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Footstep Recognition for a Smart Home Environment

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Abstract

This paper reports some experiments which assess the potential use of a footstep biometric verification system for a smart home environment. We present a semi-automatic capture system and report results on a database with independent development and evaluation datasets comprised of more than 3500 footsteps collected from 55 persons. We present an optimisation of geometric and holistic feature extraction approaches. An equal error rate of 13% is obtained with holistic features classified with a support vector machine. The database is freely available to the research community.

1. Introduction

The integration of many established and emerging technologies into smart home environments is gathering pace. Footstep signals, are is signals collected from people walking over an instrumented sensing area, have already been proposed for use in smart home environments for a number of different applications, including security, surveillance, tracking persons in an area and recognising human behaviour, as reviewed in Section 2. In this paper we present some experimental work which aims to give a more reliable assessment of the potential of footstep signals as a biometric which might find application within smart home environments.

Different biometrics have been used for many years as a means of recognising or verifying a person's identity. Some of the most researched such as the fingerprint or face biometrics have been included in passports and ID cards. Iris recognition has been recently introduced in airports, and palm vein recognition is undergoing trials for use in cash machines. These methods belong to the physiological group of biometrics. Physiological biometrics are less likely to change significantly over time whereas behavioural biometrics are relatively more likely to change over time. Voice recognition is one of the most popular behavioural biometrics due to its application in mobile phones.

Gait and footsteps are other examples of behavioural biometrics. Over the past few decades gait recognition has been investigated in a number of different fields including surveillance, medical applications and in the sport shoe industry among others. Gait refers to the manner in which a person walks and is often studied using video recordings, whereas footstep recognition is generally based on the study of signals captured from persons walking over specifically designed, instrumented floor sensors.

Gait and footsteps are closely related and future research is likely to investigate the fusion of the two biometrics.

Footstep signals can be collected covertly and this presents a significant benefit over other more established, well known biometrics. The sensing system is less likely to induce behavioural changes as well as presenting less of an inconvenience to the user. These characteristics of the footstep biometric make it especially appealing for the smart home environment.

This paper aims to assess the potential performance of the footstep biometric. We present experimental results achieved using a database comprised of more than 3500 footsteps from 55 different persons. As described in Section 3, the database has been further divided into independent development and evaluation datasets adopting a standard, best practice evaluation strategy, allowing us to present more statistically meaningful results and potentially more reliable predictions of performance than previous work. In addition we describe the development of a semi-automatic footstep capture system designed to gather the database which is publicly available to the research community at [1].

Preliminary work with geometric and holistic feature extraction approaches was presented in [2]. Extending this previously published work, this paper shows an optimisation of the two feature approaches, presented in [3], and reports results on a larger database in number of footsteps and persons, and with no person overlap between the different datasets. Using holistic features and a discriminative based classifier in the form of a support vector machine (SVM) an equal error rate (EER) of 13% is achieved for the evaluation set. These results are reviewed in Section 4, and finally our conclusions are presented in Section 5.

2. Review of footstep signals and their applications

The use of footstep signals has been investigated previously for a number of different applications including medicine to identify different gait deficiencies; surveillance to monitor human presence; smart homes for human tracking or recognition of human behaviour; biometrics to verify a person's identity; or even multimedia for music or for video game interaction. Below we review the work related to smart homes and biometrics in two sections. The first section covers smart homes where both simple person detection and the more specific case of person recognition are applicable; and the second covers footstep as a biometric which has more general application beyond smart homes.

2.1. Smart Homes

Footsteps have some potential applications in the smart home environment where footstep sensors are installed to determine the position of a person in a room or to recognise human behaviour and interact with users. In 2000 Mori *et al* [4] developed a system where multiple sensors were distributed in several locations of a "robotic room". Switch sensors installed on household appliances and windows were used to detect on/off or open/closed conditions and pressure sensors were used to monitor movement on the floor, bed, desk and chair. Footstep signals were collected from a distribution of force sensing resisters (FSRs) to specify human position in the room. A total number of

252 FSRs were installed in a 200mm x 200mm lattice shape. More recent work on the same floor [5] (2002) increased the spatial resolution of the sensors to a 64 x 64 switch sensor array in a 500 mm^2 space. Sixteen of these sensor floor units were used to produce a sensing area of 2 m^2. With this high resolution, experiments determined the positions of a human and a 4-wheeled cart and distinguished between them. In 2004 Murakita *et al* [6] reported a system for tracking individuals over a wide area by using a Markov Chain Monte Carlo Method (MCMC). They employed a basic 18 cm^2 switch block sensor to cover a total area of 37 m^2. The system was capable of tracking two different people when separated by more than 1.4 m but failed to track people in a crowded area due to the low spatial resolution and a low capture rate of 5 Hz.

