People Identification Using Gait Via Floor Pressure Sensing and Analysis

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Abstract. This paper presents an approach to people identification using gait based on floor pressure data. By using a large area high resolution pressure sensing floor, we were able to obtain 3D trajectories of the center of foot pressures over a footstep which contain both the 1D pressure profile and 2D position trajectories of the COP. Based on the 3D COP trajectories a set of features are then extracted and used for people identification together with other features such as stride length and cadence. The Fisher linear discriminant is used as the classifier. Encouraging results have been obtained using the proposed method with an average recognition rate of 94% and false alarm rate of 3% using pairwise footstep data from 10 subjects.

Keywords: Pressure analysis; gait recognition; biometrics.

1 Introduction

Recognizing people using gait is an important area in biometrics with applications in homeland security, access control, and human computer interaction. While most of research for people identification using gait has been focused on computer vision based techniques, there has been research addressing gait recognition using foot pressure information, for example [1, 4, 5, 6, 8, 9, 10, 11, 12]. Orr and Abowd [8] have researched on people identification based on the pressure profile over time during a foot step on a load-cell sensor. The footstep profile features used in these approaches include the mean, the standard deviation, and the duration of the pressure profile, the overall area under the profile, and pressure value and the corresponding time of some key points such as the maximum point in the first and last halves of the profile and the minimum point between them. In these approaches, due to the nature of load-cell based pressure sensing, the spatial pressure distribution during a foot step is not measured and only the amount of pressure and the corresponding time can be used for feature extraction and people identification. Therefore, the load-cell based gait identification approaches do not take into account the spatial pressure distribution and features such as the trajectories of center of pressure (COP). On the other hand, Jung et al. [5, 6] used a mat-type pressure sensor for gait recognition based only on the 2D COP trajectory. To recognize a person based on the foot pressure measured during a gait cycle, it is important to extract both spatial features such as the trajectories of COP and footstep pressure profile features. To address this issue, in this paper we present a gait-based

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people identification method using foot pressure obtained using a pressure sensing floor. Our goal is to develop a system that can reliably identify a subject group of 5 to 20 people. The pressure sensing floor system [14, 15] we use consists of a number of pressure sensing mats from Tekscan arranged in a rectangular shape spanning a total sensing area of about 180 square feet. Each pressure sensing mat has 2016 force sensing resistor (FSR) based sensors in a resolution of over 6 sensors per square inch. By using this large area, high resolution pressure sensing floor, we extract features both from the trajectories of the COP and the pressure profile of both left and right foot steps during a gait cycle. We also use other gait features such as the stride length and cadence as features. In our approach, the Fisher linear discriminant is used as the classifier. Encouraging results have been obtained using the proposed method with an average recognition rate of 94% and false alarm rate of 3% using pair-wise footstep data from 10 subjects. Experimental results show that the proposed method achieves better or comparable performance compared to existing methods.

However, the proposed approach is still limited in a few aspects. In our research on people identification using floor pressure, we only consider the case that people walking with their shoes off. We also assume that people are walking in a straight line at a normal speed. In addition to these limitations, the proposed approach still needs to be further evaluated, e.g. by using floor pressure data collected with various walking speeds, and a large dataset with more subjects.

2 Preprocessing of Floor Pressure Data

To recognize people using gait based on floor pressure, it is necessary to first preprocess the raw pressure data obtained using the pressure sensing floor and then extract features that can be used for gait recognition. A number of tasks need to be accomplished by this preprocessing step, including pressure data clustering, tracking of the cluster centers, recognition of left and right feet, estimation of walking directions, and rectification of the COP trajectories.

2.1 Clustering and Tracking of Centers of Pressure Using Mean-Shift

The mean-shift algorithm [2] is used to cluster floor pressure data and track the center of pressure over time. Mean-shift is a repetitively shifting process to find the sample mean of a set of data samples. In our case the data samples are the 2D locations of points on the floor with active pressure readings. The mean-shift vector $M_h(x)$ at x using a kernel $G(x)$ can be found using the following equation:

$$M_h(x) \equiv \frac{\sum_{i=1}^{n} G(\frac{x_i - x}{h}) w(x_i)(x_i - x)}{\sum_{i=1}^{n} G(\frac{x_i - x}{h}) w(x_i)} \tag{1}$$

where $w(x_i)$'s are the sample weights and h is the window size for the kernel. In our experiments, the positions of pressure data points are firstly clustered through the blurring process [2] using a Gaussian kernel. The observed pressure at a point is then used as the corresponding weight for this point. Once the process has converged, the

