Assessment of a Footstep Biometric Verification System

Rubén Vera Rodríguez, John S.D. Mason and Nicholas W.D. Evans

Abstract This paper reports some novel experiments which assess the potential of footsteps as a biometric. We present a semi-automatic capture system and report results on a large database of footstep signals with independent development and evaluation datasets comprised of more than 3000 footsteps collected from 41 persons. An optimisation of geometric and holistic feature extraction approaches is reported. Following best practice we report some of the most statistically meaningful and best verification scores ever reported on footstep recognition. An equal error rate of 10% is obtained with holistic features classified with a support vector machine. As an added benefit of the work, the footstep database is freely available to the research community. Currently, the research focus is on features extraction on a new high spatial density footsteps database.

1 Introduction

Different biometrics have been used for many years to verify the identity of persons. Some of the most researched such as fingerprints or faces have been included in passports and ID cards. Iris recognition has been introduced in airports, and palm vein recognition in cash machines. These methods belong to the group of the physiological biometrics as they do not exhibit a large variance over time. On the other hand, behavioural biometrics are more likely to change throughout different recording sessions. Voice recognition is the most popular of these biometrics because of

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its application in telephony, used worldwide.

Gait and footsteps are also considered to be behavioural biometrics. Gait recognition has been investigated over the past decades for medical applications as well as for the sport shoe industry. Gait recognition is based on the study of the way persons walk by camera recordings, whereas footsteps recognition is based on the study of signals captured from persons walking over a sensing area. Both techniques are very related and could be easily fused in the same environment.

Footstep recognition was proposed as a new biometric ten years ago, but it has been studied only by a small number of researchers. The main benefit of footsteps over the more well known biometrics is the fact that footstep signals can be collected covertly, and therefore, the sensing system is less likely to induce behavioural changes as well as presenting less of an inconvenience to the user. Also, footsteps are not as susceptible to environmental noise as in the case of speaker recognition or lighting variability in the case of face recognition. As we review in Section 2, different techniques have been developed using different sensors, features and classifiers. Results achieved are promising and give an idea of the potential of footsteps as a biometric; however, these results are related to small databases in number of persons and footsteps and this is a limitation of the work to date.

In this paper we present results achieved using a database comprised of more than 3000 footsteps from 41 persons. As described in Section 3, this 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. In addition, we describe the development of a semi-automatic footstep capture system used to gather the database, which is publicly available to the research community [1].

Preliminary work with geometric and holistic feature extraction methods was presented in [2]. Extending this previously published work, this paper presents an optimization of the two feature approaches. A discriminative based classifier in the form of a support vector machine (SVM) is used to obtain an equal error rate (EER) of 9.5% for development set and 13.5% for evaluation set for the holistic feature approach as described in Section 4. Section 5 describes the focus of our current work and presents a new footstep capture system with a high density of sensors. Finally our conclusions are presented in Section 6.

2 Review of footsteps as a biometric

Footstep recognition is a relatively new biometric certainly judged in terms of published work. Table 1 summarises the material in the open literature.

Group / Year	Database (steps / persons)	Technology	Features	Classifier	Results
The ORL Active Floor / 1997 [3]	300 steps / 15 persons	Load cells	Subsampled GRF	HMM	ID rate: 91%
The Smart Floor (USA) / 2000 [4]	1680 steps / 15 persons	Load cells	Geometric feat. from GRF	NN	ID rate: 93%
ETH Zurich / 2002 [5]	480 steps / 16 persons	Piezo force sensors	Power Spectral Density	Euclidean distance	Verif. EER: 9.4%
Ubifloor (Korea) / 2003 [6]	500 steps / 10 persons	Switch sensors	Position of several steps	MLP neural network	ID rate: 92%
EMFi Floor (Finland) / 2004 [7]	440 steps / 11 persons	Electro Mechanical Film	Geometric feat. from GRF and FFT	MLP neural network	ID rate: 79%; and 92% combining 3 consecutive steps.
Southampton University (UK) / 2005 [8]	180 steps / 15 persons	Resistive (switch) sensors	Stride length, stride cadence and heel-to-toe ratio	Euclidean distance	ID rate: 80%
Southampton University (UK) / 2006 [9]	400 steps / 11 persons	Load cells	Geometric feat. from GRF	NN	ID rate: 94%
Swansea University (UK) / 2007 [2]	3174 steps / 41 persons	Piezoelectric sensors	Geometric and Holistic feats.	SVM	Verif. EER: 9.5% for Devel 11.5% for Eval

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

One of the first investigations into footstep recognition was reported by UK researchers in 1997 [3] (first row in Table 1). They reported experiments on a database of 300 footstep 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 [4] 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, in 2002 a group from Switzerland [5] developed 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

[4] and phase plane. The best verification performance was achieved using the power spectral density of the footsteps signals with an Euclidean distance classifier obtaining an EER of 9.4%.