Making use of the hardware developed for the Active Floor [7], in 2001 Headon and Curwen [8] used the vertical component of the GRF and a hidden Markov model (HMM) classifier to recognize different movements such us stepping, jumping, drop-landing, sitting down, rising to stand and crouching. Applications of such a system exist in safety, i.e. fall detection for the elderly and entertainment, i.e. video games.

2.2. Biometrics

Footsteps were proposed as a new biometric in 1997, but have been studied only by a small number of researchers. Table 1 summarises the material in the open literature.

One of the first investigations into footstep recognition was reported by UK researchers in 1997 [7] (first row in Table 1). They reported experiments on a database of 300 footsteps signals that were captured from 15 walkers from loads cells measuring the ground reaction force (GRF). An identification accuracy of 91% was achieved with an HMM classifier and samples from the GRF as features.

In 2000, and using a similar sensor approach, in [9] a group in the USA reported results on a database of 1680 footstep signals collected from 15 persons. Signals were collected from both left and right feet and different footwear. Ten features were extracted from the GRF signal: the mean value, the standard deviation, maxima and minima, etc. An identification accuracy of 93% was reported using a nearest neighbour classifier.

Whilst focused toward the study of gait, a group from Switzerland [10] developed in 2002 a system fusing data acquired from 3 tiles of 4 piezo force sensors each and video cameras. A database of 480 footsteps was collected from 16 persons. They studied different feature extraction techniques as geometric features from GRF as [9] and phase plane. The best verification performance was achieved using the Power Spectral Density of the footstep signals with an Euclidean distance classifier obtaining an equal error rate (EER) of 9.4%.

A Korean group reported a system in 2003 [11] that used 144 simple ON/OFF switch sensors. Stride data (connected footsteps) was collected from 10 persons who each contributed 50 footsteps resulting in a database of 500 signals. An accuracy of 92% was reported with a Multilayer-Perceptron Neural Network used as an experimental identification method.

In 2004 a group from Finland investigated footstep recognition using Electro Mechanical Film (EMFi) [12]. Long strips of the sensor material were laid over an area covering 100 m^2. A database of 440 footstep signals was collected from 11 persons. Geometric features were extracted from the GRF profiles as in [9] and first FFT coefficients. Using a Distinction-Sensitive Learning Vector Quantization (DSLVQ) classifier an identification accuracy of 70.2% was achieved.

In 2005 a group from Southampton (UK) [13] reported trials with a system comprising 1536 sensors each covering an area of 3 cm^2. A database of 180 signals was collected from 15 people without wearing footwear. Three features were extracted: stride length, stride cadence and heel-to-toe ratio. An identification accuracy of 80% was reported using an Euclidean distance classifier.

In 2006 another group from Southampton [14] investigated a system similar to the work in [7,9]. A database of 400 signals was collected from 11 people. Using geometric features extracted from GRF profiles as in [9] an identification accuracy of 94% was achieved using a nearest neighbour classifier.

Recently, in 2007, our research group presented in [2,3] experiments obtained with a database comprised of 3174 footsteps collected from 41 different persons and divided into development and evaluation sets. Geometric and holistic features were extracted from the footstep signals and recognition performance using nearest neighbour (NN) and support vector machine (SVM) classifiers was compared. Using holistic features with the SVM classifier EERs of 9.5% and 11.5% were obtained for the development and evaluation sets respectively.

Table 1 summarises the material available in the open literature. It is very difficult to make a comparison between the different laboratory systems due to the fact they use different sensors, databases, features, classifiers and assessment protocols. As can be observed in the third column of Table 1, different sensor technologies have been used including load cells [7,9,14], switch sensors [11,13], piezo electric sensors [2,3,10] and electro mechanical film (EMFi) [12]. Results might suggest that load cells provide better performance than other sensors; however, the system described here uses piezo electric sensors as they are very thin (2mm), cheap, and their output is the instantaneous pressure. The complementary signal that would be obtained from load cells can be extrapolated by a simple integration of our output signal. The second column of Table 1 shows that relatively small database sizes is a common characteristic of the earlier work certainly judged in relation to other biometric evaluations where persons are normally counted in hundreds or thousands and the number of tests perhaps in many thousands. A maximum number of 16 persons and 1680 footsteps examples were gathered in all cases except in [2,3] which reports results on 3147 footsteps and 41 persons. In each case the databases are divided into training and testing sets however, with exception of [2,3], none use independent development and evaluation sets, a limitation which makes performance predictions both difficult and unreliable. As Table 1 indicates, different features are proposed, including subsamples from the ground reaction force (GRF) profile in [7], geometric features from the GRF in [9,12,14], the power spectral density in [10], position of several footsteps in [11], stride length, stride cadence and heel-to-toe ratio in [13], and geometric and holistic features from instantaneous pressure and GRF signals in [2,3]. With respect to classifiers the majority used a simple NN based Euclidean distance [9, 10, 13, 14], perhaps because of the limited data sets which make statistical modeling difficult; however [7] uses an HMM classifier, [11] a Multilayer-Perceptron Neural Network, [12] uses a DSLVQ and [2,3]