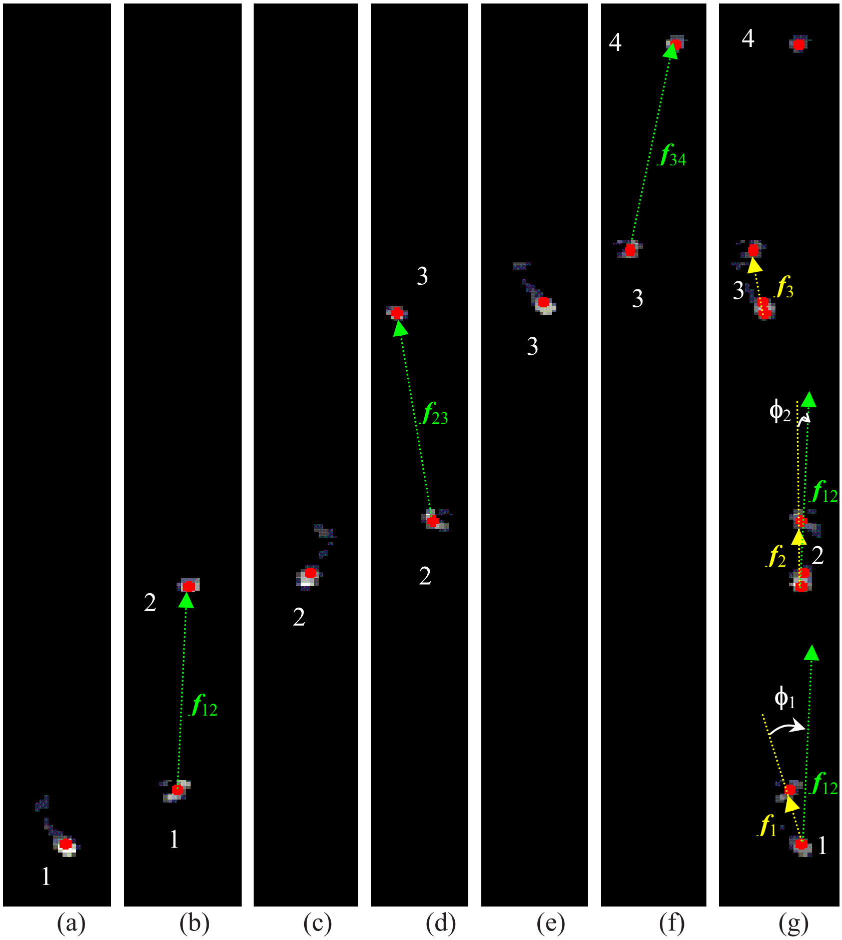

Fig. 1. Clustering and tracking results over about 1.5 gait cycles. (a) through (f) show snap shots of observed floor data and corresponding COPs (red dots) and their ID numbers (white digits). It can be seen that the IDs of the COP remain unchanged during a single footstep. The inter-foot vectors are shown by the green arrows. (g) shows overlapped floor data from (a) to (f) so that the intra-foot vectors can be visualized (the yellow arrows) properly.

data set will be tightly packed into clusters, with all of the data points located closely to the center of that cluster. The process is said to have converged either after the maximum number of iterations defined by the algorithm is reached or earlier when the mean shift of centers becomes less than the convergence threshold. After convergence, each cluster is assigned with a unique cluster ID number and every data point has a 'label' associated with corresponding cluster. For every subsequent pressure data frame, centers from the previous frame are updated through the mean shift algorithm (1) using current observed pressure values as weights and checked for convergence. In practice, entirely new data points resulting in new cluster centers can occur if there are groups of data points not assigned to any existing cluster centers. Figure 1 shows clustering and tracking results of the pressure data over about 1.5 gait cycles.

The red dots indicates the cluster centers and the white digits their ID numbers. During a *footstep*, which is defined as the period between the heel-strike and the toe-off of a foot, the COP of the foot can be correctly tracked using the mean-shift algorithm since the corresponding cluster ID is maintained. In addition, we define the *pressure related to a COP* as the sum of the pressure values of all the samples in the corresponding cluster. As a result, over a footstep, a 3D COP trajectory can be obtained, including 2D position trajectories of the COP and the pressure profile over time.

2.2 Foot Recognition

It is important to separate the left and right feet so that proper features can be extracted for people identifications. In our research, we take a simple and efficient

