Footstep Recognition

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Synonyms

Footstep identification; Footstep verification

Definition

Footstep recognition is a relatively new biometric and is based on the study of footstep signals captured from persons walking over an instrumented sensing area. Since the biometric information is embedded in a time varying signal, thereby implying some form of action (in this case those of walking or running for example), footsteps can be included in the group of behavioural biometrics.

Main Body Text

Introduction

Footstep recognition was first suggested as a biometric in 1977 by Pedotti [1], but it was not until 1997 when Addlesee *et al.* [2] reported the first experiments. Since then the subject has received relatively little attention in the literature and so it is perhaps of little surprise that reported performances fall short of those achievable with other, more popular and researched biometrics. However, recent work has demonstrated the real potential of the footstep biometric which is certainly not without its appeal.

One significant benefit of footsteps over other, better known biometrics is that footstep signals can be collected covertly with minimal client cooperation. Other benefits lie in the robustness to environmental noise (a limiting aspect of speaker recognition) or lighting variability (as in the case of face recognition). There is, however, a number of new challenges to be addressed. Footsteps can exhibit a high degree of intra-class variability, i.e. different footwear, persons carrying heavy baggage and different walking speeds, all extraneous factors which make footstep recognition an extremely challenging task.

In addressing these difficulties among others, researchers have investigated footstep signals using different sensor approaches. Systems reported in the literature include the extraction of footstep positions using video cameras, acoustic-based approaches which capture the sound of footsteps [3] and, by far the most common, under-floor contact or tactile-based sensors. These approaches range from simple ON/OFF sensors that indicate the position of the footstep [4, 5, 6, 7] to more sophisticated sensors that capture transient pressure [1, 2, 8, 9, 10, 11, 12, 13]. Pressure sensors generally measure the ground reaction force (**GRF**). An example GRF profile for a single footstep signal captured from the sensor approach reported in [13] is shown in Fig. 1. Generally there are two peaks to the GRF profile, the first peak is attributable to the heel strike and the second to the toe push-off as the body is propelled forward. Fig. 1 also illustrates some of the most common geometric features (maximum, minimum and mean values) as used in the works of [9, 12, 14] for subsequent classification.

Reported performances vary widely. The most statistically meaningful results obtained for footstep recognition with an identification protocol relate to a database comprised of 1680 footsteps from 15 persons [9]. Here an accuracy of 93% was reported. For the case of verification as a protocol, best results relate to a database comprised of 3147 footsteps from 41 persons [15]. Equal error rates (EERs) of 9.5% and 13.5% are reported for development and evaluation sets respectively. Results to date are promising and show that the use of footsteps as a biometric warrants further investigation.

The following sections present an overview of different applications of footstep signals and a review of published literature which has investigated the use of footsteps more specifically for biometrics.

Applications

It is possible to classify different biometric techniques according to the original application of the biometric signal. In the case of the fingerprint and hand geometry biometrics, signals are captured with the sole application of biometrics; whereas for speech for example the main application is communications, and biometrics can be considered a secondary application. Others biometrics such as the footsteps are in the middle of this range. A footstep is an action that can be captured for several applications. Potential uses of footstep signals in the literature include medicine, surveillance, smart homes, multimedia and biometrics, none of them dominating and therefore this overview presents the entire spectrum.

In the field of medicine, footstep signals have been used to analyse different gait deficiencies by comparing normal and pathological patterns of footstep pressure signals. Following early work on biomechanics, in 1977 Pedotti [1] studied the three orthogonal components of the GRF signal using a square force plate with four piezoelectric transducers placed in the corners, similar to other systems used later for biometrics [2, 9, 10, 12]. He studied visually around 4500 footsteps from 65 normal and 165 pathological subjects and observed stride symmetry between the left and the right feet for normal subjects but not for pathological subjects; furthermore, Pedotti noted low intra-person variability, leading to one of the first suggestions to the use of footsteps as a biometric. Commercial products today provide high resolution pressure image sequences from thin sensor mats created by printing processes. These systems are used in medicine to study for example the plantar pressure profiles, identify asymmetries between left and right feet, review dynamic weight transfer and local pressure concentrations, or identify areas of potential ulceration amongst others.

