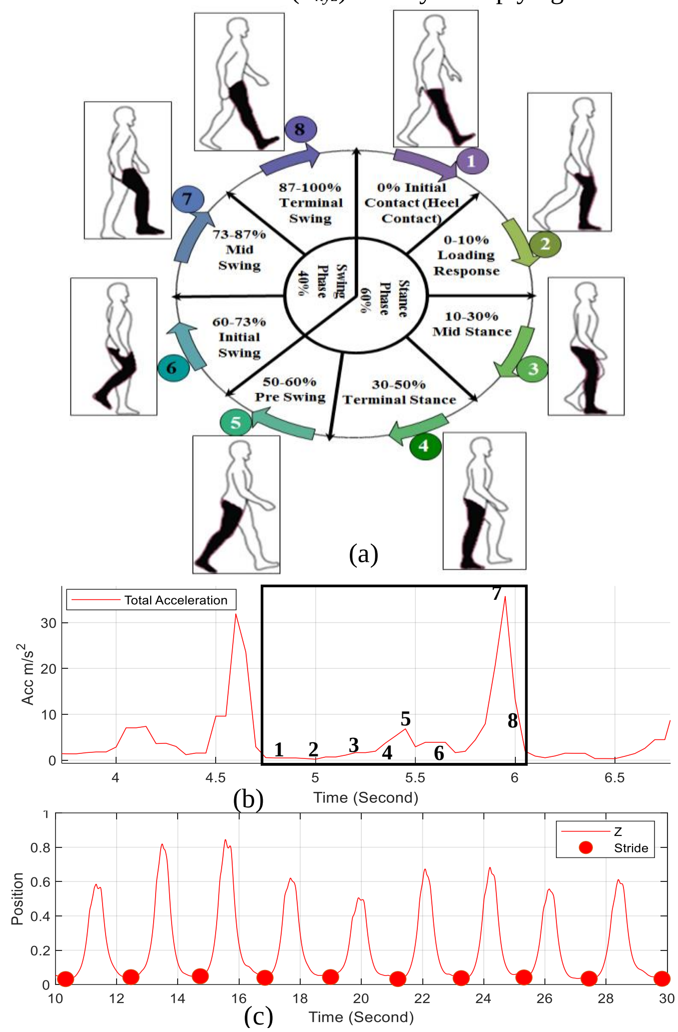


FIGURE 2. (a) Normal human gait phases and (b) Eight events of a gait cycle from accelerometer signal (c) Stride events from *MoCap*

3) Stride, stance, swing and step detection

Human walking is a series of repetitive movements described as the gait cycle. A stride is defined as the distance between the point of first foot contact and the next point of contact of the same foot [22]. A stride is therefore made up of two steps and consists of stance and swing phases. Stance is characterized by 5 and swing by 3 events. Normal human gait phases and 8 distinct events in the gait cycle are shown in Fig. 2.

In Fig. 2(a), the cycle starts at the point when the heel of the leading foot first touches the ground. The leg decelerates as the forward velocity decreases to zero. The foot is stationary as the body weight is supported on that foot till the terminal stance phase. At the pre-swing event the toe of the lead foot is being lifted off the ground. The point when the foot is completely off the ground is the start of the swing phase. In the initial swing event forward acceleration starts along a horizontal axis reaching a peak followed by a deceleration to the terminal swing event when the foot touches the ground again. These 8 events are identifiable from an IMU (Fig 2(b)). They were previously identified from accelerometer [23] and gyroscope [24] signals separately. The signals are comparable to our signal. The signal obtained shown in Fig. 2(b) identifies the separate gait events shown in Fig. 2(a).

From Fig. 2(b), we can see that the lead foot is stationary at the start and end of the gait cycle. Events 1-4 are identified in the signal as a horizontal line with zero velocity. As the foot moves from the end of the stance phase through the swing events we can see the corresponding signal from the gyroscope and accelerometer. The mid swing event which is the point of highest acceleration is identified by marker 7 and is followed by a deceleration identified by marker 8. This point 7 is a useful marker for identifying a stride.

We propose a hybrid adaptive gait phase detection approach based on the characteristics of different events. The approach of detecting stride, stance, swing and steps are described below.

STEP 1) *Filtering:* A_{xyz} is smoothed using a low-pass 1st order Butterworth filter with a sampling rate of f_s = 50 Hz, and a cut off frequency f_c = 5 Hz.

This smoothness is accomplished at the cost of diminished steepness of some peaks meaning that different frequency components of this signal are delayed by different lengths of time, causing distortion [25]. Therefore, we first filter the signal, then time reverse the signal and last filter it again with the same filter to linearize the phase [25]. The phase response is corrected when the signal is passed through the filter for the second time. A zero phase delay filter is applied for avoiding the phase distortion after the digital low-pass filter [26] to obtain AT_{xyz} (*filtfilt* in MATLAB*)*.