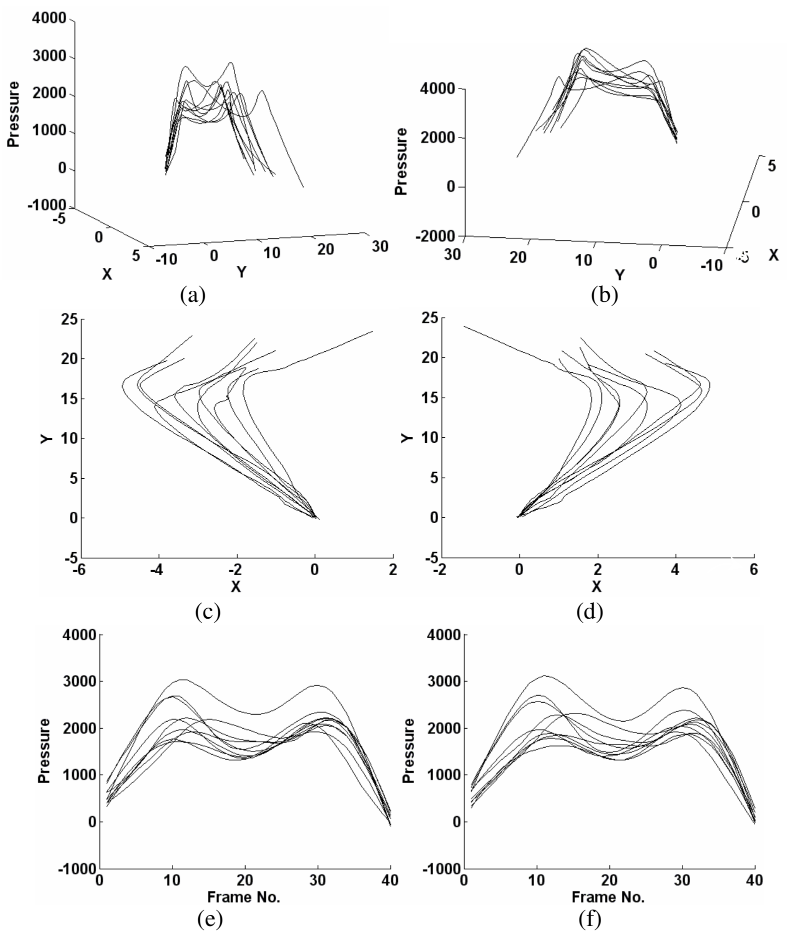

Fig. 2. Mean COP trajectories of the left (left panels) and right (right panels) footsteps using data from 10 subjects. (a) and (b) are the 3D COP trajectories including pressure and position information. (c) and (d) are the rectified 2D position COP trajectories and (e) and (f) the 1D pressure profile.

approach to foot recognition based on the COP trajectories obtained using the mean-shift algorithm. Let $C_1=\{c_1(s_1),\ldots,c_1(e_1)\}$ and $C_2=\{c_2(s_2),\ldots,c_2(e_2)\}$ be two successively detected and tracked COP trajectories over two adjacent footsteps, footstep 1 and footstep 2, where $c_1(s_1)$ and $c_1(e_1)$ represent the position of the heel-strike and toe-off of one foot, and $c_2(s_2)$ and $c_2(e_2)$ that of the other foot, and s and e are time indices. The goal is to identify which footstep corresponds to the left foot and which one to the right foot. To do that, we define two types of vectors, namely the intra-foot vectors and the inter-foot vectors. The intra-foot vectors are vectors from the heel-strike position to the toe-off position during a single footstep, for example, $\boldsymbol{f}_1=(c_1(s_1)\rightarrow c_1(e_1))$ and $\boldsymbol{f}_2=(c_2(s_2)\rightarrow c_2(e_2))$. The inter-foot vector is from the toe-off of the first footstep to the heel-strike of the second footstep. In this example, $\boldsymbol{f}_{12}=(c_1(e_1)\rightarrow c_2(s_2))$. Recall that we assume people walk in straight line.

Let $\phi_1=\angle\, \boldsymbol{f}_1\boldsymbol{f}_{12}$, and $\phi_2=\angle\, \boldsymbol{f}_2\boldsymbol{f}_{12}$ be the clockwise acute angles (possibly negative) from the intra-foot vectors to the inter-foot vector. By using $\phi_1$and ϕ_2 it is easy to separate the left foot from the right foot since when footstep 1 is the left foot, $\phi_1>\phi_2$ and vice versa. See Figure 1 for an example.

2.3 Rectification of COP Trajectories

For each foot step, a 3D COP curve can be obtained as a function over time, which consists of the 2D position trajectories and the corresponding floor pressure trajectories. After the separation of the left and right feet, the 3D COP curves of both feet spanning over a gait cycle can be obtained. At this point, the 2D position trajectories are in a global floor-centered coordinate frame. To make the COP trajectories invariant to the walking direction of the person, a rectification step is needed to rotate the COP trajectories so that the resulting trajectories are represented in a local foot-centered coordinate frame. In our research, we first estimate the walking direction as

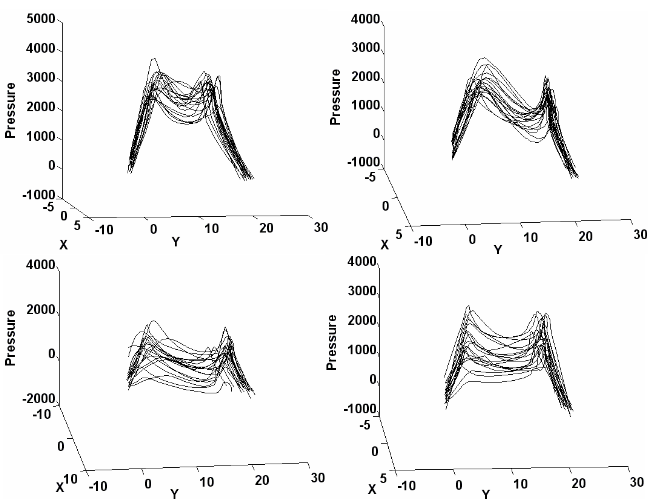

Fig. 3. Samples of the 3D COP trajectories of the left (left panels) and right footsteps from the seventh (first row) and the tenth subjects

