

Automatic Detection of Different Walking Conditions Using Inertial Sensor Data

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Abstract—Identifying different walking conditions is essential in order to monitor the activities of elderly population for active living or fast recovery of a patient following a surgery or even for prognosis and diagnosis of several conditions like Parkinson's disease. This paper looks at automatically detecting three different walking conditions (walking normally with preferred walking speed (PWS), walking while carrying a glass of water, and walking blind folded) using inertial sensor data. Tri-axial accelerometers and gyroscopes were used to acquire movement data from both feet during the three gait tasks. Five healthy young subjects undertook 10 trials per condition on a GAITRite mat. Statistical properties such as the mean, standard deviation (std), skewness (skew) and kurtosis were calculated for each trial that included several gait cycles' data. Altogether 48 features were analyzed using Fuzzy Clustering Mean (FCM) algorithm to verify the separable nature of sensor data. The results show that three clusters could be found with an almost equal number of points; however the membership was not high enough to result in complete discrete clusters. Then three different Support Vector Machine (SVM) classifiers were used to examine whether the conditions could be automatically classified based on the features that were extracted from inertial sensor data. The results indicate 83-84% of accurate classification of the three gait conditions with three SVM algorithms. The study demonstrates that the inertial sensor data could be used to classify differences in walking conditions using powerful computational intelligence techniques.

I. INTRODUCTION

As one of the most common and complex daily activities, gait attracts increasing number of researchers' interests. The performance of gait is generally assessed with four aspects: the

capability of keeping upright posture; the stability of balance during the stance phase; the floor clearance with the swing foot during the swing phase; and efficient energy use [1]. The gait features are considerably variable depending on different walking conditions in terms of energy expenditure [2] and physiological requirements [3]. Continuous monitoring of the spatiotemporal parameters of the gait, could be helpful for diagnosis and prognosis of Parkinson's disease (PD) [4], [5], diabetes [6], or posture [7] and early detection of the risk of falls in elderly population which becomes a potential killer [8].

Inertial measurement units (IMUs) are widely used for continuous monitoring of gait, as they are cheap, compact and light weight. A range of artificial intelligence techniques such as Bayesian decision making, rule-based algorithm and neural networks have been applied for the detection of the kinematic characteristics using IMU data. Several studies have been proposed for classifications and monitoring of different gait patterns. Herren et al. [9] used three accelerometers attached above the subjects ankle and deployed neural networks to define the velocity and slope of running movements. Chen et al. [8] mounted one accelerometer and two gyroscopes on the surface of a shoe to classify different conditions such as flat walking, descending stairs and ascending stair, with fuzzy logic based classifier and discrete wavelet transform. Nyan et al. [10] classified gait patterns in time-frequency domain for different walking conditions that involved walking on flat lever and descending and ascending stairs with two (vertical and anteroposterior) accelerometers attached to the shoulder region.

Given that most elderly people suffer from balance issues and visual impairments, in this study three different walking tasks were analysed normal walking with the subjects preferred speed (NW); walking while carrying a glass of water (WG) and walking blind folded (BF). The tasks were designed to challenge the balance and visual perception of healthy subjects to investigate variability in their gait patterns. The use of sensors means the detection can be in real time and is portable. The classifier models were used to determine if changes in these gait patterns could be detected autonomously - hypothesis is the elderly people would have similar gait