STEP 2) *Stride detection:* The stride phase is detected by identifying the local maximal and minimal prominences characteristics from accelerometer signal that correspond to a single stride phase shown in Fig. 2(b). We use maximal and minimal prominences described in [27], but we use a different detection method to identify them correctly. In our technique, we identify the two minimal prominences (Fig. 2(b) markers 1 and 8) and then proceed to identify the maximum peak (Fig. 2(b) marker 7) factoring out additional peaks (e.g. Fig. 2(b) marker 4) that may occur during the particular phase of the gait cycle. The apex of the peak is a measure of its height as well as how much the position in relation to other apexes. Three steps are required to measure the prominence of a peak. A marker is first positioned on the peak.

One technique of marking the peaks is to make use of the characteristic that the first derivative of a peak has a downward-going zero-crossing at the peak maximum. Second, an extended line from the horizontal axis is drawn to the left and right side until it crosses the signal or reaches the left or right end of the signal. Third, the maximum perpendicular distance from the peak to the horizontal line is calculated. The maximum prominence of the peak is identified by following these steps.

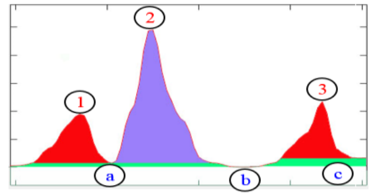


FIGURE 3. Finding the maximum prominence of the peak

An example of mentioned three steps is shown in Fig. 3. Allocate each peak to a marker labelled by *1* to *3* (peak) and mark the troughs by *a* to *c*. Draw an extension line from the horizontal axis to right and left side until the line from marker *a* reaches the left end point. Estimate the maximum perpendicular distance between the marker *a* and the endpoint. Identify the minimal prominence of the peak using the similar procedure. This method is used to find the minimal prominence and applied to AT_{xyz} signal for detecting initial contact (IC) and terminal swing (TC). The result is shown in Fig. 4.

STEP 3) *Swing detection:* After identifying each stride from the AT_{xyz}, choose a section as the length of which is the difference between a pair of consecutive strides (IC to TC). Pass the window through a low-pass filter (step 1) for smoothing. In the window locate the swing phase around middle. Identify the minimal peak prominence which is the stance and swing (SS) (marker 5 and 6 in Fig. 2(b)) from each window using Step 2.

STEP 4) *Stance detection:* identify strides and swing once. Estimate the stance phase from the starting of stride IC to the swing location SS from each stride window. The results of detecting stride, swing and stance events is shown in Fig. 4.

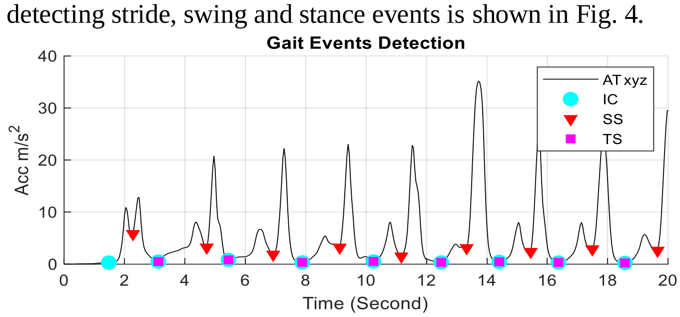


FIGURE 4. Detection of stride, stance and swing events using proposed approach

STEP 5) *Step detection:* Characterize a step by the sequential events starting at the point of first contact of the lead foot and the first contact of the other foot. Therefore, the step is the difference between IC of one leg to SS of the opposite leg shown in Fig. 5.