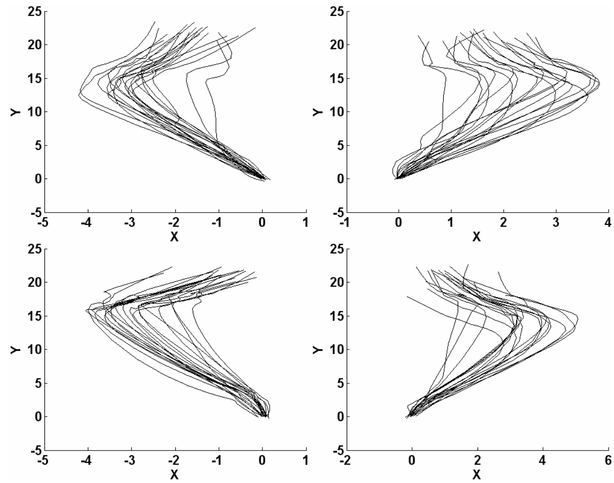

Fig. 4. Samples of the 2D COP trajectories of the left (left panels) and right footsteps from the seventh (first row) and the tenth subjects

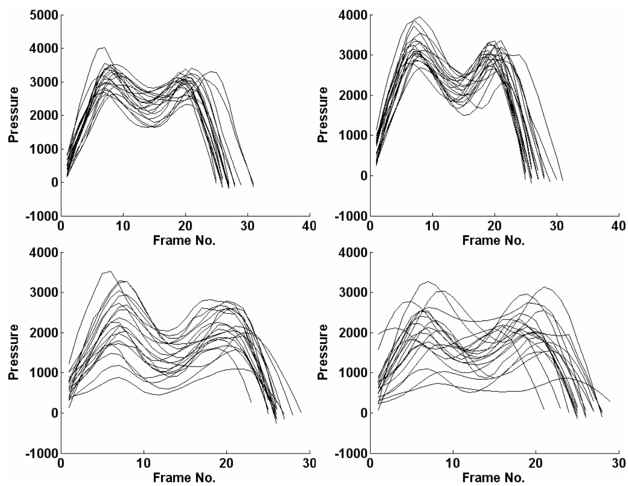

Fig. 5. Samples of the 1D pressure profiles of the left (left panels) and right footsteps from the seventh (first row) and the tenth subjects

the mean of the left and right intra-foot vectors over a single gait cycle. This walking direction is then used as the y-axis direction of the local coordinate frame and the x-axis direction is easily determined by the right-hand-rule so that the resulting z-axis (also the pressure-axis) is up. The origin of the local foot-centered frame is taken as the heel-strike point of the corresponding footstep. Figure 2 shows the mean plots of the COP and pressure trajectories of the left (a) and right (b) footsteps of 10 subjects. Panels (c) (d) and (e) (f) are the projected 2D position and 1D pressure trajectories. Figures 3 to 5 respectively show samples of the complete 3D COP and 2D position COP trajectories, and 1D pressure profiles of the left (left panels) and right footsteps

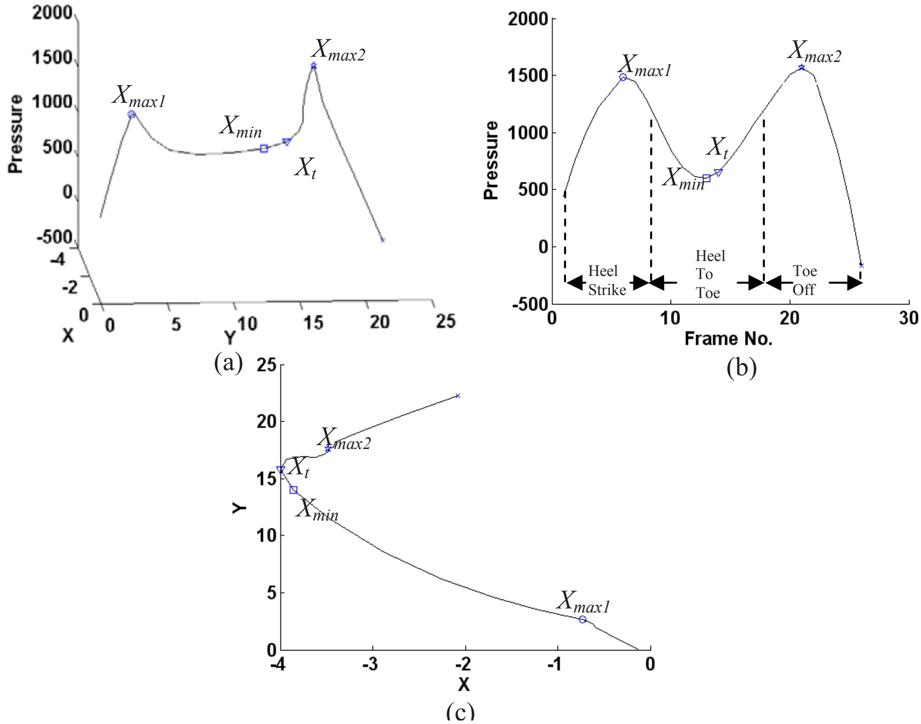

Fig. 6. A typical 3D COP trajectory of a left footstep (a), and the related 1D pressure (b) and 2D position (c) trajectories. The corresponding key points are also labeled.

from the seventh (first rows) and the tenth subjects. From these plots, it can be seen that there is certain inconsistency in the COP trajectories of the same subject from trial to trial. Meanwhile, similarity exists in the COP trajectories of the two subjects. Thus it is important to extract reliable features from the 3D COP trajectories.

