# A Multi-Algorithmic Approach for Gait Recognition

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## Abstract

Securing smartphones has increasingly become inevitable due to their massive popularity and significant storage and access to sensitive information. The gatekeeper of securing the device is authenticating the user. Amongst the many solutions proposed, gait recognition has been suggested to provide a reliable yet non-intrusive authentication approach – enabling both security and usability. Whilst several studies exploring mobile-based gait recognition have taken place, studies have largely been preliminary, with various methodological restrictions that have limited the number of participants, samples and type of features. Furthermore, prior studies have relied upon evaluating the approach on a limited number of activities - namely walking and running, and there is some concern over the capacity of the approach to correctly verify individuals when the nature of the signals across a wider range of activities is likely to be more variable. This paper has sought to overcome these weaknesses and provide a comprehensive evaluation, including an analysis of motion sensors (accelerometer and gyroscope), an investigation and analysis of features, understanding the variability of feature vectors during differing activities across a multi-day collection involving 60 participants. This is framed into two experiments involving five types of activities: normal, fast, with a bag, downstairs, and upstairs walking. The first experiment explores the classification performance of individual activities in order to understand whether a single classifier or multi-algorithmic approach would provide a better level of performance. The second experiment explored the features vector (comprising of a possible 304 unique features) to understand how its composition affects performance and for a comparison a more selective set of the minimal features are involved. Overall, results from the experimentation has shown an EER of 4.40/12.2% for a single classifier (using same/cross day methodologies). The multi-algorithmic approach achieved EERs of 0.70%/6.3%, 0.80%/12.68% and 1.10%/6.46% for normal, fast and with a bag walk respectively (using the Same/ Cross Day methodology) using both accelerometer and gyroscope based features – showing a significant improvement over the single classifier approach and thus a more effective approach to managing the problem of feature vector variability.

**Keywords**: Activity recognition; mobile authentication, gait biometrics; accelerometer; gyroscope.

### 1. Introduction

During the last decade, smartphones have become a ubiquitous technology with more than 9.5 billion users globally(THE RADICATI GROUP 2015). Currently, smartphones provide a wide range of services and features (e.g. personal communications, entertainment, and business) and are used to access/store sensitive and confidential information such as financial data and more recently health-based records. Indeed, it is highly likely that the stored information is far more valuable than the device itself (Saevanee et al 2015). As a result, smartphones should be kept secure against any illegitimate access. Current authentication approaches (e.g. password or fingerprint) that are deployed upon smartphones are typically intrusive, insecure and fail to take in to account user satisfaction and convenience (Furnell and Clarke 2013). Therefore, transparent and continuous biometric authentication systems have been proposed to provide more convenient and secure protections for mobile devices (Muaaz 2013).

Gait recognition distinguishes people by the way in which they walk or jog. Many studies in the fields of psychology, medicine, and biometrics suggest that every person's gait is unique (M. O. Derawi 2012); and it can be deployed as a transparent technique for user identification and verification purposes (Gafurov 2008). Currently, the majority of smartphones have built-in sensors (e.g. accelerometer and gyroscope) that can be used to record the user's gait information (e.g. non-gravitational accelerations and rotational paces) (Rana 2015). By using gait recognition, the user does not need an explicit action for mobile authentication as related data is continuously/already recorded while the person walks. Therefore, gait based authentication can be a valuable approach for providing transparent and continuous protection for smartphones.

This paper explores the use of gait information especially using acceleration and orientation data to transparently verify smartphone users. Whilst studies in this domain have been conducted before, this study seeks to further the research through using a larger population (60 participants) over multiple days; and analyse both the time and frequency domain features to examine their effectiveness upon system performance. Furthermore, a dynamic feature vector mechanism is employed to explore the optimum feature set towards the best performance.

The rest of this paper is organized as follows: an analysis of the current state of the art in the use of gait biometrics within smartphones is highlighted in Section 2. Section 3 describes the experimental methodology, including the data collection process and the feature extraction technique. Section 4 presents the experimental results, followed by a detailed discussion in Section 5. The concluding remarks and outline areas for future work are presented in Section 6.

## 2. Related work

Gait recognition can be captured using different sensors embedded in smartphone devices. The key advantage is that no additional hardware is needed; merely software needs to be developed. Hence, researchers started to use smartphones to record user's gait in a user-friendly, unobtrusive, and periodic manner. Table 1 illustrates a comprehensive analysis of the prior studies on gait recognition systems using the smartphone sensors.