SVM. Identification, rather than verification, was the task considered in all but three of the cases, the exceptions being [2,3,10]. Identification has the benefit of utilizing the available data to a maximum but suffers from well known scalability problems in terms of the number of classes in the set.

Group / Year	Database (step s/persons)	Technology	Features	Classifier	Results
The ORL Active Floor (UK) / 1997 [7]	300 steps / 15 p ersons	Load cells	Sub sampled GRF	HMM	ID rate: 91%
The Smart Floor (USA) / 2000 [9]	1680 steps / 15 persons	Load cells	Geometric feat. Fr om GRF	NN	ID rate: 93%
ETH Zurich (Swit zerland) / 2002 [1 0]	480 steps / 16 p ersons	Piezo electric s ensors	Power Spectral D ensity	Euclidean Dista nce	Verif EER: 9. 4%
Ubifloor (Korea) / 2003 [11]	500 steps / 10 p ersons	Switch sensors	Position of several steps	Multilayer-perce ptron neural net work	ID rate: 92%
EMFi Floor (Finla nd) / 2004 [12]	440 steps / 11 p ersons	Electro Mecha nical Film	Geometric feat. fr om GRF	Learning vector quantization	ID rate: 70%
Southampton Uni versity (UK) / 200 5 [13]	180 steps / 15 p ersons	Resistive (swit ch) sensors	Stride length, strid e cadence and hee l-to-toe ratio	Euclidean Dista nce	ID rate: 80%
Southampton Uni versity (UK) / 200 6 [14]	400 steps / 11 p ersons	Load cells	Geometric feat. fr om GRF	NN	ID rate: 94%
Swansea Universi ty (UK) / 2007 [2, 3]	3174 steps / 41 persons	Piezo electric s ensors	Geometric and Ho listic feats.	SVM	Verif EER: 9. 5% for Devel, 11.5% for Ev al

Table 1. A comparison of different approaches to footstep recognition 1997 – 2007.

3. Data capture system and database

The footstep data capture system has been designed to facilitate the capture of many thousands of footstep signals over a relatively short time period. Two piezoelectric transducers inserted into the underside of a rubber floor tile are used to capture the footstep signals. They provide a differential voltage output according to pressure upon the floor tile and are digitized using a sample rate of 1024Hz. To avoid aliasing, a Sallen-key low pass filter was added with a cut-off frequency of 250Hz. A Motorola HC11 microcontroller was chosen to be the best solution as the inclusion of an ADC and communication module is a common feature. The signals are then stored on a desktop computer via a serial connection. To maximize data capture and to reduce the variance in walking direction the instrumented floor tile is positioned in the doorway entrance of our research laboratory.

Due to the number of footsteps that are to be captured the provision for automatic labeling and rapid manual validation is deemed essential. A microphone situated a few steps ahead of the sensing area captures a 4-digit spoken ID, if provided, whilst ensuring no disturbance in the natural walking process and facilitates automatic labeling with speaker recognition. Two video cameras capture images of the face and foot which can later be used for manual validation and to record meta-data, i.e. to label different footwear etc. Footstep data may be accessed by walker, date/time and other parametric details. Web based administration allows viewing of footstep data in a graphical form and previews of video feeds ensuring a high confidence in the correct labeling of the data.

Figure 1 shows a diagram of the hardware used for the footstep capture system.