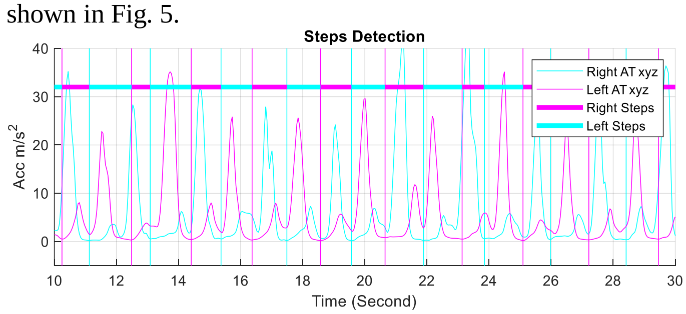


FIGURE 5. Result of step event detection using proposed approach

STEP 6) *Velocity and distance estimation:* Figure 1(a) shows that the A_x is aligned along the foot axis of the IMU sensor, the A_z points downwards so that it is aligned with gravity and the A_y is aligned at right angles to both A_x and A_z. The raw data from the sensor (Fig. 1(c)) show that the accelerometer signal at the initial level is not aligned to zero which means that the sensors are not located perfectly upright with the earth frame in the foot locations due to the initial gravity part of y and z. The sensors do not need to be perfectly upright in this study, which in any case is not user-friendly and nearly impossible. The compensation is considered resulted from the discrepancy between the sensor frame, the foot frame and the earth frame. The orientation of the IMU is estimated using Madgwick quaternion technique [21] and then gravity component is removed. We subsequently use the trapezoidal double integral approach [25] to use the accelerometer and gyroscope data to calculate the distance travelled by the subject. In the initial integration we identify the velocity and in the second integration we calculate the distance. A high-pass filter is applied to the data for removing the direct component from the acceleration and minimizing the integration drift [14]. As the stance phase is stationary, the velocity is set to zero. Stepwise graphical representation of each process is shown in the supporting document.

STEP 7) Strides from MoCap: The MCS data collected from Qualisys is preprocessed for markers tracking using Qualisys Track Manager software and stored in a C3D file. Identify each stride distance from the x-axis of MoCap data. Initially use a high-pass filter to remove the direct component from the signal. Each stride starts with the first abrupt transition point IC and the TS is located at the last abrupt transition point. The abrupt transition point is detected by minimizing a cost function over all possible numbers and locations of change points in time series data based on statistics using *findchangepts* function in MATLAB [28]. The root mean square level statistics is used and the maximum number of changes to be searched is set to three. The result is shown in Fig. 6.

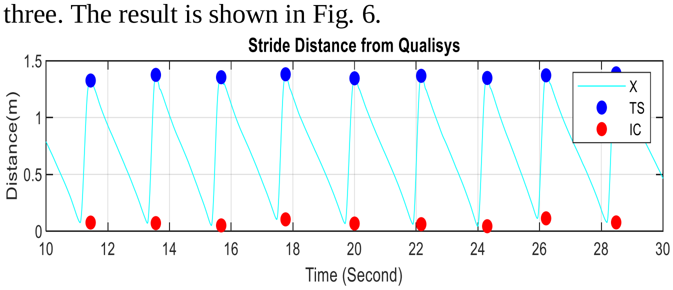


FIGURE 6. Result of strides detection from MoCap using proposed approach

4) Summary

For both experiments, the reflective markers' 3D positions are collected using the MoCap system from right and left legs. The total distance, total time, speed and stride (number, length, and time) are estimated using the position signals along the 3D coordinates information. The MoCap therefore provides positional data output and the IMU collects accelerometer and gyroscope data that is converted to displacement referred to as distance (Section 2(c) step 7). In this way the output from both can be calculated and compared.

By combining the data from IMU and MoCap, we obtain values of 14 spatiotemporal features of gait. These features are obtained from each of the lower limbs in Fig. 7. The features obtained are: number of strides; distance (m); velocity (ms^{-1}); time (s); stride time (s), length (m), velocity (ms^{-1}); swing time (s), length (m) and velocity (ms^{-1}); step time (s), length (m), velocity (ms^{-1}); stance and swing time (s). From MoCap, we obtain 10 spatiotemporal gait features from both legs. These are number of strides, total distance (m), total time (s), velocity (ms^{-1}), stride time (s), stride length (m), stride velocity (ms^{-1}), step time (s), step length (m), and step velocity (ms^{-1}). Figure 7 shows our concurrent gait features extraction method and these step visualizations are shown in the supporting document.

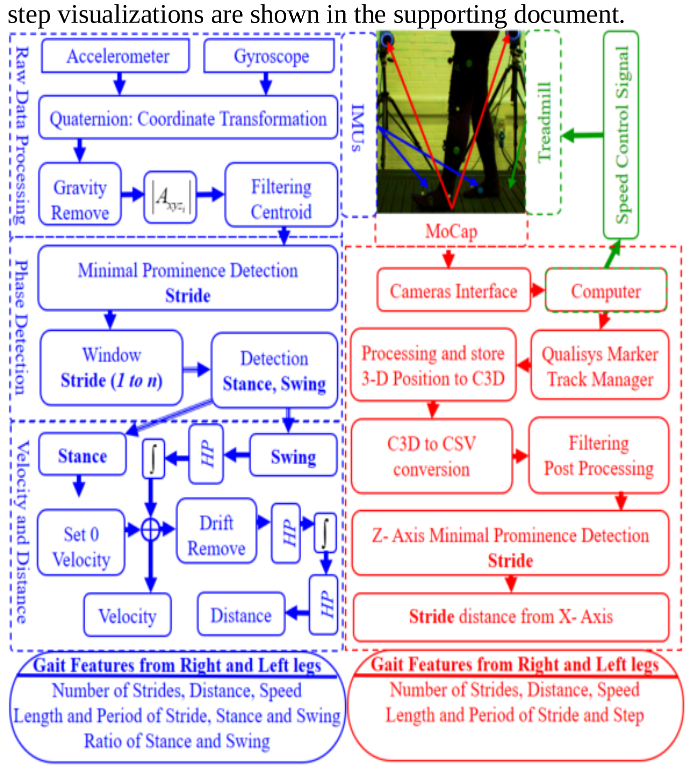


FIGURE 7. The process diagram of the automatic features extraction from IMUs, and MoCap through Treadmill