Methodologically, all the selected studies utilised smartphones (e.g. Google G1 and Motorola Milestone) that are capable of collecting user's gait activities via (principally the) accelerometer and they were placed either in a pouch or trousers packet. The data was collected at a rate ranging from 20 samples per second to 50 samples per second, with an average around 35 samples per second. The user's gait information was gathered either on the same day (SD scenario) or across two different days (CD scenario). Two approaches can be utilised for pre-processing the data: cycle-based or segment-based; in the cycle-based approach, the gait data is supposed to be a periodic signal in which each gait cycle begins as soon as the foot touches the ground and finishes when the same foot touches the ground for the second time (i.e. two steps of a human). While for the segment-based method, the data is divided into fixed time-length windows. Since gait is assumed to be periodic, each time segment is reasonably assumed to contain similar signal features; in addition, it requires less computational operations than the cycle-based method requires. Various features from the time domain (TD) and frequency domain (FD) were extracted from data samples; those samples were then processed a classification method and the experimental result is presented in the forms of equal error rate (EER) or correct classification rate (CCR).

As demonstrated in Table 1, in general, studies that were carried out under the SD scenario achieved better performance than those were under the CD scenario; this is understandable as for the SD scenario both the enrolment and test or evaluation data are collected on the same day; and the change in user's activities is smaller than those are collected on different days. Nonetheless, a more realistic result is demonstrated for the CD scenario as it is highly likely that the enrolment data and probe data are gathered on two different days in real life. Also, the majority of existing studies used data that was recorded under laboratory conditions. In comparison limited studies collected a realistic data for variant gait signal such as carrying a weight, climbing stairs, jogging, and running (Jennifer Kwapisz et al 2011, Jennifer R Kwapisz et al 2010, Nickel et al 2011).

In terms of pre-processing methods, on average, results of studies employed the segment based approach outperform those are obtained via the cycle base method. For instance, only [30] utilised cycle based method achieved better performance (in terms of EER) than several segments based approach studies [1, 19, 22]; nonetheless, [30] was evaluated under the SD scenario while others were examined under the CD scenario. Regarding features and sensors, most of the existing studies investigated the TD features from samples that were collected via the accelerometer. Little focus has been given to the examination of feature vectors across both time and frequency domains. As illustrated in Table 1, several methods can be applied for the classification process, such as hidden Markov model and j48 decision trees. All of those classification methods, studies that utilised the Support Vector Network (SVM) and Neural Network achieved the best performance in terms of both EER and CCR.

**Table 1**: Comprehensive analysis of the prior studies on gait authentication systems using the mobile sensors.

| Study | Device | Approach | Feature Domain | Classification methods | Users | Performance % | Data duration |
|---|---|---|---|---|---|---|---|
| (Sprager 2009) | Nokia N95 | C | TD | SVM | 6 | 93.3 (CCR) | CD |
| (Mohammad Omar Derawi et al 2010) | Google G1 | C | TD | DTW | 51 | 20 (EER) | CD |
| (Frank et al 2010a) | HTC G1 | S | TD | SVM | 6 | 85.48 (CCR) | CD |
| (Frank et al 2010b) | ? | S | TD | Nearest-neighbours | 40 | 100 (CCR) | SD |
| (Jennifer R Kwapisz et al 2010) | Nexus One, HTC Hero, Motorola | S | TD | J48 decision trees &Neural network | 36 | 90 (CCR) | SD |
| (Jennifer Kwapisz et al 2011) | Nexus One, HTC Hero, Motorola | S | TD | J48 decision trees &Neural network | 5 | 100 (CCR) | SD |
| (Nickel, Brandt, et al 2011a) | Google G1 | S | FD | SVM | 48 | EER (6.1) | CD |
| (Nickel, Brandt, et al 2011b) | Motorola milestone | S | TD&FD | SVM, HMM | 36 | EER (10& 12.36) | CD |
| (Nickel et al 2011) | Motorola | C | TD | Manhattan & DTW | 48 | EER (21.7) | CD |
| (Nickel et al 2011) | Google G1 | S | TD | HMM | 48 | EER (6.15) | CD |
| (Hestbek et al 2012) | Motorola Milestone | S | TD&FD | SVM | 36 | EER (10.1) | CD |
| (Nickel et al 2012) | Motorola Milestone | S | TD& FD | K-NN | 36 | EER (8.24) | CD |
| (Wolfe 2013) | HTC Nexus One | S | TD& FD | SVM | 38 | EER (1.95) | SD |
| (Muaaz and Nickel 2012) | WS &Google G1 | C | TD | DTW | 48 | EER (29.39) | CD |
| (Thang Hoang et al 2013) | Google Nexus | C | TD | SVM | 32 | CCR (100) | SD |
| (Mohammad Derawi and Bours 2013) | Samsung Nexus | C | TD | Euclidean distance and DTW | 5 | CCR (89.3) | SD |
| (Muaaz and Mayrhofer 2013) | Google G1 | C | TD | DTW | 51 | EER (33.3) | CD |
| (Thang Hoang et al 2013) | HTC Nexus One & LG Optimus G | C | TD&FD | SVM& RBF | 14 | CCR (91.33) | SD |
| (Nickel and Busch 2013) | Google G1 | S | FD | HMM | 48 | EER (6.15) | CD |
| (Watanabe 2014) | IOS iPhone? | S | TD | Neural Network | 5 | EER (1.82) | SD |
| (Thang Minh Hoang et al 2012) | HTC Google Nexus one | C | TD | Hamming distance | 34 | 8.09 (EER) | SD |
| (Watanabe 2015) | iOS iPhone 5 | S | TD | Neural Network | 8 | CCR (97.9) | SD |