A Korean group reported a system in 2003 [6] 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 2005 a group from Finland investigated footstep recognition using Electro Mechanical Film (EMFi) [10]. 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. They presented experiments in [7] combining different feature sets using a two-level classifier. On the first level three different feature sets were extracted from a single footstep as geometric features from the GRF as in [10], FFT of GRF with PCA, and FFT of the derivate GRF with PCA. Then, a product rule was used to combine the three results obtained. On the second level different footsteps from the same person were combined using an average strategy. These experiments were done for two classifiers: LVQ and a MLP neural network. Results were better for the MLP classifier in all cases, having a recognition rate of 79% for the case of a single footstep and a 92% for three consecutive footsteps.

In 2005 a group from Southampton (UK) [8] 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 [9] investigated a system similar to the work in [3, 4]. A database of 400 signals was collected from 11 people. Using geometric features extracted from GRF profiles as in [4] an identification accuracy of 94% was achieved using a nearest neighbour classifier.

More recently, in 2007, our research group presented [2] experiments obtained with a database comprised of 3174 footsteps of 41 persons and divided into development and evaluation sets. Geometric and holistic features were extracted from the footstep signals and NN and SVM classifiers were compared. Results of 9.5% EER for development and 11.5% EER for evaluation sets were obtained for holistic features with an SVM classifier.

Table 1 summarises the material in the open literature. The second column 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 footstep examples were gathered in all cases except in [2] which reports results on 3147 footsteps and 41 persons. In each case the databases are divided into training and testing sets however, with the exception of [2], none use independent development and evaluation sets, a limitation which makes performance predictions both difficult and unreliable. Identification, rather than verification, was the task considered in all but three of the cases, the exceptions being [2, 5]. 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.

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 footstep signals. They provide a differential voltage output according to pressure upon the floor tile and are digitized using a sample rate of 1024 Hz. The signals are then processed with an in-situe micro-controller and 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. The audio tokens facilitate 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 metadata, 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.

The work described here relates to a database comprised of 3174 footsteps collected from 41 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 17 persons with an average of 170 footsteps per person (2884 total footsteps) and an impostor set of 24 persons with an average of 15 footsteps per person (290 total footsteps). Each person in the client set provided footsteps with at least two different shoes.

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 two evaluation sets were used to test the established system with new unseen data.

	Devel		**Eval 1**		**Eval 2**	
	Train	Test	Train	Test	Train	Test
Clients	P1-P8	P1-P8	P1-P17	P1-P17	P1-P17	P1-P17
Footsteps per Client	40	40	40	40	45	87
Impostors	P18-P41	-	P18-P41	-	P18-P41	-
Impostor Footsteps	290	-	290	-	290	-
Subset Data	610	320	970	680	1055	1479
Total Set Data	930		1650		2534	

Table 2. Distribution of footsteps in the datasets.

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 two evaluation sets. The development set is comprised of footsteps from clients P1 to P8, who each contribute 40 footsteps for training and another 40 footsteps for testing. Evaluation set 1 is a balanced set comprised of footsteps from clients P1 to P17 where, for each client, there are 40 footsteps for training and another 40 for testing. Evaluation set 2 uses all the footsteps available in the database and is thus an unbalanced set in terms of the number of footsteps per person. It is comprised of footsteps from clients P1 to P17 with 45 footsteps per client for training, and an average of 87 footsteps per client for testing, the range being 40 to 170 footsteps per client. Thus evaluation set 1 is a subset of evaluation set 2.

As a part of the recognition system, the impostor footsteps are the same for all three datasets and come from persons P18 to P41 with a total number of 290 footsteps.

4 Experimental work

In this section we present experiments carried out with the footstep database described. 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 one of the development and evaluation datasets following the structure utilised by the international NIST SRE [11].