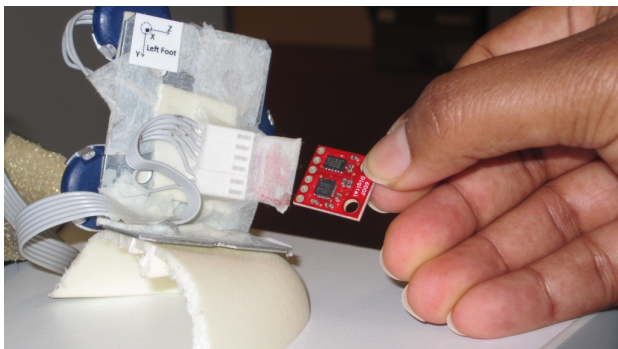


Fig. 1. Measuring unit consist of triaxial accelerometer and gyroscope

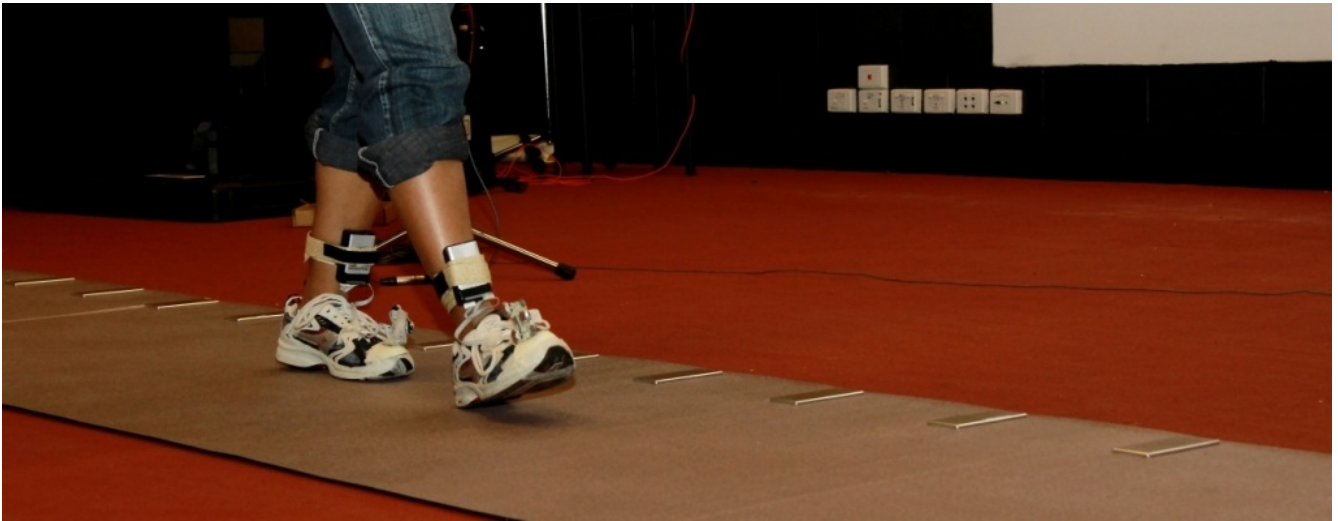


Fig. 2. A subject performing walking on the GAITRite mat with measuring units attached to both the feet

patterns due to problems in balance/vision which would then be detected with the models built.

This paper is organized as follows: Section 2 introduces the instrument and outlines the experimental protocol. Section 3 explains the data processing techniques such as feature extraction, fuzzy clustering and SVM classification. Section 4 presents the experimental results followed by the discussion and conclusion in section 5. The final section recommends future works of this study.

II. METHODOLOGY

A. Wireless Foot Sensor Unit

Two wireless foot sensor units were developed for this experiment. Each unit was equipped with a Sparkfun IMU digital combo board with 6 degrees of freedom (DOF) consisting of an accelerometer - ADXL345 and a gyroscope- ITG3200 used to measure the distal foot accelerations and rotations (Fig. 1). The ultra low-powered tri-axis accelerometer is capable of measuring $\pm 16g$ in full-scale with a sensitivity of 31.2 LSB/g and possesses maximum of 3200 Hz bandwidth. The ITG3200 16 bit digital gyroscope has sensitivity of 14.375 LSBs per $^{\circ}/\text{sec}$ and a full-scale range of $\pm 2000^{\circ}/\text{sec}$. The sensing unit was powered with a Sony Ericsson BST-41 Li-Polymer rechargeable Battery. It has an energy capacity of 1500 mAh and could run the unit at 100 Hz sampling frequency for approximately 11 hours before recharge was required. The embedded onboard system was implemented by a Freescale Semiconductor MCU (8-bit MC9S08SH8) and Bluetooth 2.0/EDR communications were used to (Sena ESD200/210) transfer the sensor data to computer. A MATLAB GUI was written to communicate with the sensor units.

B. Data Collection

A group of 5 healthy young subjects consisting of 4 males and 1 female with no known gait disorders were recruited for this study. All gait data collection was carried out within the

TABLE I
AGE, HEIGHT, WEIGHT AND GENDER INFORMATION OF THE SUBJECTS INCLUDED IN THE STUDY

Subject ID	Age	Height (m)	Mass (kg)	Gender
A	24	1.77	79.2	M
B	29	1.77	64.1	M
C	25	1.67	53.2	F
D	27	1.52	76.1	M
E	28	1.65	65.3	M

Biomechanics Laboratory of Victoria University, Melbourne, Australia. At the start of the experiment subjects age, height, mass, gender, right and left limb length and foot size were noted (Table I).

