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Recognising humans by gait via parametric canonical space

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Abstract

Based on principal component analysis (PCA), eigenspace transformation (EST) was demonstrated to be a potent metric in automatic face recognition and gait analysis by template matching, but without using data analysis to increase classification capability. Gait is a new biometric aimed to recognise subjects by the way they walk. In this article, we propose a new approach which combines canonical space transformation (CST) based on Canonical Analysis (CA), with EST for feature extraction. This method can be used to reduce data dimensionality and to optimise the class separability of different gait classes simultaneously. Each image template is projected from the high-dimensional image space to a low-dimensional canonical space. Using template matching, recognition of human gait becomes much more accurate and robust in this new space. Experimental results on a small database show how subjects can be recognised with 100% accuracy by their gait, using this method.

Keywords: Principal component analysis; Eigenspace; Canonical analysis; Gait recognition; Template matching

1. Introduction

Biometrics are methods to automatically recognise a person based on a physiological or behavioural characteristic. Examples of human traits used currently for biometric recognition include fingerprints, speech, face, handwritten signature. Face recognition has already been used in numerous commercial and law enforcement applications. Gait is a new biometric aimed to recognise subjects by the way they walk.

The earliest approach to recognising people by their gait was proposed by Cutting and Kozlowski [1] in early 1970s. They used retroreflective material wrapped around walker's joints. Viewers recognised their friends from the video-taped images. Recently, Niyogi and Adelson [2] distinguished different walkers by extracting their spatio-temporal gait patterns obtained from the curve-fitting by ''snakes'' [3]. Cunado et al. [4] proposed a technique which considers the legs as an interlinked penduli and uses phase-weighted Fourier magnitude spectra as the feature to recognise different subjects. Little and Boyd [5] extracted frequency and phase features from the computation of optical flow to recognise different people by their gait. However, these feature-based methods, which used boundaries, lines, edges or optical flow are dependent on the reliability of the feature extraction process. Murase and Sakai [6] proposed a template matching method which used the parametric eigenspace representation applied for face recognition [7,8] to recognise different human gait. This can be applied to various object sets, and is robust to relatively clean environments. Based on principal component analysis (PCA), *eigenspace transformation* (EST) has actually been demonstrated to be a potent metric in automatic face recognition and gait analysis, but without using data analysis to increase classification capability.

Since early 1960s [9], automatic face recognition has been investigated and conducted on various aspects in psychophysics, neurosciences and engineering over the past 20 years. Two survey papers by Samal and Iyengar [10], and Chellappa et al. [11] discussed a variety of approaches ranging from Karhunen–Loève expansion [7,8], feature matching [12,13], and neural networks [14] in face recognition, using different sources such as video, profile and range imaginary. Face image representations based on PCA have been used successfully for various face recognition [7,8]. However, computed from the global covariance matrix of the full set of image data, PCA is not sensitive to class structure in the data. In order to increase the discriminatory power of various facial features, Etemad and Chellappa [15] adopted linear discriminant analysis (LDA), also called canonical analysis (CA), which can be used to optimise the class separability of different face classes and improve the classification performance. The features are obtained by maximising between-class and

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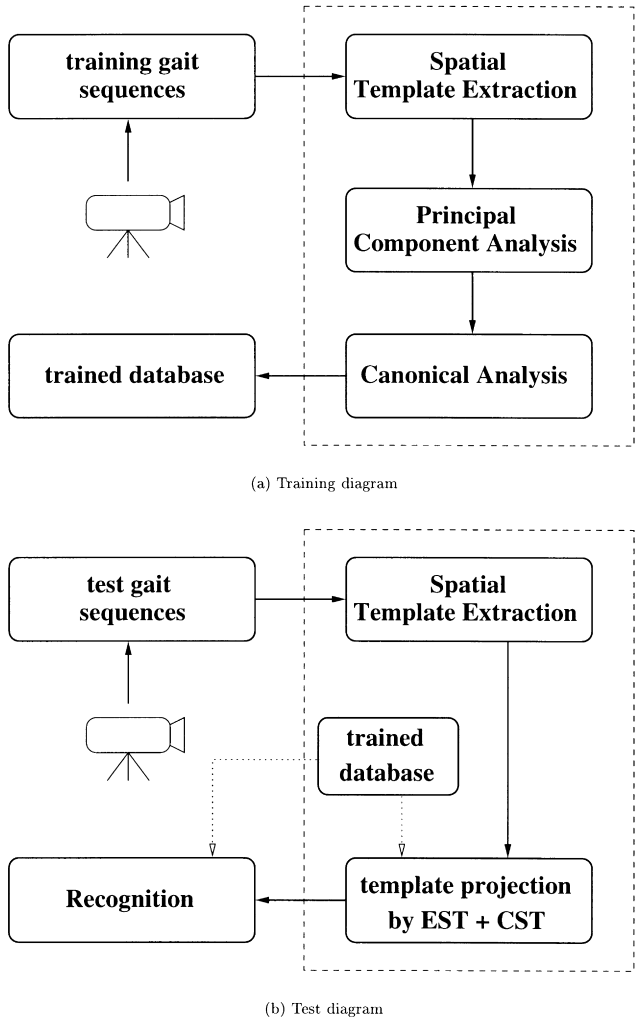