More focused on the detection of footsteps for surveillance applications, footstep signals have been used to detect human presence in a determined area. The work described in [3] reports some experiments carried out with a database comprised of five people walking ten times toward a microphone. The aim of the research was not only on footstep detection but person identification using mel-cepstrum analysis. Other work reported in [16] used piezoelectric accelerometers to detect impulses induced by walking. Footsteps were identified from three or more impulses where the sensor was excited at its resonant frequency, having satisfactory results in most occasions.

One particularly appealing application of footstep signals is found in the field of smart homes. In 2000 Mori *et al.* [17] developed a robotic room where multiple sensors were distributed in several locations. Footstep signals were collected from a distribution of force sensing resistors (FSRs) to specify human position in the room. A total number of 252 FSRs were installed in a 200 mm x 200 mm lattice shape. More recent work on the same floor [4] (2002) increased the spatial resolution of the sensors to a 64 x 64 switch sensor array in a 500 mm^2 space. With this higher resolution, experiments determined the positions of a human and a 4-wheeled cart and distinguished between them. In 2004 Murakita *et al.* [5] reported a system for tracking individuals over an area of 37 m^2 employing basic block sensors of 18 cm^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 [2], in 2001 Headon and Curwen [18] used the vertical component of the GRF and a hidden Markov model (HMM) classifier to recognise different movements including stepping, jumping or sitting down. Applications of such a system exist in safety (i.e. fall detection for the elderly) and entertainment (i.e. video games). More recently, in 2008 Liau *et al.* [19] developed a system which used load cells over an area of 4 m x 4 m to track people and addressed the cross-walking problem where the paths of two or more people intersect.

Footstep signals have also been used for multimedia applications. In 1997 Paradiso *et al.* [20] developed a system which he called The Magic Carpet to be used in an audio installation where users created and modified complex musical sounds and sequences as they wandered about the carpet. The sensor floor comprised a 16 x 32 grid of piezoelectric wires in an area of 1.8 m x 3 m carpet. Later in the same year, the same laboratory developed a system installing PVDF (polyvinylidene fluoride) and FSR sensors into a dancing shoe [21]. The goal was to capture many degrees of expression and use them to drive music synthesizers and computer graphics in a real-time performance. More recently, in 2005 Srinivasan *et al.* [8] developed a portable pressure sensing floor constructed of modular high resolution pressure sensing mats. A sensor mat comprised 2016 sensors made from a pressure sensitive polymer and covered an area of 62 cm x 53 cm, sampling each sensor at a frequency of 30 Hz. Initial applications of the system were to study interactive dance movement and video game controlling.

Review of Footsteps as a Biometric

It is now addressed work in the open literature which considers the use of footsteps specifically as a biometric. One of the first investigations into footstep recognition was reported by UK researchers in 1997 [2]. They reported experiments on a database of 300 footsteps signals that were captured from 15 walkers in one session. The system was comprised of four load cells measuring the vertical component of the ground reaction force (GRF) and placed on the corners of a tile working at a sampling frequency of 250 Hz. They divided the database into train and test and an identification accuracy of 91% was achieved with an HMM classifier and samples from the GRF of a single footstep signal 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 using a frequency sampling of 150 Hz. Signals were collected from both left and right feet and different footwear having 20 footsteps per condition using half of them for training and half for testing. Ten geometric features were extracted from the GRF of a single footstep signal including the mean value, the standard deviation, maxima and minima, etc. They considered each combination of user, foot and shoe type as a cluster. Then a nearest neighbour classifier was used to measure the Euclidean distance of a footstep from the test set to each cluster. An identification accuracy of 93% was reported regardless of whether the correct shoe or foot was given. In 88% of the cases, a user's footstep was more similar to other footsteps for that same user than for another user, concluding from these results that footwear does not greatly affect the ability of their approach to identify the user by his footsteps.