The inertial sensors were attached to the end of the distal foot of both right and left leg (Fig. 2). The transmission units were secured around the shanks using Velcro (neoprene) tapes.

After attaching the sensors, each subject was requested to stand static for 10 s to collect initial, static position of the sensors. The main experiment involved walking on a GAITRite mat with 3 different walking conditions. The 1st condition is walking normally with preferred walking speed (PWS) of the subject. The 2nd condition is walking with a glass of water, without spilling the water on the same surface. The final condition walking on the mat blind folded. Subjects were given directions if he/she tends to go out of the mat when he/she was blind folded. Each condition had 10 trials and each trial for had about 5-11 gait cycles per limb. To reduce the possibility of subject getting used to one particular condition and learning it well, only 5 trials were done consequently for a condition and then the conditions were altered randomly. Timing gate was placed at the start and the end of the GAITRite mat to measure the time taken to walk 7m on the mat. The pressure and temporal measurements were captured using the GAITRite software. The measurements from IMU sensors were collected and stored using a MatLab script.

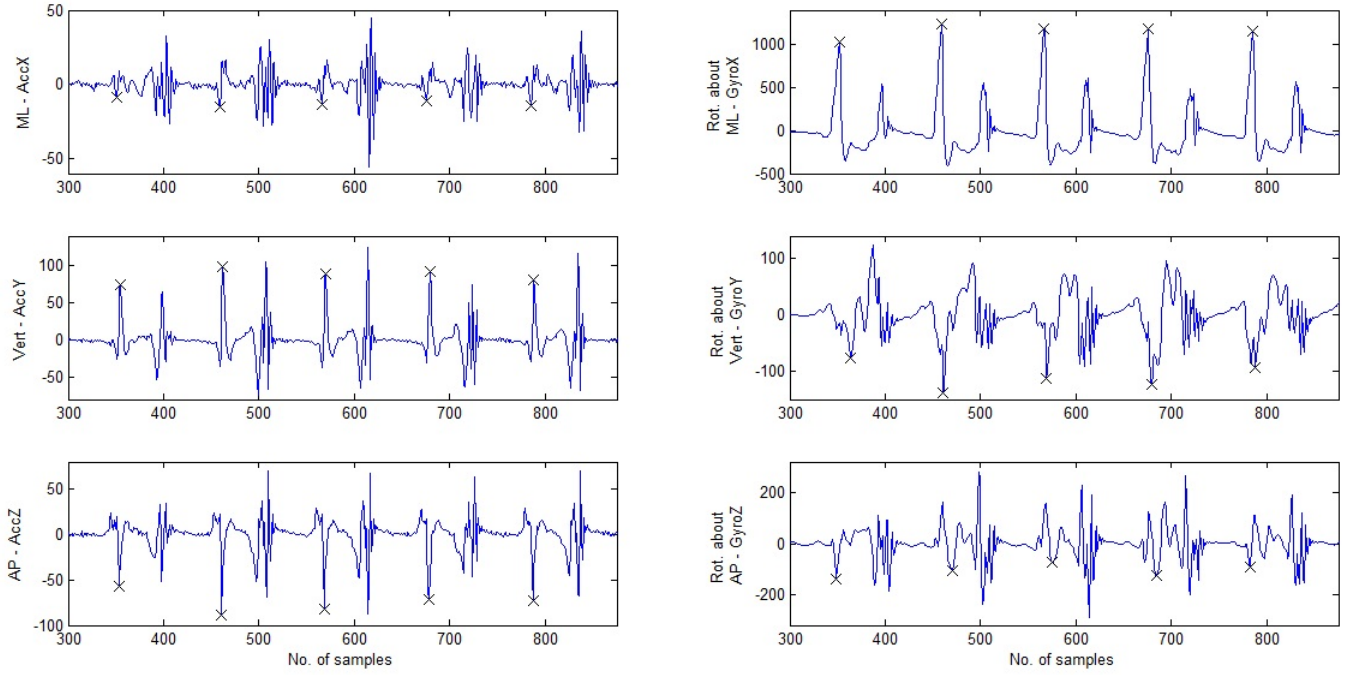


Fig. 3. Peak feature extractions from IMU sensor data. the left column shows the IMU sensor output of the accelerometer AccX, AccY and AccZ, which denotes the foots acceleration respectively in medio-lateral axis, vertical axis and the anterior-posterior axis for a single trial consists of multiple gait cycles. The right column shows the rotations of the foot about respectively the medio-lateral axis, vertical axis and the anterior-posterior axis. Accelerations are given in m/s^2 and rotations are given in $^\circ/\text{s}$