First we describe an optimisation of the geometric and holistic feature approaches followed and second the results of the footstep recognition evaluation. As regards the classification technique, a support vector machine (SVM) [12, 13] was used in all cases. A comparison between a nearest neighbour and a SVM classifiers is reported in [2] showing better performance for an SVM classifier as could be expected. The SVM is a statistical discriminative based classifier that finds an optimal hyperplane which maximises the margin between in-class and out-of-class data. Different Kernel functions 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) [14, 15] curves as is popular with many biometric studies.

4.1 Feature optimisation

In this section we present an optimisation of the features extracted from the footstep signals in order to improve performance with the SVM classifier. As described in [2], two different feature approaches, geometric and holistic, have been followed.

4.1.1 Geometric features

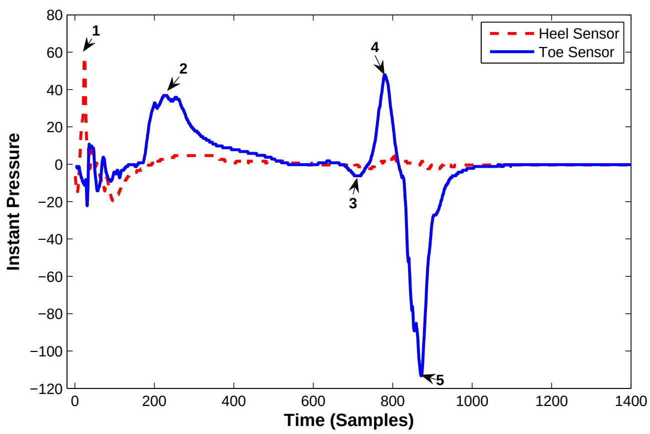

Fig. 1 Instant pressure against time. Relevant points for geometric feature extraction are indicated.

The signals that our system produces relate to the instantaneous pressure for each sensor along the footstep. Figure 1 shows a typical footstep waveform. The relevant points, shown by the numbers in Figure 1, were chosen as an indication of the behaviour of the signals along time, similar to the work of [3, 4, 9]. These points

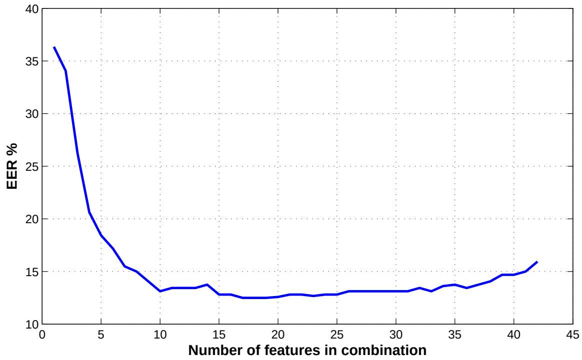

Fig. 2 EER against number of features in combination for geometric features.

coincide with some of the relative and absolute maxima and minima present in the footstep signals. Point 1 corresponds to the effect of heel pressure on the first sensor, the dashed profile in Figure 2. Points 2 to 5 correspond to the second sensor, the solid profile in Figure 1, and show the effect of the toe. Point 2 shows the initial pressure of the toe, point 5 shows the effect of the pushing off of the toe and points 3 and 4 mark the transition between points 2 and 5. 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.

The optimization 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 raking 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 feature were used. Figure 2 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.

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 3 (a) and (b)), and also the first 1400 samples of the GRF (as in Figure 3 (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.

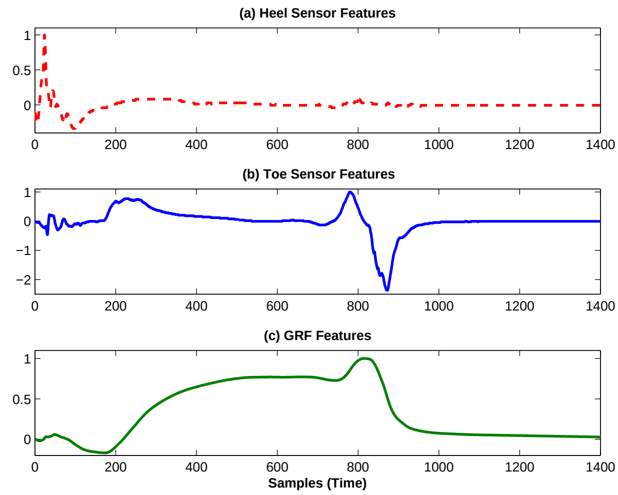

Fig. 3 Holistic features used. (a) Heel sensor features. (b) Toe sensor features. (c) GRF features.