Legend: **C**: Cycle-based; **S**: Segment-based; **TD**: Time Domain; **FD**: Frequency Domain; **DTW**: Dynamic Time Warping; **HMM**: Hidden Markov Model; **SVM**: Support Vector Machine; **K-NN**: k-nearest Neighbour; **EER**: Equal Error Rate; **CCR**: Correct Classification Rate; **SD**: Same-Day; **CD**: Cross-Day; ?: not defined.

The prior work has shown some significant promise; however, with a number of limitations that require further investigation. The results from the same-day and cross-day experiments demonstrate a high-degree of variance within the feature vector, which raises the concern whether successful classification could be achieved in practice over time and across a range of differing activities. The composition of the feature vector itself will also play a significant role in recognition performance; however, few studies have explored this across accelerometer and gyroscope sensors in both time and frequency domains. Finally, studies have sought to evaluate their approaches using relatively few activities and user populations – thereby limiting the extent to which the results can be generalised.

## 3. Experimental Methodology

The paper aims to further explore the following:

- To investigate the composition of the feature vector using both accelerometer and gyroscope sensors.
- To evaluate the performance of gait recognition across a wider range of user walking activities.

The experiment will be conducted in both the same-day and cross-day methodologies using a user population of 60. Each participant was asked to perform a range of activities during each session in order to provide sufficient samples for analysis. This provided the basis for exploring classification strategies. Following on from the prior work, all activities were applied to a single classifier; however, each activity was also separated and applied to different classifiers. Given the variability in the gait signal and subsequently resulting feature vector, it was felt a multi-algorithmic approach to classification (i.e. each activity having its own classifier) might provide a more refined classification and thus improve recognition performance.

### 3.1 Data Collection

Due to its wide range of built-in sensors (e.g. Accelerometer, Barometer, Gesture Sensor, GPS, Gyroscope, Heart Rate Monitor, and Proximity Sensor), the Samsung Galaxy S6 smartphone was employed to gather individuals' data. A user was requested to place the smartphone in the belt pouch while their data was continuously collected at a rate of 30-32 samples per second for the x, y, and z-axes of both accelerometer and gyroscope sensors. During the data collection process, the user was asked to walk normally, fast, and normally with a bag on flat ground for three minutes for each activity, and then to walk down stairs for three levels and upstairs for three levels on a predefined route. The user was also asked to stop for 15 to 20 seconds between activities in order to easily separate those activities later. For more realistic scenarios, the participant had to stop in order to open the door, and walked along the corridor back and forth many times for 3 minutes across each of the activities. Ten sessions of user's activities were collected per user: 5 sessions were from one day and the other 5 sessions were collected a week later. The users were free to change their footwear and clothes for the second day's data collection. In total, 60 users participated the data collection exercise; 35 participants were male, and 25 participants were female, and they were aged between 18 and 56.

Upon completing the data collection process, user's activities were divided into five datasets aligned to each activity (normal walk, fast walk, walk with a bag, downstairs walking, and upstairs walking). Then the tri-axial raw accelerometer and gyroscope signals were segmented into 10 second segments by using a sliding window approach with no overlapping. As a result, 68 samples were collected for each user per day; and in total 8,160 samples were collected for the entire dataset.