III. DATA PROCESSING

The data collected from IMU were processed in Matlab v7.2, (Mathworks, USA). The sensor outputs were first converted to acceleration and angular velocities from voltage readings using their respective sensitivities. Inertial sensor signals were band-pass filtered twice with a lower cut-off frequency of 1Hz and a higher cut-off frequency of 35Hz to remove electrical noise and bias drifts. Butterworth filters of order 10 were used to guarantee designed filter stability. The signals were filtered in the forward and backward direction to minimize phase shift effects using the *filtfilt* function in MatLab

A. Gait event detection

Gait event detection i.e., identifying gait cycles using the inertial sensor data was done by using the maximum toe angular velocity in the sagittal plane, i.e., rotation about the medio-lateral axis (GyroX), following the method proposed by Sabatini et al [11].

B. Features Extraction

After gait event detection, the prominent acceleration and rotation values near the toe-off point were extracted using maximum/ minimum point around the toe-off point. In Fig. 3 the left column shows the IMU sensor output of the accelerometer AccX, AccY and AccZ, which denote the foots acceleration respectively in medio-lateral axis, vertical axis and the anterior-posterior axis for a single trial consists of multiple gait cycles. The right column shows the rotations of

the foot about respectively the medio-lateral axis, vertical axis and the anterior-posterior axis. For each trial the statistical properties such as mean, standard deviation (std), skewness (skew) and kurtosis of the above mentioned IMU sensor points were calculated across multiple gait cycles for both right and left limbs. This implies 3 conditions x 10 trials x 6 features x 4 statistical properties x 2 sides x 5 subjects = 7200 datapoints.

C. Features Analysis

To understand how the features differ according to different walking conditions across the subjects, mean vs std graphs across all subjects for all 150 trials were plotted for each feature. It was hard to draw any conclusion by visually inspecting the graphs (Fig. 4), hence we used an unsupervised clustering method to cluster three walking conditions trials.

Fuzzy C-Means Clustering(FCM): Unsupervised clustering method FCM was used to verify the separability of the three walking conditions using the extracted features from IMU sensor data. This method automatically groups data into separate clusters based on a distance measure e.g. Euclidean. In this case, we are looking for 3 clusters. The FCM method [12] is based on solving the following objective function

$$J_m = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m \|x_i - c_j\|^2, 1 \leq m \leq \infty \quad (1)$$

where m is any real number greater than 1, u_{ij} is the membership of x_i in the cluster j , x_i is the i^{th} of d-