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 walking barefoot using a sampling frequency of 300 Hz. The database was further divided into train and test. They studied different feature extraction techniques as geometric features from GRF as [9] and phase plane (as area within the curve, position of the loop, maxima, minima, etc.). The best verification performance was achieved using the power spectral density (PSD) of the derivative GRF of footsteps signals in the band of 0-20 Hz with generalised principal component analysis (GPCA), obtaining a verification EER of 9.5% with an Euclidean distance classifier.

A Korean group reported a system in 2003 [6] that used 144 simple ON/OFF switch sensors in a total area of 1 m x 3 m. Stride data (connected footsteps) was collected from 10 persons who each one walked 50 times across the ubiFloor resulting in a database of 500 walking samples. Then the database was divided into training, validation and testing data randomly. The position of several connected footsteps was used as users walking features instead of the pressure of one footstep, as proposed in [2, 9]. An accuracy of 92% was reported with a multi-layer perceptron (MLP) neural network used as an experimental identification method.

In 2004 a group from Finland investigated footstep recognition using electro mechanical film (EMFi). Long strips of the sensor material were laid over an area covering 100 m^2. A database of around 440 footstep signals (of both feet) was collected from 11 persons at a frequency rate of 100 Hz. In their publication [11] they reported experiments with a two level learning vector quantisation (LVQ) based classifier and considered three consecutive footsteps of a person to carry out a single test. On the first level each of the three single footstep signals was classified independently, and on the second level the decisions of the three consecutive footsteps were taken into account having a final acceptance if a majority of the footsteps were classified to the same class. The recognition rate reported was 89% of accuracy with an 18% of rejection rate. In the same year they reported different experiments [14] based on the same database. Geometric features were extracted from the GRF profiles as in [9] and first FFT coefficients. Using a Distinction-Sensitive LVQ (DSLVQ) classifier for a single footstep an identification accuracy of 70% was achieved. Later in 2005, they presented experiments in [22] 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 [14], FFT of GRF with PCA, and FFT of the derivative 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 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) [7] reported trials with a system comprising 1536 sensors arranged in a 3 m x 0.5 m rectangular strip with an individual sensor area of 3 cm^2. A database of 180 signals was collected from 15 people without wearing footwear at a frequency of 22 Hz. Each person walked over the mat 12 times and in each case two complete gait cycles (4 foot falls) were captured. Three features were extracted: stride length, stride cadence and heel-to-toe ratio. An identification accuracy of 80% was reported using a nearest neighbour classifier to measure the Euclidean distance between each feature vector and the mean feature vector of the experimental population, i.e. the whole database. This work along with the early work of [6], differs from other published material in using binary signals rather than sampled waveforms and capture stride information from a short series of footfalls. Stride characteristics are also considered by [11, 22] as stated above.

In 2006 another group from Southampton [12] investigated a system similar to the work in [2, 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 in the same way as in [7].

More recently, in 2007, a research group from Swansea (UK) presented in [13, 15] experiments obtained with a database comprised of 3174 footsteps from 41 different persons in different sessions and shoes from two piezoelectric transducers sampled at a frequency of 1024 Hz. The database was further divided into independent development and evaluation datasets adopting a standard best practice evaluation strategy, and therefore, presenting more statistically meaningful results and potentially more reliable predictions of performance. The database is freely available to the research community [23]. Due to the amount of data collected, a semi-automatic footstep capture system was developed to facilitate automatic labeling and rapid manual validation. Fig. 2 shows a screenshot of the footstep capture system user interface. A microphone captured a spoken ID used for automatic speaker recognition to label the data (bottom part of Fig. 2); and two video cameras, one recording the face and the other the foot (top and bottom right part of Fig. 2 respectively), were used for manual data validation; the sensor responses are illustrated in the top left part of Fig. 2 as a function of time (horizontal axis). For feature extraction, two approaches were followed, namely geometric and holistic. The geometric approach was based on the extraction of main characteristic points of the footstep profile: the area, mean, length, maxima/minima, etc. The holistic approach was based on both sensor outputs and the GRF profile after PCA to reduce dimensionality of the data. In [13] two different classifiers, a nearest neighbour and SVM were also compared finding as expected that SVM outperforms the NN, and surprisingly holistic features outperforms the geometric features. Results of 9.5% and 11.5% EER were obtained for development and evaluation sets respectively for holistic features with an SVM classifier. Following best-practice, a formal assessment protocol was defined for the footstep recognition evaluation presented in [15]. The protocol reflects that utilised by the international NIST Speaker Recognition Evaluations. Also, an optimisation of the two feature approaches was carried out obtaining results of 9.5% EER for the development set and 13.5% EER for the evaluation set using optimised holistic features with an SVM classifier. EER given of 13.5% corresponds to 1697 errors of each class (false acceptance and false rejection) from a total number of 25143 tests. Such simple analysis allowing comparison across systems comes from adopting the task with verification. Work is continuing with a multi sensor stride capture system with the primary goal of improving confidence in the assessment of footsteps as a biometric.