### 3.2 Feature Extraction

Regarding the feature extraction process, both time domain and frequency domain features were extracted from user's data segments. The time domain features were calculated directly from the raw data samples while a Fourier transform was applied upon the samples before frequency domain features were gathered. Details of those feature (including name and description) are demonstrated in Table 2. In total, drawing upon the prior art, 304 unique features were generated from both the accelerometer and gyroscope data samples.

**Table 2:** Presents the time and frequency domain features

| Features | Domain | Description |
|---|---|---|
| Mean (3) | TD, FD | The mean values in the segment. |
| Standard Deviation (3) | TD, FD | The standard deviation of the data in the segment. |
| Median (3) | TD, FD | The median values of the data points in the segment. |
| Variance (3) | TD, FD | A measure of how far each value in the segment points is from the mean. |
| Covariance (3) | TD, FD | A measure of how much two variables change together. |
| Zero crossing rate Minimum | TD, FD | The rate value of sign changes in the segment. |
| Interquartile range | TD, FD | The range amidst the data. It is the distinction between the upper and lower quartiles in the segment. |
| Average Absolute Difference (3) | TD, FD | Average absolute difference between the value of each of the segment points from the mean value over the segment values (for each axis). |
| Root mean square (3) | TD, FD | Square root of the mean of the squares of the acceleration values of the segment. |
| Skewness (3) | TD, FD | A measure of the symmetry of distributions around the mean value of the segment. |
| Kurtosis (3) | TD, FD | A measure of the shape of the curve for the segment point's values. |
| Percentile 25 (3) | TD, FD | The percentile rank is measured by the following formula: R= (P/100)*(N+1). Where **R** is the rank order of values, **P** percentile rank, **N** total number of the data points in the segment. |
| Percentile 50 (3) | TD, FD | Similar to the Percentile 25feature; but with the setting of P=50. |
| Percentile 75 (3) | TD, FD | Similar to the percentile 25 feature but with the setting of P=75. |
| Maximum (3) | TD, FD | The largest four values of the segment are calculated and averaged. |
| Minimum (3) | TD, FD | The largest four values of the segment are calculated and averaged. |
| Correlation coefficients (3) | TD, FD | The relationship between two axes is calculated. The correlation coefficient is measured between X and Y axes, X and Z axes and Y and Z axes. |
| Average resultant acceleration (1) | TD, FD | Average of the square roots of the sum of the values of each x, y and z axes in the segment squared. |
| Difference (3) | TD | Difference of maximal and minimal value of the segment (each axes). |
| Maximum value (4) | TD | The largest four values of the segment are calculated and averaged. |
| Minimum value (4) | TD | The smallest four values of the segment are calculated and averaged. |
| Binned distribution (3) | TD | Relative histogram distribution in linear spaced bins be- tween the minimum and the maximum acceleration in the segment. Ten bins are used for each segment. |
| Maximum peaks (3) | TD | The average of the largest 4 peaks in the segment. |
| Minimum peaks (3) | TD | The average of the smallest 4 peaks in the segment. |
| Peak Occurrence (3) | TD | Calculate how many peaks are in the segment. |
| Time between peaks (3) | TD | Time in milliseconds between peaks in the sinusoidal waves associated with most activities is calculated and averaged (for each axis). |
| Interquartile range (3) | TD | Calculating the median of the lower and upper half of the data. |
| Entropy (3) | FD | The average amount of information produced by a probabilistic stochastic source of data |
| Energy (3) | FD | The signal energy is equal to the summation across all frequency components of the signal's spectral energy density. |

The large number of features would place a burden on the classification (particularly on processing/battery limited mobile devices) and therefore a dynamic feature selection approach was devised that can select features based upon their uniqueness for individual users. It is envisaged that the effectiveness of each feature towards the classification can vary; with some features having a more significant impact for some users over others. The dynamic feature selection mechanism selects features based upon a calculation of the standard deviation of user's features with the smaller standard deviation being selected. Standard deviation was utilised due to the need to reduce the variability of the feature vector and improve the permanence.

### 3.3 Methodology

The effectiveness of the 304 created features for authentication methods were examined in two scenarios; same day (SD) and cross day (CD). In the SD scenario, the dataset was split in 60-40: 60% of the data was used for the classifier training and the remaining 40% was utilised for testing. In the CD scenario, the first day data was used for training and the second day data was utilised for testing. For each scenario, all user's gait activities were treated as a single dataset; then each activity was studied individually. Due to the prior art and preliminary experiments the Support Vector Machine (SVM) classifier was employed as the default classifier. The system performance was evaluated by using the standard Equal Error Rate (EER) metric.