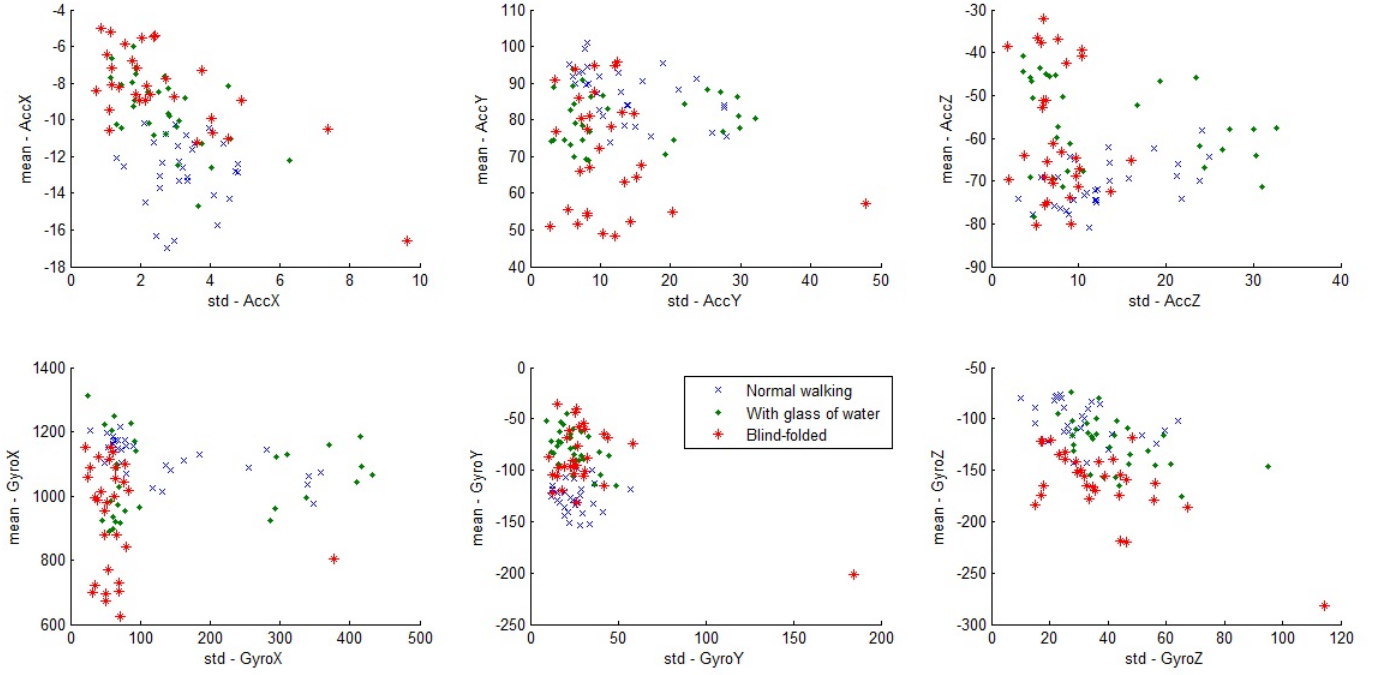


Fig. 4. Mean vs std of features AccX, AccY, AccZ, GyroX, GyroY and GyroZ graphs across all subjects for all 150 trials. x denotes normal walking, . denotes walking with a glass of water and * denotes walking blind-folded.

dimensional measured data, c_j is the d -dimension center of the cluster, and $\| * \|$ is any norm expressing the similarity between the feature vector and the class center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$U_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - c_i\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}, c_j = \frac{\sum_{i=1}^N u_{ij}^m x_i}{\sum_{i=1}^N u_{ij}^m} \quad (2)$$

The algorithm stops when $\max_{ij} \{|u_{ij}^{k+1} - u_{ij}^k|\} < \varepsilon$, where ε is a predefined termination criterion between 0 and 1, and k are the iteration steps. This procedure converges to a local minimum or a saddle point of the fuzzy objective function J_m . In this paper, we use the fuzzy clustering algorithm in Matlab v7.9, and used the Euclidean norm as the distance measure. The parameter m was varied from 2 to 5. We report the partitioning results against threshold membership grades and the percentage of points within each cluster (Table II).

D. Walking Conditions Classification

After verifying that the IMU sensors features could be used to identify 3 different walking conditions, supervised classification methods were used to automatically detect the walking conditions using IMU sensor features. Leave-one-out (LOO) trial method was followed to verify each condition.

Multiclass Support Vector Machines: Support vector machines (SVMs) [13]–[15] are binary classifiers based on Vap-

nik's structural risk minimization theories [14] which achieves a trade-off between empirical risk (training set error) minimisation (ERM) and regularisation to avoid the problem of overfitting. Moreover, by using the kernel trick the SVM is able to overcome the so-called curse of dimensionality [16]–[19].

The SVM approximates the relation between input parameters $\mathbf{x} \in \mathbb{R}^{d_L}$ and class labels y using a function of the form:

$$g(\mathbf{x}) = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b$$

where $\boldsymbol{\varphi} : \mathbb{R}^{d_L} \rightarrow \mathbb{R}^{d_H}$ is the feature map into a d_H -dimensional *feature space* given a-priori, $\mathbf{w} \in \mathbb{R}^{d_H}$ the weight vector and $b \in \mathbb{R}$ the bias. Given a training set of N pairs (\mathbf{x}_i, y_i) the weight vector \mathbf{w} and bias b are chosen to solve the primal training problem:

$$\begin{aligned} \min_{\mathbf{w}, b} R(\mathbf{w}, b) &= \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{C}{N} \sum_{i \in \mathbb{Z}_N} \xi_i \\ \text{such that: } &\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_i) + b \leq y_i + \xi_i \quad \forall i \in \mathbb{Z}_N \\ &\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_i) + b \geq y_i - \xi_i \quad \forall i \in \mathbb{Z}_N \\ &\xi_i \geq 0 \quad \forall i \in \mathbb{Z}_N \end{aligned} \quad (3)$$

The first term in the cost R is a regularisation term included to minimise overfitting, while the second term is a measure of empirical risk (i.e. training set error). The parameter $C \in \mathbb{R}^+$ controls the trade-off between risk minimisation and regularisation.