D. *Statistical analysis*

The validation study is conducted where the gait features extracted from IMU against gait features extracted from MoCap. Treadmill and MoCap are considered to be either gold or clinical standards. Treadmill provides the speed information and the stride number, stride length, stride time, total distance, total time, and speed are calculated from MoCap data. The Shapiro-Wilk test is applied to the collected gait features confirmation the normality in data. Accuracy between IMU and MoCap is calculated for different features using equation (1).

$$Accuracy = \left(100 - \left|\frac{ActualValue - EstimatedValue}{ActualVale}\right| \times 100\right)\% \tag{1}$$

The absolute agreement level between the IMU extracted gait features and the MoCap gait features are analyzed with Interclass correlations (ICC) by ICC(2,1) [29] for consistency (two-way mixed). To validate IMU features and MoCap we use Lin's concordance correlation coefficients (LCC) [30]. This test provides an index of how well results of a new test correlate with gold standard tests by capturing subtle deviations in agreement between captured data and reference criteria. The strength of the linear association between extracted IMU features and MoCap is measured using Pearson's correlation coefficient (r). r is a poor indicator of validity as it only shows whether measurements can be fixed with calibration and does not account for absolute agreement. For example, if the PCC of a variable is high, to get absolute agreement an offset can be applied [31].

We calculate the means, standard devastation (SD)s and 95% confidence interval (CI) for both MoCap and IMU systems. Bland-Altman (B&A) plots are generated to visually interpret heteroscedasticity by plotting the difference between the two systems against the mean of both the systems for each subject [32]. *T*-tests are also used to identify differences in IMU gait extracted features and MoCap measurements.

III. Experimental Results

A. Experiment 1: Results

In experiment 1, data from MoCap and IMU are collected concurrently. The treadmill speed is set to 0.6, 1.0, 1.4, 1.8, 2.0, 2.2 and 2.5 ms^{-1} and each subject walks 30 strides on the treadmill at each speed. 3360 strides are collected from all subjects (8 subjects x 30 strides x 7 speeds x 2 legs). The collected data is analyzed to estimate the accuracy of total travelled distance and the total time of each subjects. The analysis is performed for stride to stride basis. The accuracy of IMU gait extracted features time, distance, and speed show very high, indicating that the measurements are significant comparing with MoCap. The accuracy between IMU and MoCap measurements are presented in Table I.

TABLE I
IMU Gait Extracted Features Accuracy with MoCap & Treadmill

Subjects	Experiment 1: Treadmill Speed = 0.6 m/s											
	MoCap				IMU				Accuracy (%)			
	Right Leg		Left Leg		Right Leg		Left Leg		Right Leg		Left Leg	
	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)
1	26.34	38.66	25.51	37.61	26.60	38.47	24.63	37.45	98.99	99.49	96.54	99.57
2	19.75	32.92	19.73	32.88	20.39	32.89	20.12	32.96	96.77	99.91	97.99	99.75
3	31.96	49.69	31.96	50.31	32.26	49.84	31.94	50.20	99.05	99.70	99.96	99.79
4	40.44	67.40	40.42	67.37	42.61	67.48	41.38	67.20	94.65	99.89	97.63	99.76
5	15.38	25.63	15.32	25.53	15.12	25.66	15.03	25.57	98.33	99.92	98.08	99.87
6	15.32	25.53	15.35	25.59	15.01	25.54	14.70	25.60	97.99	99.97	95.75	99.94
7	36.98	61.64	38.19	62.32	40.78	61.51	38.30	62.19	89.75	99.80	99.72	99.78
8	19.45	32.42	19.48	32.47	22.28	32.40	20.22	32.50	85.48	99.92	96.23	99.91
AV	**25.70**	**41.74**	**25.75**	**41.76**	**26.88**	**41.72**	**25.79**	**41.71**	**95.13**	**99.83**	**97.74**	**99.80**