3 Feature Extraction

It is obvious that the observations we have, i.e. the 3D position-pressure COP trajectories contain all the information used by existing methods, including the footstep-based approaches [8], and the 2D position COP based approaches [5, 6]. It is expected that by using the comprehensive 3D COP trajectories improved people identification results can be achieved. People identification using gait based on floor pressure is essentially a pattern classification problem, where the dynamic foot pressure distribution of a walking subject is a pattern that need to be recognized and then the subject can be identified. Such a pressure distribution pattern is reflected by the two 3D COP curves during the left and right footsteps. To tackle this classification problem, we need to extract features from the 3D COP trajectories. In our research, we first identify a set of key points along a 3D COP trajectory according to the pressure and

Table 1. Definition of key points of a footstep

Key point	Definition
Xmax1	The first dominant local maxima in the pressure trajectory
Xmax2	The second dominant local maxima in the pressure trajectory
Xmin	The local minima in the pressure trajectory between Xmax1 and Xmax2
Xt	The turning point in the 2D position COP trajectory
Xend	The end of the entire COP trajectory

position values of the COP. These key points are defined in Table 1. The key points of a typical COP trajectory of a left footstep are shown in Figure 6. Among these key points, Xmax1, Xmax2 and Xmin are also used by the footstep-based methods, e.g. [7].

Within a footstep, Xmax1 corresponds to the toe-off moment of the other foot. Xmin appears during full foot contact on the floor. Xmax2 takes place when the heel of the other foot is about to strike on the floor. Xt is defined when the absolute value of the x coordinate (orthogonal to walking direction) of COP reach maximum. Xt reflects the degree of wiggle of the subject during walking. For each key point, the corresponding position, pressure value, and curve length (measured from the start of the COP trajectory), relative frame numbers (counted from the start of the COP) can be used as features. Such key-point based features from a pair of successive (e.g. right and left) footsteps are used as a feature vector for people identification. In our experiments, we tried different feature combinations and compared their performances. In addition to these features, the sum of the mean pressure of such a pair of successive footsteps is also used as a feature that encodes the body weight of the subjects. Furthermore, stride length and stride cadence are also extracted as part of the feature set.

4 People Identification Using Fisher Linear Discriminant

Many machine learning algorithms exist that can solve supervised pattern classification problems, including the Bayesian classifiers, the k-nearest neighbors (KNN) method, the support vector machine (SVM) method, and the linear discriminant analysis (LDA) method, just to name a few. An overview of these methods can be found in a standard machine learning textbook, e.g. [3]. In our experiments, we selected the binary version of the LDA, namely, the Fisher linear discriminant (FLD) method as the classifier, due to its simplicity in training and testing. We made use of a Matlab statistic pattern recognition toolbox [13] for FLD training and testing.

An M-class classification problem can be solved by training M FLD classifiers, one for each class in a one-vs.-the-rest framework. For each FLD classifier, training data are split into an in-class sample set which has samples in the corresponding class and an out-of-class sample set with the remaining training samples of other classes. In the training of an FLD classifier, an optimal linear transformation parameterized by (W,b) needs to be found to maximize the between-class separability and to minimize the within-class variability, thus achieving maximum class discrimination. The parameters (W,b) can be found by solving a generalized eigenvalue problem. Once (W,b) are found, whether a test point x is in the class or not is based on the sign of the discriminant function $q(x)$ given by

$$q(x) = W^{T}x + b \tag{2}$$

When $q(x)$ is nonnegative, the test point is classified as an in-class data, otherwise, it is not in the class.

5 Experimental Results and Performance Analysis

5.1 Data Collection

In our experiments, we collected floor pressure data from 10 subjects, 8 men and 2 women, with an age range of 24 to 50, and the height range 165cm to 180cm. For each subject, we collected about 2-4 minutes of pressure data during normal walking. After foot recognition and COP tracking using mean-shift, 36 to 76 pairs of 3D COP trajectories are extracted from pairs of successive footsteps for each subject. In total, 529 pairs of 3D left and right foot COPs were used in training and testing.

5.2 Feature Selection

In Section 3, a number of features are introduced for people identification. Some of the features are related to the key points such as the locations, pressure values, curve lengths, and frame number of the key points, and some of them contain summarizing features of the subject's gait, such as the stride length and stride cadence. In our experiments, we tried different feature sets and compared their performances. There are a number of things we have in mind when we chose the features. The first thing is whether the feature set is invariant to walking speed. It is ideal to have a people ID system that can recognize the subject across changing walking speed. Although the current data set was collected at normal walking speeds of individual subjects, it is still valid to compare the performance of a speed-invariant feature set and that of a speed-variant feature set. The second thing we want to see is how important the pressure values are in people identification. As a result, we tested the performance of the following four sets of features.

Feature sets 1 makes use of the relative frame numbers of the key points and the stride cadence, which are tightly related to the walking speed. Therefore, FS-1 is considered to be a speed-variant feature set. FS-2 uses normalized frame numbers of the key points by the frame length of the corresponding gait cycles. Thus it is less dependent on the walking speed. However, since FS-2 includes the stride length, it is considered to be partly speed-variant. On the other hand, FS-3 removes the stride length as a feature, it is thus speed-invariant. Finally, all the pressure values are removed from FS-3 to get FS-4, which is both speed-invariant and free from using pressure values.