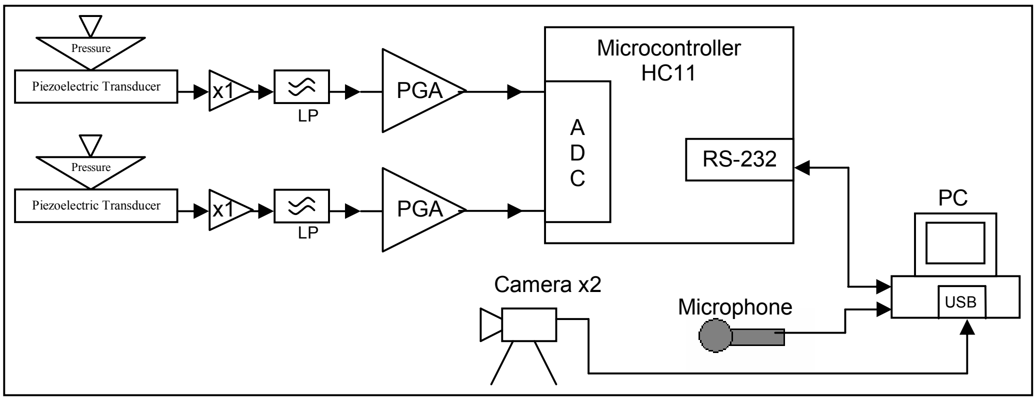

Figure 1. Connection of the hardware used for the footstep capture system.

Figure 2 shows a screenshot of the footstep capture system user interface. The sensor responses are illustrated in the top left corner as a function of time (horizontal axis). The bottom left corner shows the microphone output, a 4-digit ID identified later by the automatic speech recognizer. The top and bottom right corners show frames from the videos that are captured during footstep data collection, one of the face and one of the foot.

The work described in this paper relates to a database comprised of 3550 footsteps collected from 55 persons who were each instructed to place their right foot over the centre of the instrumented floor tile. Two subsets have been identified: a client set of 20 persons with an average of 160 footsteps per person (3157 total footsteps) and an impostor set of 35 persons with an average of 11 footsteps per person (393 total footsteps). Each person in the client set provided footsteps with at least two different shoes.

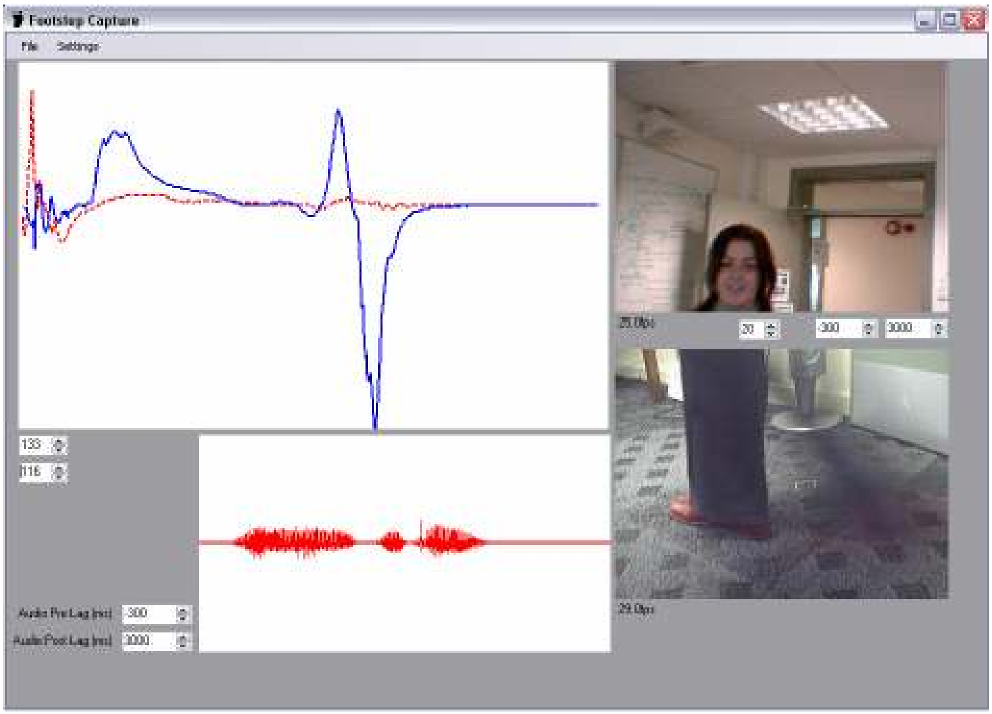

Figure 2. Screenshot of the footstep capture system software.

The database has been further divided into independent development and evaluation datasets, and each of them is comprised of training and testing datasets. This is accomplished with random selection. The development set was used to set the different parameters and features of the recognition system, and the evaluation set was used to test the established system with new unseen data.