Results

The first experiment was conducted to investigate the impact of the dynamic feature selection technique and the effectiveness of TD and FD domain features upon the system performance. The results on users' accelerometer (Acc) and gyroscope (Gyro) data for all activities under both the SD and CD scenarios are presented in Table 3 and Figure 2.

**Table 3:** The EER results on Acc and Gyro data for all activities by using SD and CD scenarios

| Features (TD and FD)/ Acc & Gyro Sensors | Dynamic | | Static | |
|---|---|---|---|---|
| | Number of Features (NF) | EER (%) | All Features | EER (%) |
| SD Acc | 45 | 7.80 | 152 | 10.20 |
| SD Gyro. | 45 | 8.70 | 152 | 12.50 |
| CD Acc | 75 | 11.76 | 152 | 12.85 |
| CD Gyro. | 70 | 14.25 | 152 | 15.45 |

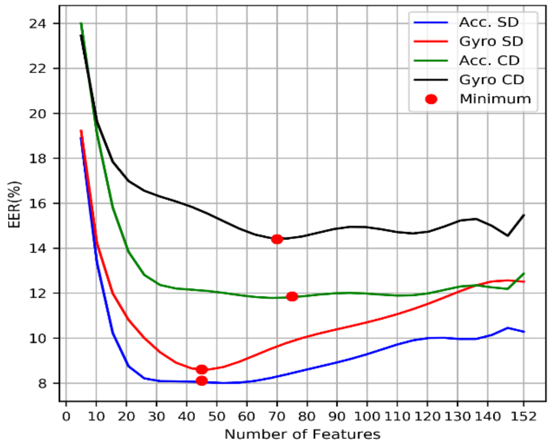


**Figure 1:** The EER results on Acc and Gyro data for all activities by using SD and CD scenarios

Both the Figure 1 and Table 3 demonstrate that better performances are achieved regarding user's gait activity (both Acc and Gyro data) when the dynamic feature selection technique is applied (the table presents the best results achieved under a complete set of experiments involving various feature vector lengths). Indeed, the best performance of 7.80% EER is shown by using user's accelerometer data with 45 features under the SD scenario. Also, when the dynamic feature selection method is used, the biggest performance gap can be observed on the user's gyroscope data under the SD scenario: 8.70% EER is obtained by using the 45 dynamic selected features while 12.50% EER is achieved by utilising the whole 152-feature set.

Regarding to the performance of the SD and CD scenarios, the SD scenario always outperforms its CD counterpart regardless whether the dynamic feature selection process is used; this is understandable as human walking behaviour will change overtime due to various reasons, including changing in shoes, clothes, mood, or health and is in line with what the prior-art has found. However, notably the better performance is achieved using fewer features in both SD and CD scenarios – although the CD required a larger number of features than the SD. This phenomenon suggests that more gait features are required as the variability of the signal increases and therefore additional features would be required when the technique is applied in real life.

With the aim of investigating the impact of individual gait activities upon the classification performance, a multi-algorithmic approach was evaluated across the different activities (i.e. normal walking, fast walking, walk with a bag, walk down stairs and walk upstairs). All user's activities from both accelerometer and gyroscope sensors were examined to set a benchmark for comparison purposes. The experimental results are fully presented in Table 4.

**Table 4:** Results of user's Acc and Gyro data and all activities by using SD and CD scenario.

| TD and FD Features/ Acc & Gyro Sensors | Same Day | | | Cross Day | | |
|---|---|---|---|---|---|---|
| | Dynamic | | Static with All feature (304) | Dynamic | | Static with All feature (304) |
| | No. of Features | EER (%) | EER (%) | No. of Features | EER (%) | EER (%) |
| Normal | 110 | 0.70 | 1.60 | 160 | 6.30 | 7.50 |
| Fast | 135 | 0.80 | 2.30 | 10 | 12.69 | 13.92 |
| With Bag | 85 | 1.10 | 2.70 | 65 | 6.46 | 6.94 |
| Down Stairs | 90 | 3.50 | 21.60 | 10 | 31.10 | 34.10 |
| Upstairs | 50 | 4.50 | 25.0 | 10 | 31 | 33.70 |
| All activities | 245 | 4.40 | 4.70 | 250 | 12.00 | 12.18 |

Initially, similar patterns are exhibited by the result regarding the impact of the dynamic feature selection process, with the results using the dynamic feature selection process outperforming those obtained by using the full feature set (i.e. 304 features from both Acc and Gyro signals). Notably, the SD scenario 'all activities' performance using the dynamic feature approach shows a significant improvement over the previous results (4.4% in comparison to 7.8%). This same improvement was not seen in the CD approach.