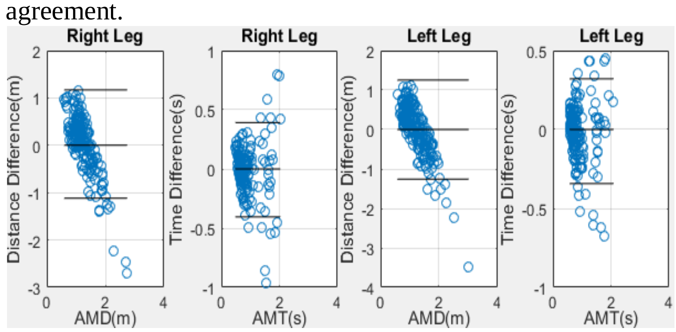
The accuracy of walking time shows good in comparison with the distance as it is recorded directly from the signal. Distance and speed are obtained from accelerometer. Therefore, the distance and speed accuracy show lower comparing with the accuracy of time. The relative accuracy of IMUs is ranged between 85.48% - 99.96% for travelled distance and 99.49%-99.97% for time. It shows that 85.48% is the lowest accuracy in distance travelled from the right leg of subject 8. The speed of 0.6 ms^{-1} is very low in comparison with normal human walking and hence, subjects adjust their gait due to the speed. However, the accuracy of different speeds shows high. A paired *t*–test is performed between the IMU estimated distance (μ = 26.33, σ = 10.19) and the MoCap distance (μ = 25.72, σ = 9.57) where the correlation r = 0.993 and p=0.76. These results indicate no significant difference in the measurements.

Table V shows the agreement levels using ICC(2,1), LCC and r between IMU and MoCap. The results show high (from 0.71 to 1) agreement for distance and time extracted from IMU and MoCap at different speeds for both legs of all subjects. The mean, SD and 95% CI are provided in the supporting document.

TABLE II
Validity of the IMU Gait Features Against MoCap with Treadmill

Subjects	Experiment 1: Treadmill with different speed											
	Interclass correlations				Lin's correlation coefficients				Pearson's correlation coefficients			
	Right Leg		Left Leg		Right Leg		Left Leg		Right Leg		Left Leg	
	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)
	ICC	ICC	ICC	ICC	LCC	LCC	LCC	LCC	r	r	r	r
1	0.88	0.97	0.88	0.97	0.79	0.94	0.78	0.93	0.81	0.94	0.81	0.93
2	0.99	1.00	0.99	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00
3	0.98	1.00	0.98	0.99	0.96	1.00	0.96	0.99	0.96	1.00	0.96	0.99
4	0.93	1.00	0.96	1.00	0.83	1.00	0.91	1.00	0.88	1.00	0.93	1.00
5	1.00	1.00	1.00	1.00	0.99	1.00	0.99	1.00	0.99	1.00	0.99	1.00
6	0.99	1.00	0.99	1.00	0.97	1.00	0.98	1.00	0.98	1.00	0.99	1.00
7	0.94	1.00	0.97	1.00	0.89	1.00	0.93	1.00	0.89	1.00	0.94	1.00
8	0.97	1.00	0.99	1.00	0.94	1.00	0.97	1.00	0.94	1.00	0.98	1.00

The B&A plots are generated for subject 1 shown in Fig. 8. The B&A plots for all subjects are provided in the supporting document. Figure 8 demonstrates the validity of the extracted gait features measured with the IMU compared to the MoCap using a treadmill at a speed of 0.6 ms^{-1}. The x is the average of the 2 measurements and the y is the difference between the two systems. The middle line passing through the zero axis represents the difference on average for the total sample. Upper and lower lines represent the 95% limits of agreement. Figure 8 shows that the difference of the two estimations is zero and the most of the differences lie in between the 95% limits of agreement.



AD=Average Distance(m), AT=Average Time(s)
FIGURE 8. B&A plots for validity of distance & time measured for right & left legs with IMU & MoCap with treadmill=0.6 ms^{-1} from subject 1.

B. Experiment 2: Results

The accuracy between the IMU and the MoCap extracted gait features is presented in Table III. In experiment 2, the average accuracy of the distance travelled is 97.99% (95% CI ±1.41), the average accuracy of time shows 99.01% (95% CI ±0.26), the average accuracy of speed 97.39% (95% CI ±1.44). The estimated speed on average is 1.53 ms^{-1} and this agrees with expected human walking speed averaging 1.5-2.5 ms^{-1} [33]. There is no significant difference between IMU estimated distance (μ=7.49, σ=0.39) and MoCap distance (μ=7.67, σ=0.26); *t*-test p=0.94 there is a strong correlation between the two; Pearson correlation coefficient (r=0.81).

Table IV shows ICC(2,1), LCC and Pearson's correlations (r). Table V shows IMU gait extracted features information on average for both legs conducted in experiment 2 for 20 young subjects. Stride and step numbers achieve 100% accuracy. The stride length for both legs are identical and the leg difference is low. In the normal gait cycle the stance phase lasts 60% and the swing phase 40% of the cycle [14]. Table V shows that the closest 60:40 split is found for average stride, stance and swing.