Table 1 presents a comparison of this related work. 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 [13, 15] which reports results on 3147 footsteps and 41 persons. In each case, except for [7, 12], the databases are divided into training and testing sets, but none use independent development and evaluation sets, with exception of [13, 15], 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 [10, 13, 15]. Identification has the benefit of utilising the available data to a maximum but suffers from well known scalability problems in terms of the number of classes in the set. Also, it is interesting to point out that some systems present classification results for stride data (consecutive footsteps) [6, 7, 11, 14, 22] while the rest only for a single footstep [2, 9, 10, 12, 13, 15]. In [22] an identification accuracy of 79% using a single footstep as a test was improved to 92% when three consecutive footsteps were used. This equates to a relative improvement of 16%.

Summary

Footstep recognition is a relatively new biometric relative to other biometrics in terms of the research reported in the literature. As reviewed, footstep signals have been used for different applications, thus different capture systems have been developed. In the field of biometrics the same trend is observed; researchers have developed systems with different sensors, extracting different features, and with different assessment protocols. Recently, in 2007, the world's first freely available footstep database was released to the research community [23]. Of particular importance to this development is, not only the size of the database both in terms of the number of footsteps and clients, but the standard, best practice evaluation protocols that accompany the database. For the first time researchers will be able to develop and assess new approaches on a common and meaningfully-sized database. As has happened for many other biometric modalities, it is hoped that this will stimulate new interest in the footstep biometric, lower the cost of entry and provide a solid foundation for future research.

Given its current state of development the future of footstep recognition research is difficult to predict. Some obvious avenues include new features and novel normalisation approaches to reduce the effects of extraneous factors. Other possibilities include further investigation into connected footsteps, i.e. stride information, information that isn't captured by single footstep systems. This research would explore the middle ground between footsteps and gait. Gait is another biometric that finds applications in different areas such as in medicine, the sport industry and biometrics. In the biometrics context, gait aims to recognise persons from a distance using walking characteristics extracted from video recordings. In contrast, footsteps are a more controlled biometric due to the fixed, constrained sensing area. It would thus seem natural for future research to investigate the fusion of the two biometrics.

Related Entries

Gait recognition

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Definitional Entries

GRF (Ground Reaction Force)

The ground reaction force is, according to Newton's Law of Reaction, the force equal in magnitude but opposite in direction produced from the ground as the reaction to the force the body exerts on the ground. The ground reaction force is used as propulsion to initiate and control the movement, and is normally measured by force sensor plates.