Table 2 illustrates the distribution of the footsteps data into the different datasets. It is worth noting that there is no data overlap between the Development Set and the Evaluation Set. For the Development Set, clients P1 to P10, the same data was used for testing and training. The purpose here is to establish the parameters for the evaluation, not to assess the biometric per se. The average number of footsteps across clients P1 to P10 is 158, the range being 66 to 263 footsteps per client. The Evaluation Set is comprised of footsteps from clients P11 to P20 and for each client there are 40 footsteps for training and an average of 117 footsteps per client for testing, the range being 65 to 295 footsteps per client. Each recognition test is performed on just one footstep and each individual score contributes directly to the DET plot.

As a part of the recognition system, the impostor footsteps are the same for the two datasets and come from persons P21 to P55 with a total number of 393 footsteps.

	Development Set		**Evaluation Set**	
	Train	Test	Train	Test
Clients	P1-P10	P1-P10	P11-P20	P11-P20
Footsteps/Client	158	158	40	117
Impostors	P21-P55	-	P21-P55	-
Impostor Footsteps	393	-	393	-
Subset Data	1976	1583	793	1174
Total Set Data	1976		1967	

Table 2. Distribution of footsteps in the datasets.

4. Experimental work

As an assessment protocol of the footstep recognition evaluation, index files were created to provide a list of the footstep signals to use in each of the Development and Evaluation datasets. The index files reflect the structure utilised by the international NIST SRE [15].

First we describe an optimization of the geometric and holistic feature approaches followed, and second we present the results of the evaluation of our footstep system. As regards the classification technique, a support vector machine (SVM) [16,17] was used in all cases. A comparison between a nearest neighbour and a SVM classifier was carried out in [2] showing a better performance for SVM as could be expected. The SVM is a statistical discriminative based classifier that finds an optimal hyperplane which maximizes the margin between in-class and out-of-class data. Different Kernels were tested having a better performance with a radial basis function (RBF), case used in all the experiments described above. Finally, results are presented with detection error trade-off (DET) curves [18] as is popular with many biometric studies.

4.1. Feature Optimisation

Here we present some experiments to optimise feature extraction in order to improve performance with the SVM classifier. Two different feature approaches, geometric and holistic, have been assessed. The experiments reported here relate to a database comprised of 3147 footsteps from 41 persons as described in [2,3].

4.1.1. Geometric features: The signals produced by our system relate to the instantaneous pressure upon each sensor. Figure 3 shows a typical footstep waveform. A large amount of footstep signals were visually analysed to determine five relevant points, shown by numbers (1 to 5) in Figure 3, as an indication of the signal's behaviour along time, similar to the work of [7,9]. These points coincide with some of the absolute and relative maxima and minima present in the footstep signals. Point 1 is the absolute maxima of the ‘Heel Sensor’ of Figure 3, and corresponds to the effect of heel pressure. Points 2 to 5 correspond to the ‘Toe Sensor’, and show the effect of the pressure of the toe. Point 2 indicates the initial pressure of the toe and corresponds to a maxima of the first part of the profile; points 3 and 4 show the pressure exerted from the pushing down on the floor and correspond to a minima and maxima respectively, and finally point 5 indicates the decrease in pressure when the toe leaves the sensor tile and correspond to the absolute maxima of the profile. The time and magnitude of these 5 points result in the first 10 features. Then, the inter-difference between each pair of points results in another 20 features (10 magnitude features and 10 time features). Finally, 12 additional features, the area, norm, mean, length and standard deviation of both sensors and a relation for magnitude and time for the toe sensor, are concatenated to obtain a feature vector with a total of 42 geometric features for each footstep signal. These features were normalised with respect to the absolute maxima of the profile.

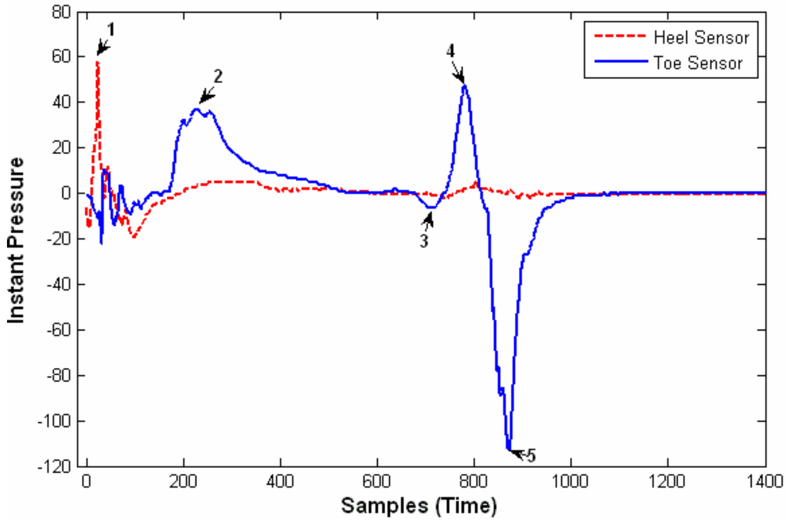

Figure 3. Instant Pressure against time. Relevant points for geometric feature extraction are indicated.