TABLE III
IMU GAIT EXTRACTED FEATURES ACCURACY WITH MOCAP (D=DISTANCE, T=TIME)

Subjects	Experiment 2: Self-selected (free) walking											
	MoCap				IMU				Accuracy (%)			
	Right Leg		Left Leg		Right Leg		Left Leg		Right Leg		Left Leg	
	D	T	D	T	D	T	D	T	D	T	D	T
1	7.51	7.94	7.62	7.87	7.49	7.96	7.61	7.80	99.70	99.75	99.87	99.11
2	7.77	7.94	7.76	7.87	7.74	7.91	7.63	8.00	99.68	99.62	98.33	98.35
3	7.42	7.38	7.14	7.03	6.94	7.31	6.67	7.14	93.50	99.05	93.34	98.44
4	7.69	7.38	7.63	7.03	6.78	7.25	7.20	7.13	88.18	98.24	94.38	98.58
5	7.56	9.78	7.48	9.72	7.49	9.71	7.52	9.83	99.07	99.28	99.51	98.87
6	7.74	9.78	7.84	9.72	7.70	9.75	7.79	9.64	99.53	99.69	99.35	99.18
7	7.98	8.72	8.12	8.28	7.81	8.88	8.06	8.18	97.85	98.17	99.26	98.79
8	8.18	8.72	7.98	8.28	8.13	8.74	7.75	8.15	99.33	99.77	97.03	98.43
9	7.40	12.67	7.46	12.33	7.16	12.83	7.33	12.28	96.66	98.74	98.27	99.59
10	7.65	12.67	7.52	12.33	7.61	12.51	7.46	12.33	99.44	98.74	99.16	100.0
11	7.58	7.65	7.41	7.52	7.81	7.85	7.86	7.83	97.00	97.45	94.28	96.01
12	7.49	7.40	7.40	7.46	7.49	7.53	7.58	7.85	99.92	98.27	97.57	95.03
13	8.11	8.18	7.90	7.98	8.28	8.58	7.95	8.02	97.96	95.34	99.30	99.49
14	8.04	7.98	8.00	8.12	8.12	8.20	8.39	8.58	99.00	97.37	95.35	94.59
15	7.71	7.74	7.75	7.84	8.10	8.20	7.94	8.23	95.10	94.44	97.54	95.29
16	7.49	7.56	7.56	7.48	7.64	7.65	7.68	7.72	97.96	98.81	98.42	96.85
17	6.47	6.69	6.73	6.63	6.74	6.82	6.93	6.85	96.07	98.07	97.08	96.82
18	6.22	6.42	6.19	6.14	6.30	6.49	6.24	6.36	98.69	98.88	99.23	96.49
19	7.74	7.77	7.55	7.76	8.04	7.84	7.62	7.91	96.26	99.13	99.13	98.06
20	7.48	7.51	7.59	7.62	7.62	7.94	8.06	7.87	98.27	94.53	94.15	96.77
AV	**7.56**	**8.39**	**7.53**	**8.25**	**7.55**	**8.50**	**7.56**	**8.39**	**97.46**	**98.17**	**97.53**	**97.74**

TABLE IV
VALIDITY OF THE IMU GAIT FEATURES AGAINST MOCAP (D=DISTANCE, T=TIME, R (PEARSON'S CORRELATION COEFFICIENT))

Subjects	Experiment 2: Self-selected (free) walking											
	Interclass correlations				Lin's correlation coefficients				Pearson's correlation coefficients			
	Right Leg		Left Leg		Right Leg		Left Leg		Right Leg		Left Leg	
	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)	D(m)	T(s)
	ICC	ICC	ICC	ICC	LCC	LCC	LCC	LCC	r	r	r	r
1	0.98	1.00	0.80	0.99	0.96	1.00	0.67	0.99	0.96	1.00	0.71	0.99
2	0.99	1.00	0.99	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00
3	0.98	1.00	0.80	0.99	0.96	1.00	0.67	0.99	0.96	1.00	0.71	0.99
4	0.97	1.00	0.99	1.00	0.94	1.00	0.97	1.00	0.94	1.00	0.98	1.00
5	0.94	1.00	0.98	1.00	0.89	1.00	0.96	1.00	0.89	1.00	0.96	1.00
6	0.99	1.00	0.99	1.00	0.97	1.00	0.98	1.00	0.98	1.00	0.99	1.00
7	0.94	1.00	0.98	1.00	0.89	1.00	0.96	1.00	0.89	1.00	0.96	1.00
8	0.97	1.00	0.99	1.00	0.94	1.00	0.97	1.00	0.94	1.00	0.98	1.00
9	0.99	0.94	0.73	0.97	0.98	0.89	0.88	0.94	0.98	0.89	0.84	0.94
10	0.99	1.00	0.99	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00
11	0.99	0.94	0.73	0.97	0.98	0.89	0.58	0.94	0.98	0.89	0.64	0.94
12	0.99	1.00	0.99	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00
13	0.98	1.00	0.80	0.99	0.96	1.00	0.67	0.99	0.96	1.00	0.71	0.99
14	0.91	1.00	0.84	1.00	0.93	1.00	0.68	1.00	0.97	1.00	0.74	1.00
15	1.00	1.00	1.00	1.00	0.99	1.00	0.99	1.00	0.99	1.00	0.99	1.00
16	0.99	1.00	0.99	1.00	0.97	1.00	0.98	1.00	0.98	1.00	0.99	1.00
17	0.94	1.00	0.98	1.00	0.89	1.00	0.96	1.00	0.89	1.00	0.96	1.00
18	0.97	1.00	0.99	1.00	0.94	1.00	0.97	1.00	0.94	1.00	0.98	1.00
19	0.93	1.00	0.96	1.00	0.99	1.00	0.99	1.00	0.96	1.00	0.96	0.99
20	0.95	1.00	0.97	1.00	0.97	1.00	0.98	1.00	0.91	1.00	0.93	1.00