5.3 Cross Validation and Performance Analysis

To validate the performance of different feature sets and obtain an overall picture of the proposed approach, we ran cross-validation over the entire data set. One hundred runs were taken. For each run, a random sample set of 20 COP pairs was drawn from the data set of each subject. The remaining samples were then used as testing data set. In each run, using the same training and testing sets, the results obtained using the

Table 2. Four feature sets

Feature set ID	Key points included	Features used for each key point	Other features	Invariant to speed?	Pressure values used?
FS-1	Xmax1, Xmax2, Xmin, Xend	- rectified position, - pressure, - curve length, - relative frame no.	-stride length -stride cadence - mean pressure of both footsteps	No	Yes
FS-2	Xmax1, Xmax2, Xmin, Xend	- rectified position, - pressure, - curve length, - relative frame no. normalized by the number of frames of related gait cycle,	-stride length - mean pressure of both footsteps	somewhat	Yes
\FS-3	Xmax1, Xmax2, Xmin, Xend	- rectified position, - curve length, - pressure - relative frame no. normalized by the number of frames of related gait cycle,	- mean pressure of both footsteps	Yes	Yes
FS-4	Xmax1, Xmax2, Xmin, Xend	- rectified position, - curve length, - relative frame no. normalized by the number of frames of the related gait cycle,		Yes	No

four feature sets were compared. The recognition rate (RR) and the false alarm rate (FAR) are used to evaluate the performance of the proposed people identification method. The RR is defined as the ratio of the number of correct recognitions (NCR) and number of total in-class data (NTI). The FAR is the ratio between the number of false alarms (NFA) and the number of total out-class data (NTO).

$$RR = \frac{NCR}{NTI} \times 100\% \text{, } FAR = \frac{NFA}{NTO} \times 100\% \tag{3}$$

Figure 7 shows the resulting RR (top panel) and FAR over 100 trials using the four feature sets. The results for each trial are the average RR and FAR of the 10 subjects. It can be seen that FS-1 and FS-2 have the highest RR and lowest FAR, which is reasonable since both of them includes most of the features. This result indicates that using the normalized timestamp (i.e. frame number) of the key points has no noticeable effect on the performance. The performance of FS-3 drops compared to those of FS-1 and FS-2, which means that the stride length is a contributing feature to recognition. In addition, it is clear from Figure 7 that the FS-4 has the worst performance indicating that it is important to include pressure values as part of the feature vector.

The average performances of the proposed methods with the four feature sets for each person are presented in Tables 3 and 4. It can be seen that FS-1 and FS-2 share the same RR while FS-2 has slightly larger FAR than that of the FS-1. The performance of FS-4 is the worst among the four feature sets. While the performance of FS-3 is in the middle of the performances of feature sets 1 and 2, and FS-4.