The optimisation of the geometric features was computed by an exhaustive search in order to find a combination of features which produces the minimum EER using the development set. Experiments were conducted using each one of the 42 geometric features separately to obtain a ranking in terms of performance. The feature with the minimum EER was identified and then a second set of experiments was conducted using the best feature together with each one of the remaining features to obtain another rank. This procedure was repeated until all 42 features were used. Figure 4 shows the EER against the optimum combination of the features. As it is observed the set of the first 17 features produces an EER of 12.5% compare to the EER of 16% of the total combination of features. This equates to a relative improvement of 22% in terms of EER. This optimum combination of features is comprised of five features related to time, six related to magnitude and also the norm, area and deviation for both sensors.

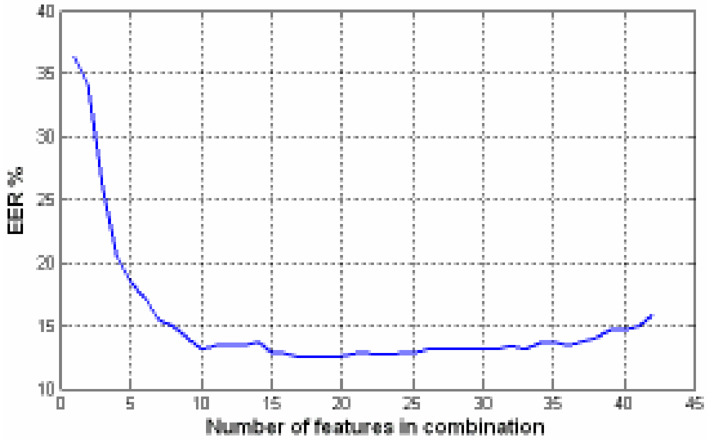

Figure 4. EER against number of features in combination for geometric features.

4.1.2. Holistic features: Holistic features are comprised of the first 1400 samples (1.37 seconds) of the Heel and Toe sensor (as the example of Figure 5 (a) and (b)), and also the first 1400 samples of the GRF (as in Figure 5(c)), calculated as the integration over time for these two sensors. In total 4200 holistic features have been obtained after normalization of each sensor and the GRF by its maxima.

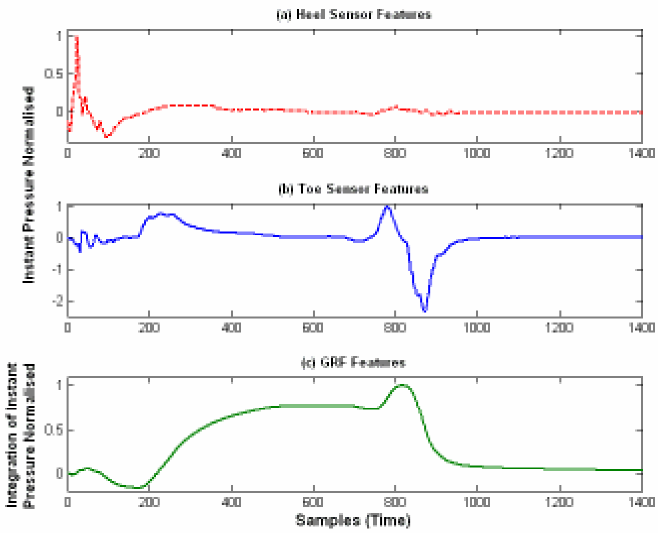

Figure 5. Holistic features used. (a) Heel sensor features. (b) Toe sensor features. (c) GRF features.

Due to the high dimensionality of this holistic feature vector, principal component analysis (PCA) [19] was used to distil the information content. Thus, after PCA, a set of principal components is obtained, where each of them is a linear combination of the original feature set. Figure 6 shows the information contained in the principal components of the training data of Development set. It is observed how using the first

80 principal components, more than 96% of the original information is retained whilst achieving a 98% reduction in dimensionality.