TABLE V
GAIT FEATURES INFORMATION FROM YOUNG SUBJECTS (* ACTUAL VALUE = RECORDED USING DIGITAL TAPE, ** ESTIMATED VALUE = USING IMU GAIT EXTRACTED FEATURES MEASUREMENTS)

	Right Leg					Left Leg				
Gait Features	**Mean**	**Std**	**Var**	**Min**	**Max**	**Mean**	**Std**	**Var**	**Min**	**Max**
Stride Length (m)	1.08	0.11	0.01	0.59	1.06	1.08	0.11	0.01	0.58	1.05
Stride Time (s)	1.43	0.20	0.04	1.11	1.98	1.41	0.19	0.04	1.07	1.92
Stride Velocity (m/s)	0.76	0.63	0.63			0.77	0.64	0.64		
Cadence (step/min)	34.64					34.64				
Step Velocity (m/s)	0.83	0.74	0.67			0.84	0.75	0.69		
Step Length (m)	0.56	0.10	0.01	0.11	0.64	0.55	0.13	0.02	0.12	0.62
Step Time (s)	0.69	0.19	0.04	0.21	1.17	0.72	0.24	0.07	0.32	1.25
Stance Time (s)	0.71	0.16	0.03			0.70	0.17	0.02		
Swing Length (m)	1.09	0.51	0.31			1.10	0.68	0.39		
Swing Time (s)	0.71	0.12	0.02			0.69	0.19	0.02		
Swing Velocity (m/s)	1.54	1.35	1.35			1.58	1.36	1.83		

C. *Comparison with other methods*

The results using the proposed algorithm can be compared with the previous methods. A wide range of algorithms are reported using peak threshold, window size and/or zero-crossing [34-37] techniques to detect gait events from accelerometer or gyroscope signals due to their simplicity and low computational demands. These approaches are amongst the most popular and are usually extended with special enhancements in order to improve robustness. One disadvantage of these algorithms is that any motion with a similar periodicity of walking will trigger for a false stride event. Researchers [34-39] use a particular threshold value to detect a peak of acceleration corresponding to the marker 7 (See Fig. 2(a)). The peak of this acceleration can vary due to various factors such as intrinsic factors including age, muscle weakness, walking style or left to right differences; extrinsic factors such as shoes or walking surface [40]. In addition, the gait cycle is characterized by more than one peak of varying acceleration. If the sensing threshold of the IMU is set too low, it will detect all these peaks as strides. To illustrate this, using the peak threshold method [37], healthy subject 4 shows the detection rate of 109.4% and 271.2% in the gait abnormality group. The fact that the detection rate is more than 100% indicates multiple detection of the same event. Another important point is that when a subject walks with a different speed, there is poor acceleration and it is crucial to detect the gait cycle. For this reason first strike is not considered for gait analysis [41]. A window based threshold calculation [42] is used to obtain an acceptable level of accuracy. If the window size is not appropriate, step detection accuracy will degrade because the threshold calculated from a larger window may not be able to effectively handle the variation [43].

Our study shows that the gait events detection based on prominence characteristics has a higher accuracy. Our proposed stride and step detection technique achieves 100% accuracy compared to an accuracy ranging from 109.4% to 271.2% [37]. There are machine learning [44] and pattern recognition approaches [45] that require more data and we will explore in the future.

IV. DISCUSSION

The results of two experiments demonstrate that our hybrid adaptive gait phase detection method (Section II.C.3) can detect the various phases of a gait cycle. The process diagram of the automatic parallel features extraction from both IMUs and MoCap through Treadmill is shown in Fig. 7. The accuracy of the extracted gait features from IMUs are very high compared to MoCap, as a 'gold standard'. Three separate (Interclass, Lin's and Pearsons) analysis demonstrate high correlations between the features extracted from IMUs compared to MoCap. In addition to that, B&A plots show that the difference between the two measurements of features extracted is negligible and most of the differences lies in between the 95% limits of agreement. A dedicated mobile phone application is used for collecting accelerometer and gyroscope synchronous data from IMUs and the raw data are shown in Fig. 1(c) and 1(d) improving the usability in real-time. Our method provides a comprehensive spatiotemporal gait information.