In practice, rather than solving the primal (3) directly the

TABLE II
CORRECT PARTITIONING RESULTS AGAINST THRESHOLD MEMBERSHIP GRADES AND THE PERCENTAGE OF POINTS WITHIN EACH CLUSTERS

Membership Threshold	0.50	0.60	0.70	0.80	0.90	0.95	0.99
% pts at correct clustering	0.980	0.833	0.807	0.760	0.800	0.753	0.440
% pts in Cluster 1	0.373	0.373	0.380	0.300	0.093	0.093	0.093
% pts in Cluster 2	0.313	0.313	0.393	0.507	0.720	0.720	0.720
% pts in Cluster 3	0.313	0.313	0.227	0.193	0.187	0.187	0.187

dual form of (3) is solved [15], namely:

$$\begin{aligned} \min_{\alpha} Q(\mathbf{w}, b) &= \frac{1}{2} \sum_{i,j \in \mathbb{Z}_N} K_{ij} \alpha_i \alpha_j - \sum_{i \in \mathbb{Z}_N} \alpha_i \\ \text{such that: } & -\frac{C}{N} \leq \alpha_i \leq \frac{C}{N} \quad \forall i \in \mathbb{Z}_N \\ & \sum_{i \in \mathbb{Z}_N} \alpha_i y_i = 0 \end{aligned} \quad (4)$$

where $K_{ij} = K(\mathbf{x}_i, \mathbf{x}_j)$ and $K(\mathbf{x}, \mathbf{y}) = \boldsymbol{\varphi}^T(\mathbf{x}) \boldsymbol{\varphi}(\mathbf{y})$ is the kernel function.

The trained machine may be written in terms of the dual variables as:

$$g(\mathbf{x}) = \text{sgn}\left(\sum_{i \in \mathbb{Z}_N} \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b\right)$$

Note that any function $K : \mathbb{R}^{d_L} \times \mathbb{R}^{d_L} \rightarrow \mathbb{R}$ satisfying Mercer's condition [20], [21] may be used directly in the above working without explicit knowledge of the feature map $\boldsymbol{\varphi} : \mathbb{R}^{d_L} \rightarrow \mathbb{R}^{d_H}$ encompassed therein, allowing $d_H \gg d_L$ without added complexity.

In the present paper we consider the 1vs1, 1vsAll and directed acyclic graphs (DAG) multiclass methods [22], with the following kernels [16], [19]:

- 1) Linear kernel: $K(\mathbf{x}, \mathbf{y}) = \mathbf{x}^T \mathbf{y}$.
- 2) Polynomial kernel: $K(\mathbf{x}, \mathbf{y}) = (1 + \mathbf{x}^T \mathbf{y})^d$ (where $d \in \mathbb{Z}^+$).
- 3) RBF kernel: $K(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{1}{\sigma} \|\mathbf{x} - \mathbf{y}\|^2\right)$ (where $\sigma \in \mathbb{R}^+$).

SVMHeavy¹ was used for all SVM experiments. Processor Intel Core 2 Duo: E4600 at 2.4GHz with 4GB was used for processing. C ranged over 1e-3, 3e-3, 1e-2, ..., 100, 300. Kernels were linear, polynomial (order 2,3,4) and gaussian RBF ($g = 1e-3, 3e-3, 1e-2, \dots, 100, 300$). All data was normalised to zero mean, unit variance for each feature before testing.

IV. RESULTS

A. Unsupervised Clustering Results

It was found that $m = 2$ yielded the best clustering results for this dataset. Higher values of m , were found to yield clusters with points that had low membership grades i.e. $u < 0.5$. Given that the number of points or examples for each walking condition were equal i.e. 50 each for normal walking, walking with a glass of water and blindfold walking, we investigate clustering solutions that give clusters with almost balanced number of points. This would determine if the three walking conditions are separable as represented by the inertial sensor features.