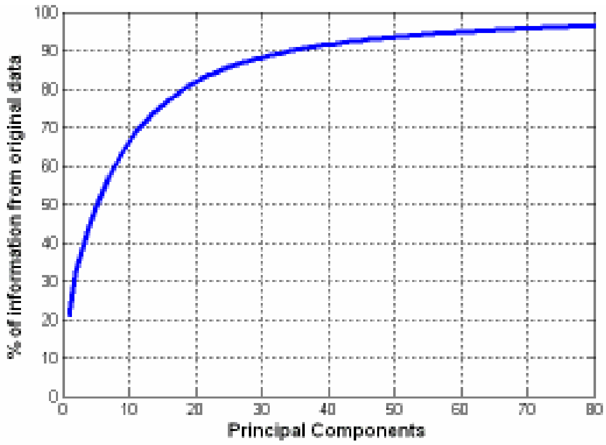

Figure 6. Percentage of information from original data against number of principal components.

The purpose of an optimization of the holistic features is to find the number of components of PCA with a minimum EER for the Development set. For this experiment, the variation in EER is measured on the EER when adding more principal components to the SVM classifier. Figure 7 shows the EER against the variation in the number of principal components chosen as features to the SVM classifier. It is observed that a best EER of 9.5% is achieved when the first 60 principal components are used.

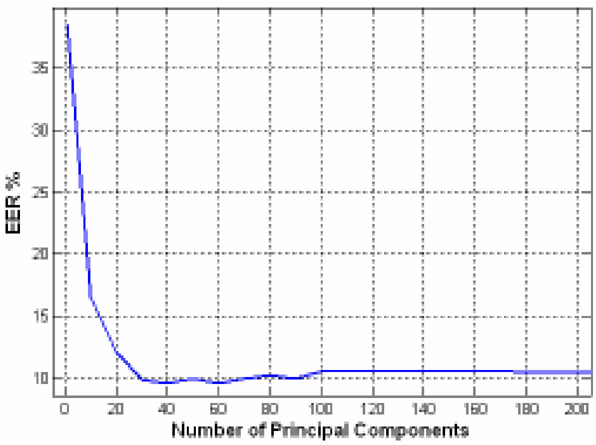

Figure 7. EER against number of principal components for holistic approach.

4.2. Footstep Recognition Evaluation.

Here we present an evaluation of our footstep recognition system using the database presented in Section 3 and the optimised geometric and holistic features described in Section 4.1. As mentioned previously, for the Development Set identical data sets are used for both testing and training. This results in the classifier being able to learn the data and consequently give unrealistically high scores. However, the purpose is to determine system parameters rather than evaluate the biometric. Figure 8 shows the

DET curve result for Development Set for the case of geometric and holistic features. An EER of 12% and 3% are observed for the geometric and holistic features respectively, resulting in a relative improvement of 75%.

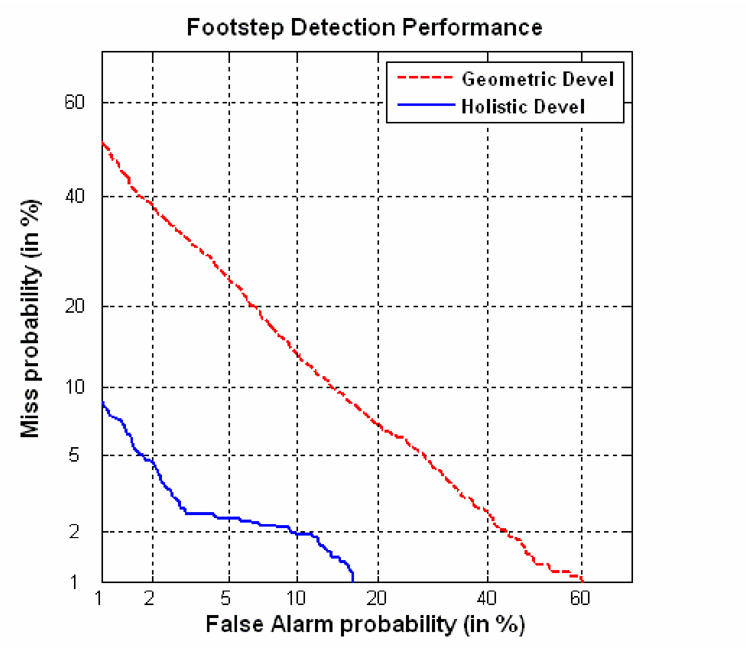

Figure 8. DET curves for geometric and holistic features for the Development set.

The purpose of having an evaluation set is to test our footstep system with new unseen data. For this experiment we apply to the Evaluation Set data all the parameters learnt from the Development Set, which are the PCA, scaling and normalising coefficients. Also, in this database there is neither data nor person overlap between the Development and Evaluation sets, as illustrated in Table 2. Thus data from the Development Set has been used to train a world model for the Evaluation Set, providing out-of-class data to train a model for each client with the SVM classifier. These tried and tested, best practice experimental protocols have been adopted by all major international biometrics evaluations. They add credibility to our results and ensure a more reliable prediction of system performance.