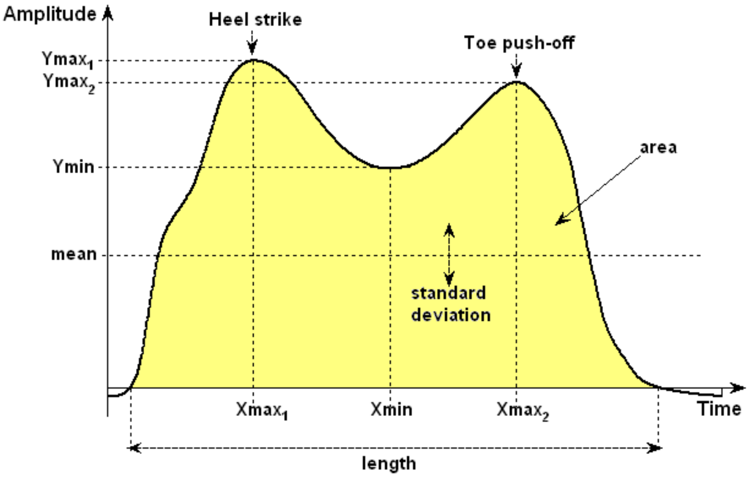
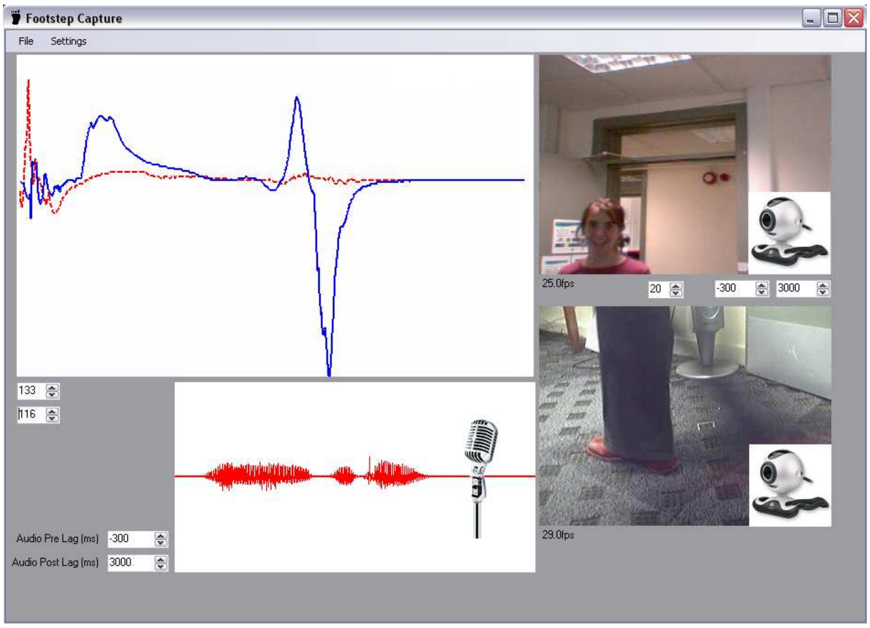


Fig. 1. Example of a GRF profile against time for a single footstep. The first peak corresponds to the heel strike and the second corresponds to the toe push-off.



Audio Pre Lag (ms) -300

Audio Post Lag (ms) 3000

Fig. 2. Screenshot of the footstep capture system software developed in [13, 15].

Group Year	Database (total steps/persons)	Technology	Features	Classifier	Results
The ORL Active Floor (UK) 1997 [2]	300 steps, 15 persons	Load cells	Sub sampled GRF	HMM	ID rate: 91%
The Smart Floor (USA) 2000 [9]	1680 steps, 15 persons	Load cells	Geometric from GRF	NN	ID rate: 93%
ETH Zurich (Switzerland) 2002 [10]	480 steps, 16 persons	Piezo force sensors	Power spectral density	Euclidean distance	Verif EER: 9.5%
Ubifloor (Korea) 2003 [6]	500 steps, 10 persons	Switch sensors	Position of several steps	MLP neural net.	ID rate: 92%
EMFi Floor (Finland) 2004 [14, 11, 22]	440 steps, 11 persons	Electro mechanical film	Geometric from GRF, and FFT	MLP neural net. and LVQ	Best ID rate [22] of 92% using 3 footsteps as test
Southampton University (UK) 2005 [7]	180 steps, 15 persons	Resistive (switch) sensors	Stride length, cadence and heel-to-toe ratio	Euclidean distance	ID rate: 80%
Southampton University (UK) 2006 [12]	400 steps, 11 persons	Load cells	Geometric from GRF	NN	ID rate: 94%
Swansea University (UK) 2007 [13, 15]	3174 steps, 41 persons	Piezoelectric sensors	Geometric and Holistic	SVM	[15] Verif EER: 9.5% for Devel, 13.5% for Eval

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