Due to the high dimensionality of this holistic feature vector, principal component analysis (PCA) [16] 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 4 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.

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 5 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.

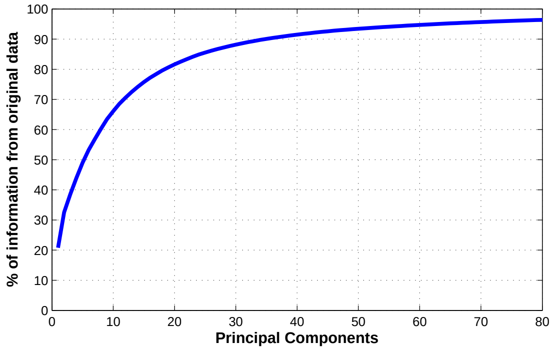

Fig. 4 Percentage of information from original data against number of principal components.

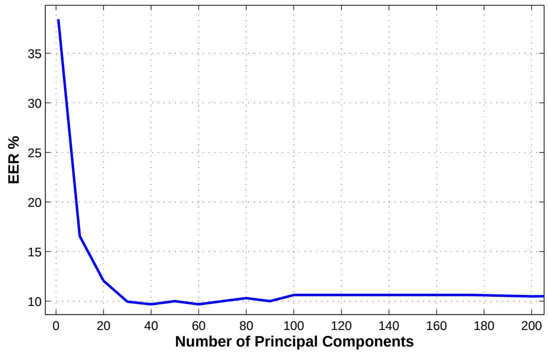

Fig. 5 EER against number of principal components for holistic approach.

4.2 Footstep recognition evaluation

In this section we present the results of the footstep recognition evaluation. Figure 6 shows the DET curves result for the development, evaluation 1 and evaluation 2 datasets for the case of geometric and holistic features. It is observed that holistic features outperform geometric features in all cases. For the development set, EERs of 12.5% and 9.5% were achieved for the geometric and holistic features respectively as stated above. These are the best results as could be expected as the optimisation of the features has been carried out for the development set.

The purpose of the evaluation set is to test the footstep recognition system with new unseen data. For this experiment, all the parameters learnt from the development set like the PCA, scaling and normalising coefficients are applied to the evaluation sets. For evaluation set 1, an EER of 19% is achieved for geometric features. This contrasts with an EER of 15% obtained when the holistic features are applied to the same classifier, having a relative improvement of 21%. For evaluation set 2 the same trend is observed. An EER of 18.5% is achieved for geometric features compare to an EER of 13.5% for holistic, what equates to a relative improvement of 27%. It is observed that the DET curves for evaluation set 2 have a better performance than for evaluation 1 in general, this is because as it was stated in [2] more data was used to train the models as is illustrated in Table 2.

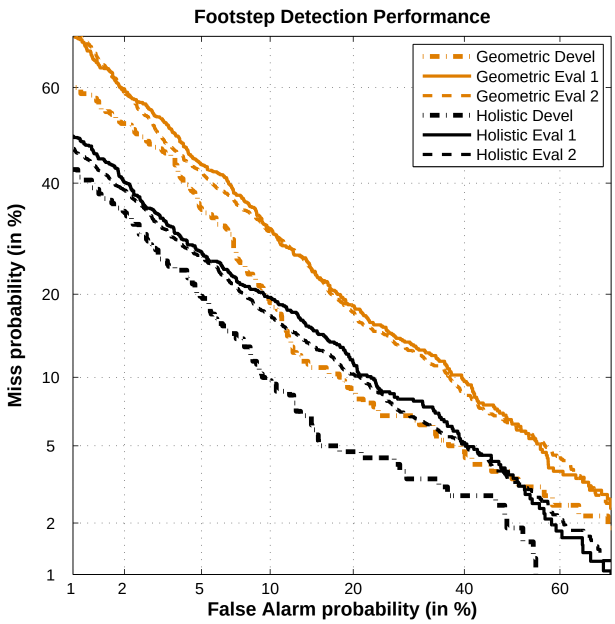

Fig. 6 DET curves for geometric and holistic features for development set and evaluation set 1 and 2.

It is worth noting that results achieved with the optimization of the geometric features are better than the results obtained in [2]. Only results for the evaluation sets with holistic features are marginally worse. This is due to previously published work used both train and test data to evaluate the PCA. This makes the new experiments more realistic and statistically meaningful.