Figure 9 shows DET curve results for the Evaluation Set using both geometric and holistic features. The same trend is observed, but in this case the relative improvement between holistic and geometric features is not so pronounced. In this case an EER of 17% is achieved for geometric features compared to an EER of 14% for holistic features, giving a relative improvement of 21% in terms of EER.

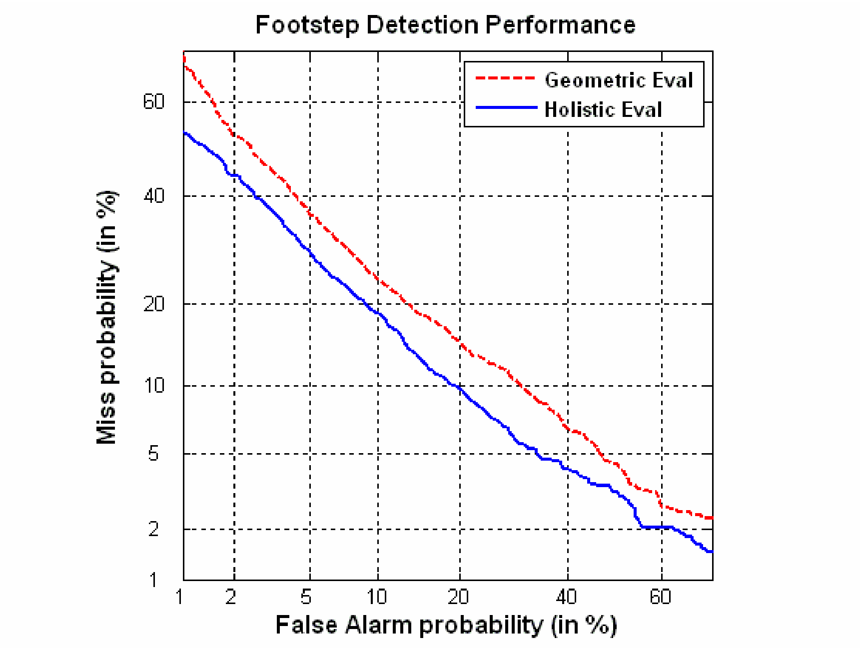

Figure 9. DET curves for geometric and holistic features for Evaluation set.

Table 3 compares the results obtained from the Evaluation Set in this paper with results in [2,3]. Note the data sets are not identical; however some observations and comparisons can be made. As mentioned above, an EER of 17% is achieved here for geometric features which corresponds to a relative improvement of 8% compared to the result presented in [3]. The improvements over results presented in [2] are due to the fact that in this paper the features have been optimised using the Development set. Regarding the holistic features, the EER of 13% is of the same order as that presented in [3] and marginally worse than that presented in [2].

The dependence of system performance on the quantity of training data was illustrated in [2]. As with all biometrics, the more valid data per client that is used to train a model, potentially the better the system performance. It is worth noting that for the results presented here 40 footsteps have been used per client to train each model, compared to the case of [2,3] where 45 footsteps where used. Also, in this case a larger database with more footsteps and more persons has been used, giving a more reliable indication of likely performance.

	Geometric-SVM	Holistic-SVM
Current Results	17%	13%
Results in [3]	18.5%	13.5%
Results in [2]	23.5%	11.5%

Table 3. Comparison between EER results from the different Evaluations.

5. Conclusions and future work

This paper describes a semi-automatic system for capturing footsteps used to gather a database comprised of more than 3500 footsteps from 55 persons, the biggest ever database used to assess footsteps as a biometric. This allows us to present more statistically meaningful results and potentially more reliable predictions of performance compared to related work. Also, this database is publicly available to the research community.

Experimental work has been conducted following best practice using independent development and evaluation sets. In addition, we describe an optimisation of the two feature extraction approaches and report an evaluation protocol of the footstep system which shows results of around 13% EER, a figure close to that of previously reported work. An improvement on system performance using geometric features compared to previous work is reported, but the relative improvement obtained by using holistic features remains approximately 21% in terms of EER.

Some appealing applications of a footstep biometric within the smart home environment have been proposed. They include security access, surveillance or interaction between people and technology.

We are currently collecting a new footstep database with a higher sensor resolution and larger sensor area. When complete the new database will allow us to capture more detailed footstep information and consequently to improve the performance of the system using new approaches to capture finer dynamic detail.

6. Acknowledgements

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7. References

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