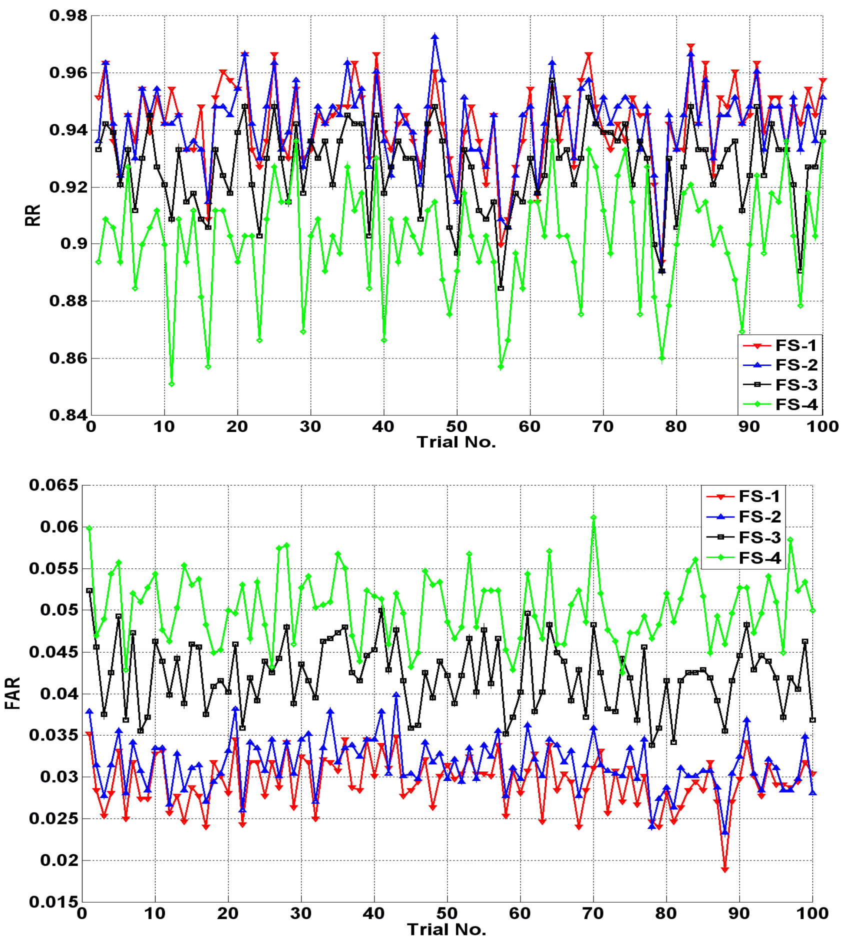

Fig. 7. The RR (top) and FAR of 100 trials using the four feature sets

In addition to the comparison among the four feature sets, we also compared the results of the proposed method to those of the existing people identification methods using floor pressure. The comparison is summarized in Table 5. It can be seen that according to the features used, existing methods can be roughly clustered into methods using only pressure profiles [1, 8, 9, 10], methods using only 2D positional COP trajectories [5, 6], and methods based on explicit gait features such as stride length, cadence [7, 11, 12]. In general, the method only using 2D COP performed the worst among all the methods. Excellent people recognition results have been reported using the pressure profile [8] and gait features [11, 12]. The features used in the proposed method explore the 3D COP trajectories which contains both the pressure profiles and the 2D positional trajectories. In addition, stride length and cadence are also used in the proposed method. Therefore, the proposed method makes use of a nearly comprehensive feature sets which include nearly all the key features of the existing methods. This is made possible by using a high-resolution pressure sensing floor and robust

Table 3. Average recognition results of FS-1 and FS-2 over 100 trials

Subject ID#	Recognition					False Alarm				
	NTI	**FS-1**		**FS-2**		NTO	**FS-1**		**FS-2**	
		NCR	*RR %*	NCR	*RR %*		NFA	*FAR %*	NFA	*FAR %*
1	26	25.9	*99.6*	25.9	*99.5*	303	3.3	*1.09*	3.21	*1.06*
2	51	46.7	*91.6*	46.7	*91.6*	278	13.5	*4.87*	17.1	*6.15*
3	56	55.3	*98.7*	55.4	*98.8*	273	7.72	*2.83*	7.12	*2.61*
4	16	15.4	*96*	15.3	*95.8*	313	5.47	*1.75*	5.51	*1.76*
5	34	31.4	*91.6*	30.8	*90.6*	295	20.8	*7.04*	21.8	*7.4*
6	44	37.7	*85.7*	38	*86.3*	285	7.37	*2.59*	7.41	*2.6*
7	22	22	*100*	22	*100*	307	1.32	*0.43*	2.2	*0.7*
8	35	33.5	*95.7*	33.5	*95.7*	294	6.54	*2.22*	8.19	*2.79*
9	25	24.7	*98.8*	24.7	*98.7*	304	5.2	*1.71*	5.07	*1.67*
10	20	17.7	*88.5*	17.8	*88.8*	309	15.9	*5.13*	15.7	*5.07*
Overall	**329**	**310**	***94.2***	**310**	***94.2***	**2961**	**87.1**	***2.94***	**93.3**	***3.15***

Table 4. Average recognition results of FS-3 and FS-4 over 100 trials

Subject ID#	Recognition					False Alarm				
	NTI	**FS-3**		**FS-4**		NTO	**FS-3**		**FS-4**	
		NCR	*RR %*	NCR	*RR %*		NFA	*FAR %*	NFA	*FAR %*
1	26	25.9	*99.6*	25.7	*99.5*	303	4.1	*1.35*	5.8	*1.91*
2	51	44.6	*87.5*	40.9	*91.6*	278	22.4	*8.04*	33.3	*12*
3	56	55.3	*98.8*	55.2	*98.8*	273	9.61	*3.52*	10.3	*3.77*
4	16	15.3	*95.8*	14.7	*95.8*	313	5.49	*1.75*	4.97	*1.59*
5	34	30.3	*89*	29.1	*90.6*	295	26.8	*9.08*	31.3	*10.6*
6	44	36.7	*83.5*	35.4	*86.3*	285	9.26	*3.25*	16.3	*5.7*
7	22	21.9	*99.8*	21.8	*100*	307	12.9	*4.21*	12.5	*4.06*
8	35	33.4	*95.5*	33	*95.7*	294	8.34	*2.84*	9.78	*3.33*
9	25	24.8	*99*	24.3	*98.7*	304	4.94	*1.63*	4.72	*1.55*
10	20	16.6	*83.2*	16.7	*88.8*	309	21	*6.8*	20.2	*6.52*
Overall	**329**	**305**	***92.7***	**297**	***90.2***	**2961**	**125**	***4.21***	**149**	***5.03***

pressure clustering and tracking algorithm using mean-shift. At a result, the performance of the proposed approach is superior to nearly all the existing methods. Furthermore, the proposed method achieved top performances compared to the existing methods. None of the results of the existing methods was based on cross-validation as what we have done in our research. Hence it is not clear whether the reported recognition results of the existing methods were based on results of a number of trials or just one trial. The performance of an algorithm can vary by different selection of training and testing data set. In the second column to the right of Table 5, we have included the ranges of the RRs and FARs of our proposed methods. It can be seen that the peak RRs for FS-1 and FS-2 are equal or above 97%.