5 Current work

Currently we are in the process of collecting a new database. We have developed a new footstep capture system which is comprised of two sensor mats each containing 88 piezoeletric sensors. The system captures two consecutive footstep signals, as illustrated in Figure 7, and uses a sampling frequency of 1.6 kHz.

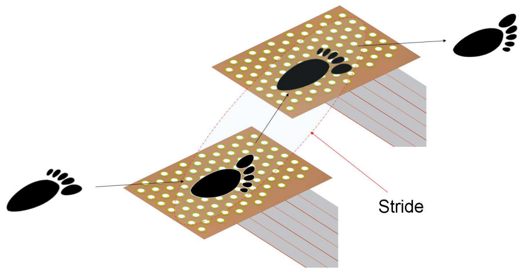

Fig. 7 Spatial distribution of the piezoeletric sensors.

Figure 8 shows a screenshot of the footstep capture system user interface. A distribution of the sensors activated by an example footstep stride is illustrated in the middle of the figure. Below that is the microphone output corresponding to the 4-digit ID which is post-processed by the automatic speech recognition system for labelling purposes. The images to the right show frames from the videos that are captured during the footstep data collection. The top image shows the face and the bottom image shows the gait.

For the moment we have collected footstep data from more than 100 people. Data is collected in different sessions and with different conditions, namely with different footwear, including a barefoot condition, when the person carries a load (to examine weight variability effects), and also when they walk at different speeds. This will allow us to study, for the first time, how these conditions affect the performance of person verification using their footsteps.

The high sensor density of the new footstep capture system allows us to extract more information from the footstep signals compared to our previous capture system. Figure 9(a) shows a typical footstep signal in the time domain. In the order of 15 sensors are active for each footstep thus giving a much more detailed account of the footstep dynamics. It is possible to create a 3D image of the footstep signals using the signals captured by the new system and an example is illustrated in Figure 9(b). This gives us a more readily interpretable illustration of the footstep dynamics and illustrates how persons distribute their weight on the floor.

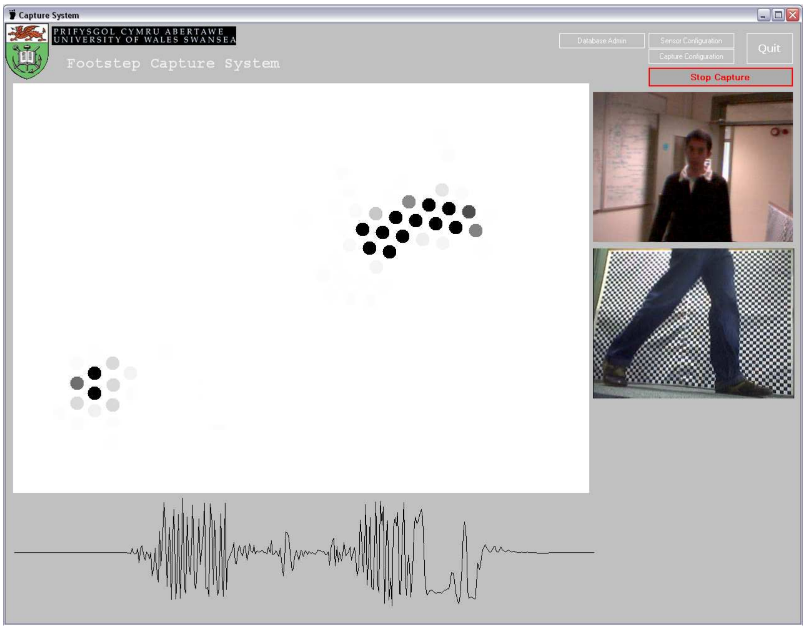

Fig. 8 Screenshot of the footstep capture system software.

A significant feature of the new system is the ability to capture two consecutive footsteps, i.e. stride data. The stride data allows the study of the differences between the right and left footsteps, as well as velocity, and angle between the feet, i.e. new features which have the potential to improve the discrimination of persons using their footsteps. These aspects are currently under investigation.