In Experiment 1, different speeds are set using a treadmill that allow each subject to walk in different pace. On a treadmill gait there is less variability than over ground [46]. This allows us to correct for instrumentation error from measurement error arising from the natural biological variation in walking patterns. There is very good correlation between MoCap and our IMU based system for all parameters. The contribution for intra-individual variability performance is minimized as each subject walked in different speeds. The gait features extracted from IMU and MoCap indicate that the error in the instrumentation is acceptable for most of the gait variables. The accuracy of our system is comparable with that of MoCap.

In evaluating correlations, ICCs are often believed to be more reliable than Person's r and Spearman's rho test. Results need to be carefully interpreted as an elevated ICC does not necessarily imply excellent reliability, especially in circumstances where there is a wide variety of readings within the same subject. To tackle this, an absolute measure of reliability such as the coefficient variation or agreement limitations [47] is often used. The coefficient of variation is not influenced by the existence of a heterogeneous sample so that if the coefficient of variation is big, a test having an elevated ICC may not be accurate. The determination of appropriate limitations of the coefficient of variation is determined based on the level of agreement that the investigator aims to accomplish when comparing group or intervention results. Measurements using LCCs needs less assumptions than using ICC and subtle distinctions are identified between our measured variables and reference criteria. We also use the correlation coefficients (r) of Pearson to assess the power of the linear connection between the measurements of IMU and MoCap. Such correlations do not show complete agreement but merely indicate whether measurements can be corrected with recalibration and are therefore bad validity markers [31]. For IMU gait extracted and MoCap measurements, B&A plots are produced to visually show any systematic errors in our IMU measurements. Our results show that the average reading for features extracted from both legs is 0 indicating that there is no bias in extracting results using the two methods.

This study however has a number of limitations. A total of 28 young subjects are recruited for this study where they have no gait abnormality. The calibration of the IMU is an essential part for extracting gait features. Gait varies from person to person and any algorithm should calibrate for such variability. We factor in such calibration but individual characteristics such as heel strikes or up and down body movements while walking can also influence the results. IMU use may also lead to errors of drift, stability and repeatability. Although the accuracy of IMUs is improved such measurement errors are unavoidable with current technology especially when using micro-electro-mechanical (MEMS) sensors. We take measures to reduce errors as much as possible by fitting sensors tightly. We detect the zero-velocity in the non-stationary period of stance phase to reduce the integration drift. The IMU used has the intelligence to calibrate itself. However, our study can be considered a proof of concept that validates the proposed method for extracting automatic gait features. In the future accuracy can be improved by focusing on MEMS sensor error modelling and accommodation [48]. Other probable area of error can arise from friction from the relative movement of the sensors against clothing or footwear. However, in our experiment we compare our results to what is currently considered as “gold standard” MoCap and Treadmill which show high accuracy making the effect of those errors acceptable.

Coincidentally a gender bias is present with most subjects being male. The study’s aim is to validate gait features collected from IMU against MoCap and not to study the differences in gait between the genders. This bias is therefore unlikely to impact the value of our results and what we are trying to achieve. Our subjects are also of healthy young age. Our study aims at determining whether our method is effective at slow-high gait speeds. Having older adults is not required for this purpose as the treadmill speed could be adjusted. In future research we aim to study the effects of age on such correlations and will recruit older patients with different gait patterns.

V. Conclusion and Future Work

For the validation of our proposed system we conduct two experiments. The important findings in these experiments confirm that the proposed hybrid method provides acceptable results comparing with the ‘gold standard’ MoCap system. It is also found that gait extracted features from IMU are highly valid for spatiotemporal gait variables. The estimated ICC, LCC and r values from the IMU system compare well to the MoCap and treadmill measurements. These finding have significant implications in developing technologies to use IMUs for the evaluation of gait. This has significant potential to broaden the availability of gait assessment in clinical practice. This study develops novel opportunities for use based on currently available technology. This relates to the current state of the art by opening up new possibilities to assess gait out of hospitals and gait laboratories into out-patients’ areas, homes and sporting environments. Using it over a period of time can be beneficial for the follow-up of patients undergoing treatments to monitor progress. We have shown that our system can work in slow walking speeds as well as faster ones. This also opens up possibilities for use in elderly patients where such an automatic system needs to have sufficient sensitivity to detect gait features at low speeds. In future work we plan to explore the possible use of our technology to identify abnormal gait patterns in elderly patients with a view of facilitating diagnosis and monitoring treatment and rehabilitation.

Ethical approval

Bournemouth University ethical review committee granted Ethical approval for this research. Participant Information Sheet and a Participant Agreement Form were given to subject participated in the study.

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Conflicts of Interest

The authors declare no conflict of interest.

VI. References

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