Exploring the value of a multi-algorithmic approach, the results, particularly for SD but can also be observed in most results within the CD results, show an improvement in the recognition performance over the single classifier approach. The best result was observed with the normal walking activity using the SD approach, with an EER of 0.7%. Also, all individual activities utilise significantly fewer features in comparison with the number of features used by all activities with a minimum difference of 110 features in comparison to 245.

The results show gait recognition whilst walking up and down stairs was not particularly good, even when applying the dynamic feature selection approach. Further analysis of the data showed that this data still suffered from a high degree of variability, which subsequently made classification challenging.

## 4. Discussion

In comparison with existing studies presented in Table 1, this research utilised a dataset containing a larger number of gait samples (8,160 samples) across more users (60 users in total) and covering both same day and cross day scenarios. In addition, the research examined a variety of activities offering the opportunity to learn the user's walking behaviour across more realistic scenarios than simple walking under laboratory conditions. The signals that are extracted from both the accelerometer and gyroscope sensors contributing to the creation of a larger feature vector. The study also proposed a dynamic feature selection and a multi-algorithmic approach to classification.

In terms of performance, for user's normal walk activity under the same day scenario, the obtained results are 0.70% EER (by using 110 features) and 1.60% EER (by using the full 304 features) as shown in Table 4, both of which are better than the performance of existing studies 1.95% EER of [23] and 1.82% EER of (Watanabe 2014); regarding the same activity under the cross day scenario, the obtained results (i.e. 6.30% EER with 160 features and 7.50% with the full 304 features) are in line with prior work including 6.1% EER of [15] and 6.15% EER of [21, 28]; nonetheless, those three prior studies employed the majority and quorum voting technique, which may improve the classification up to 50%; in addition, they utilised 20% less users for their experiments than this study and hence it could be easier to distinct individual users.

As demonstrated in Table 4, the impact of the proposed multi-algorithmic approach is effective for the same day scenario as most of the individual activities (apart from walk down and upstairs) achieve better performance than when they are treated as one activity. However, walking on the stairs resulted in a poor recognition performance, suggesting that the approach should not be applied to such scenarios.

Similar patterns are also observed from the impact of dynamic feature selection process upon the performance. As shown in Table 4, for the same day scenario, a 56% decrease in EER can be obtained when the dynamic feature selection method is applied upon individual activities with least than 45% of the number of features being utilised. In comparison, for the cross-day scenario, the number of features that are used to achieve the best performance for individual activities (apart from normal walk) decrease dramatically (e.g. with only 65 or 10 features out of the total 304 features); nonetheless, only small improvement on the performance is visible. It is common that people's walking behaviour can change over time due to various factors such as weight, mood and footwear. Also, there was a 7-day gap between the training and testing data for the cross-day scenario. It is envisaged that the time gap will be reduced for real life case, e.g. only previous two days' data will be used for training, and as a result a better performance could be observed.

## 5. Conclusion and Future Work

The study sought to investigate the performance of gait recognition across a wider range of activities and participants. Based upon 60 participants, the investigation has provided significant evidence to suggest gait-based data can be used as a reliable means of transparently verifying users whilst moving. However, the performance of cross-day over the same-day methodology does demonstrate feature vector variance that a practical system would need to carefully manage in practice. To aid this, the study has explored the use of a multi-algorithmic approach (where different classifiers are used based upon the nature of the activity) and found that such an approach can achieve a better level of performance over a single classification approach.

The study has also sought to evaluate the feature vector and found that a dynamic approach rather than a static (all feature) approach is beneficial to both the performance that can be achieved but with the added benefit of reducing the computational load upon the classifier.

Whilst the use of a multi-algorithmic classification scheme would provide better recognition performance, the problem has now transitioned into how the system will know which classifier to utilise. Therefore, further research will focus upon how to determine the nature of the activity the user is undertaking through devising context-awareness. Further research will also focus upon the collection of longitudinal real-life gait-based data to more thoroughly evaluate the recognition performance under non lab-based conditions.

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