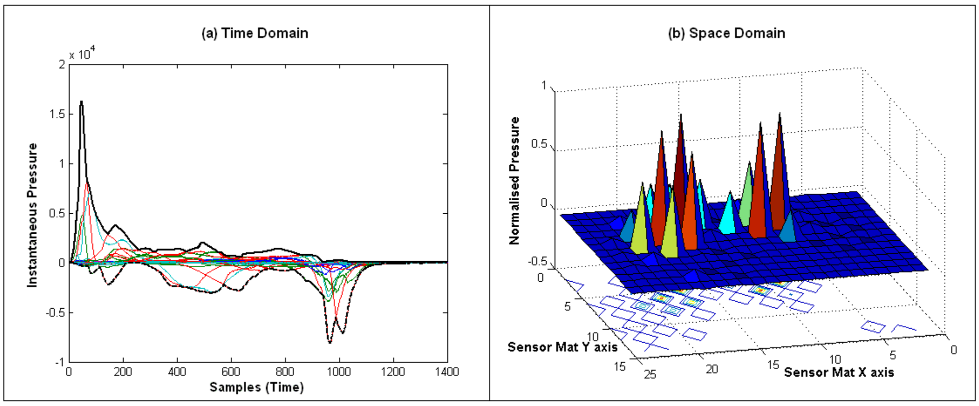

Fig. 9 New possibilities on feature extraction. (a)Time domain profiles. (b) A 3D representation of the footstep signal in the space domain

6 Conclusions

This paper describes a semi-automatic system for capturing footsteps. A database comprised of more than 3000 footsteps has been gathered, allowing 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 report an optimization of the two feature extraction approaches. Interestingly, holistic features show better performance with a relative improvement of around 27% in terms of EER compare to geometric features.

Finally a new footstep capture system has been presented. The new system has a high density of piezoelectric sensors. This facilitates the study of new footstep and stride-related features. The new database will also allow us to better investigate session variability and to study how different factors such as shoes, carried loads and speed affect recognition performance.

7 Acknowledgements

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References

1. S.U.: Footstep recognition at Swansea Universtity available at. http://eeswan.swan.ac.uk
2. Vera-Rodriguez, R., Evans, N.W.D., Lewis, R.P., Fauve, B., Mason, J.S.D.: An experimental study on the feasibility of footsteps as a biometric. In: Proceedings of 15th European Signal Processing Conference (EUSIPCO'07), Poznan, Poland (2007) 748–752
3. Addlesee, M.D., Jones, A., Livesey, F., Samaria, F.: The ORL Active Floor. IEEE Personal Communications. **4** (1997) 235–241
4. Orr, R.J., Abowd, G.D.: The Smart Floor: A Mechanism for Natural User Identification and Tracking. In: Proceedings of Conference on Human Factors in Computing Systems. (2000)
5. Cattin, C.: Biometric Authentication System Using Human Gait. Swiss Federal Institute of Technology, Zurich. PhD Thesis. (2002)
6. Yun, J.S., Lee, S.H., Woo, W.T., Ryu, J.H.: The User Identification System Using Walking Pattern over the ubiFloor. In: Proceedings of International Conference on Control, Automation, and Systems. (2003) 1046–1050

7. Suutala, J., Roning, J.: Combining classifiers with different footstep feature sets and multiple samples for person identification. In: Proceedings of International Conference on Acoustics, Speech, and Signal Processing (ICASSP). Volume 5. (2005) 357–360
8. Middleton, L., Buss, A.A., Bazin, A.I., Nixon, M.S.: A floor sensor system for gait recognition. In: Proceedings of Fourth IEEE Workshop on Automatic Identification Advanced Technologies (AutoID'05). (2005) 171–176
9. Gao, Y., Brennan, M.J., Mace, B.R., Muggleton, J.M.: Person recognition by measuring the ground reaction force due to a footstep. In: Proceedings of 9th International Conference on Recent Advances in Structural Dynamics. (2006)
10. Suutala, J., Roning, J.: Towards the adaptive identification of walkers: automated feature selection of footsteps using distinction-sensitive LVQ. In: Proceedings of International Workshop on Processing Sensory Information for Proactive Systems. (2004) 61–67
11. NIST: Speaker recognition evalutaion website. http://www.nist.gov/speech/tests/spk/index.htm
12. Vapnik, V.N.: Statistical Learning Theory. Wiley.
13. Burges, C.J.C.: A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery. Springer. **2**(2) (1998) 1–47
14. Martin, A., Doddington, G., Kamm, T., Ordowski, M., Przybocki, M.: The DET curve in assessment of detection task performance. In: Eurospeech. Volume 1. (1997) 1895–1898
15. NIST: Det-curve software for use with matlab. Available at http://www.nist.gov/speech/tools
16. Jolliffe, I.T.: Principal Component Analysis. Springer Series in Statistics. (2002)