Table 5. Performance comparison of methods for people identification using floor pressure

Method	Floor sensor	Major features	Classifier	# of sub.	RR (%)	FAR (%)	Cross Validated ?	Invariant to speed?
Addlesee et al., 1997, [1]	Load-cells	Pressure profile over a footstep	HMM	15	<50	N/A	No	Possible
Jung, et al., 2003, [5]	Pressure mats	2D trajectories of COP	HMM	8	64	5.8	No	Possible
Pirttikangas et al., 2003, [9]	Pressure floor	Pressure profile over the entire floor during walking	HMM	3	76.9	11.6	No	Possible
Pirttikangas et al., 2003, [10]	Same as [9]	Same as the above [9]	Learning VQ	11	<78	N/A	No	Possible
Jung, et al., 2004, [6]	Pressure mats	2D positional trajectories of COP	HMM-NN	11	79.6	2.05	No	Possible
Middleton et al., 2005, [7]	Force sensitive resistor (FSR) mats	Stride length, stride cadence, heel-to-toe ratio	N/A	15	80	N/A	No	No
Yun et al., 2003, [12]	Floor w/ on/off switch sensors,	Compensated foot centers over **5** consecutive footsteps	NN	10	92.8	N/A	No	No
Orr et al., 2000, [8]	Load-cells	Key points from pressure profile	KNN	15	93	N/A	No	No
Yoon et al., 2005, [11]	Floor w/ on/off switch sensors,	Compensated foot centers and heel-strike and toe-off time over **5** consecutive footsteps	NN	10	96.2	N/A	No	No
Proposed-FS-1	**FSR mats**	**See Table 2**	**FLD**	**10**	**94.2**	**2.94**	**Yes RR: 89.4-97 FAR:1.89-3.5**	**No**
Proposed-FS-2	**FSR mats**	**See Table 2**	**FLD**	**10**	**94.2**	**3.15**	**Yes RR:89.1-97.2 FAR:2.33-4**	**Possible**
Proposed-FS-3	**FSR mats**	**See Table 2**	**FLD**	**10**	**92.7**	**4.21**	**Yes RR:88.5-95.7 FAR:3.38-5.2**	**Yes**
Proposed-FS-4	**FSR mats**	**See Table 2**	**FLD**	**10**	**90.2**	**5.03**	**Yes RR:85.1-93.6 FAR:4.26-6.1**	**Yes**

Yoon et al. reported (non cross-validated) results [11] that seems to be better than ours (average after cross-validation). A close look reveals that this might not be the case. The system in [11] was restricted in the sense that a subject has to walk along a floor strip in a fixed direction at a normal speed. Furthermore the subject needs to walk on the floor for at least five steps. Features over five steps are concatenated to form a large feature vector for recognition. In contrast, our proposed method can recognize people walking in any direction. Once a pair of successive footsteps is captured, recognition can be conducted. If our approach were given data from five consecutive footsteps to recognize a person, the recognition rate can be much higher. Five pairs of left and right COP trajectories can be extracted from five steps. Assume that a person is recognized only when three or more pairs are correctly recognized. Let P=0.927 be the current recognition rate (FS-3) using a single COP pair of the proposed approach. If we treat the five pairs of data to be independent, the probability that the subject can be correctly recognized using five pairs of COPs can be computed as P5=C53 P3(1-P)2 + C54 P4(1-P) + C55 P5 = 0.9965. Similarly the FAR can be computed in this case as 0.06%. However, the independency of the five left-right COP trajectory pairs is not true. Thus, in practice, the recognition rate of a subject using data from five steps can be lower than P5. On the other hand, intuitively using more data will improve the performance. Thus we expect the recognition rate of our approach using data from five steps will be somewhere between P and P5. More experiments need to be carried out to further compare the recognition performance of our approach and that reported in [11].

In addition, our proposed method takes into considerations of the speed-invariance, which can possibly recognize people at different walking speed. Another advantage of our proposed method is that it uses Fisher linear discriminant, which is a much more computationally efficient method than those used by existing methods such as hidden Markov models and neural networks. This makes the training and testing of the proposed method very fast. Using Matlab, it takes only 12.7 seconds to run the 100 trials with each trial including the training and testing of the four feature sets.

6 Conclusions and Future Work

A robust people identification approach using gait based on floor pressure is presented in this paper. Promising people identification results are obtained by using features extracted from the 3D COP trajectories in the pressure and position spaces. The proposed approach makes use of simple linear classifier for computational efficiency. This indicates that the features used in our approach from different people are mostly linearly separable. In the selection of the feature set, we also consider the issue of walking-speed invariance by normalizing the time stamps of the key points by the length of the corresponding gait cycle. Our experimental results show that by doing so the performance only slightly decreases. The proposed approach achieves better or comparable people recognition results compared to existing methods for people identification using floor pressure.

One of the limitations of the reported results in this paper is that it is based on a relatively small data set from 10 subjects walking in straight line without shoes in a normal walking speed. As part of our future work, we will collect more data especially those with varying walking speeds/patterns from an enlarged testing population

(~20 people) to further test the performance of the proposed method in these scenarios. Furthermore, we will evaluate the system performance by using more foot steps to better compare the proposed approach to that in [11].

Pressure sensors have been integrated with other sensors including tile angle sensor, gyroscope, bend sensor, and accelerometer for people identification using gait [4]. Excellent people identification results have been reported in [4] based on a testing population of 9 subjects. The approach proposed in [4] makes use of pressure sensors of low spatial resolution. Another research direction we will pursue in the future is to integrate the high resolution pressure sensing floor with other sensors such as those used in [4] to further improve people identification using gait e.g. by increasing the size of testing population that the system can reliably recognize.

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