The results in Table II show that three clusters could be found with an almost equal number of points, however the points had low membership grades of 0.5 and 0.6. Partitions with points that had memberships higher than 0.8 showed unbalanced number of points in the clusters. For example, for the clustering result that achieved 80% of points with memberships larger than 0.9, the clustering was heavily biased to cluster 2, while clusters 1 (9.3% of total points) and cluster 3 (18.7%) were sparsely populated.

B. Supervised Classification Results

Table III shows the best leave-one-out (LOO) results of the 1vsAll, 1vs1 and DAGSVM algorithms. All three methodologies showed almost identical classification power, i.e. accuracy of 83-84%. Tables IV - VI depicts the confusion matrices of the different classifiers. In 1vsAll method, for the best LOO with $C=3$ and $g=10$, out of 50 normal walking trials, 41 trials were labeled correctly, whereas 3 trials were mislabeled as walking with glass of water and 6 as walking blindfolded. Similar observations could be found for other walking conditions with other classifiers.

V. DISCUSSION AND CONCLUSION

This study reports a novel experimental protocol which included assessment of walking function using GAITRite mat and computational intelligence techniques. The three walking tasks included walking with subjects' preferred walking speed, with a glass of water (a challenging gait task that would interfere with the walking balance) and blind folded (where the sensory visual feedback would be missing). These different activities were detected using advanced classifying techniques, as the differences in walking conditions would require varying level of effort, attention, and feedback from the environment, which would consequently affect the lower limb foot movement kinematics. The hypothesis was the elderly people would have similar gait patterns due to problems in balance/vision which would then be detected with the models built.

Firstly an unsupervised clustering algorithm, FMC as an exploratory method to analyse the features that we extracted from IMU sensors for different walking conditions was reported.

TABLE IV
CONFUSION MATRIX OF 1VSA CLASSIFIER FOR THE BEST RESULTS FOR DIFFERENT WALKING CONDITIONS (WC)

WC	NW	WG	BF
NW	41	3	6
WG	2	42	6
BF	2	6	42

¹ Available at <http://people.eng.unimelb.edu.au/shiltona/svm/index.html>

TABLE III

CLASSIFICATION ACCURACY RESULTS, OPTIMAL C VALUE, OPTIMAL G PARAMETER (GAUSSIAN RBF PARAMETER) AND TRAINING TIMES OF THE SVM ALGORITHMS: 1VSALL, 1VS1 AND DAG

Method	Accuracy (%)	C	g	Real time (s)	User Time (s)	System Time (s)
1vsA	83.3	3	10	0.884	0.720	0.028
1vs1	84.0	10	100	3.780	3.396	0.076
DAG	83.3	10	100	0.971	0.768	0.032

TABLE V

CONFUSION MATRIX OF 1VS1 CLASSIFIER FOR THE BEST RESULTS

WC	NW	WG	BF
NW	44	3	3
WG	4	41	5
BF	3	6	41

TABLE VI

CONFUSION MATRIX OF DAGSVM CLASSIFIER FOR THE BEST RESULTS

WC	NW	WG	BF
NW	42	3	5
WG	4	41	5
BF	2	6	42

The results suggested that three clusters could be found with an almost equal number of points. This proved the hypothesis and showed that the IMU sensors could pick up subtle differences in the walking conditions. Motivated by the primary results, multiclass supervised classifiers 1vs1, 1vsAll and DAG were applied to verify whether the walking conditions could be automatically detected. LOO method, demonstrated that the walking conditions could be classified with a minimum of 83% accuracy. These results further strengthen our previous study [23] on using shoe-mounted inertial sensor data to estimate the end point foot trajectory points such as Minimum Toe Clearance (MTC) to assess walking performance.

VI. FUTURE WORK

Future work of this study may involve analyzing the sensor data of consecutive gait cycles (time series analysis) rather than looking at the statistical properties of each trial. This would further explore the option of using sensor data to identify risky gait events for falls prevention in elderly and other populations. Further analysis would involve multi class SVMs and proper feature selection methods such as hill-climbing or F-score based feature selection for reduced computational tasks and better classification results. Additional data will also be necessary from more young healthy subjects and balance impaired populations such as the elderly to validate the generalizability of the classifiers across populations.

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