Fig. 1. Block diagrams of training and test.

minimising within-class variations. Unfortunately, this approach has high computation cost. Hence, it can only be tested with small images. Moreover, the within-class covariance matrix obtained via CA alone may be singular. In this article, we call this approach the *canonical space transformation* (CST).

Based on the hypothesis that to recognise different gait by human vision depends on the spatial changes of human body, we choose the method of template matching for gait recognition. In this article, we propose an approach which combines EST with CST for feature extraction from each image template. This method can reduce the data dimensionality and optimise the class separability of different gait sequences simultaneously. Each image template is projected from the high-dimensional image space to a low-dimensional canonical space. Using template matching, recognition of human gait becomes much more accurate and robust in this new space. Similar approaches have also been successfully used in image retrieval from a database [16] and face recognition [17]. Fig. 1 gives an overview of our gait recognition system for the steps in training and test procedures. Fig. 1(a) describes the steps in the training procedure and Fig. 1(b) shows how to recognise a gait sequence in the test procedure. The block of template projection in Fig. 1(b) is shown in Fig. 2. Details will be explained in the following sections.

Basically, this article is organised as follows. In Section 2 we describe the basic theories of our approach and how to project each template into the canonical space by EST and CST. In Section 3 we show how spatial templates are extracted from a gait sequence. Then, Section 4 shows experimental results for gait recognition using EST and CST. The comparison of the EST approach, the frequency approach of Little and Boyd and our combined approach is also shown here. Results are also discussed in this section, prior to conclusions in Section 5.

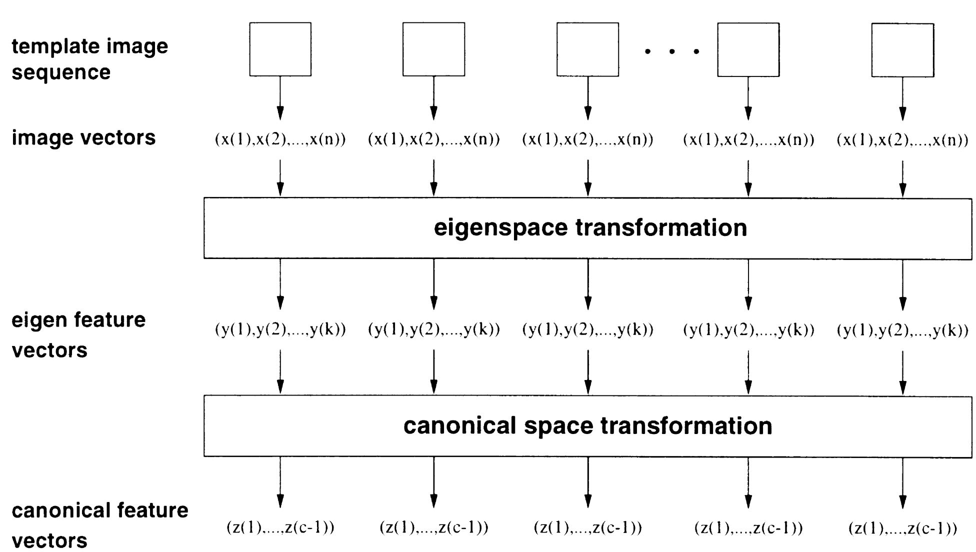


Fig. 2. Template projection by EST + CST.

2. Method

In a nutshell, we combine two transformations—EST based on PCA and CST based on CA for dimensionality reduction and class separation. Image templates in the high-dimensional image space are converted to a low-dimensional eigenspace using EST. After this, the vector thus obtained is further projected to a canonical space using CST and recognition is accomplished in the canonical space. Fig. 2 illustrates the projection steps that generate feature vectors by EST and CST. Each individual image template is transformed to an one-dimensional canonical vector. Patently, the reduced dimensionality results in concomitant decrease in computation cost.

Assume that there are c training classes to be learned. Each class represents a walking sequence of a single person. $\mathbf{x}'_{i,j}$ is the jth image in class i, and N_i is the number of images in ith class. The total number of training images is $N_{\mathrm{T}} = N_1 + N_2 + \cdots + N_c$. This training set is represented by

$$[\mathbf{x}'_{1,1}, \ldots, \mathbf{x}'_{1,N_1}, \mathbf{x}'_{2,1}, \ldots, \mathbf{x}'_{c,N_c}], \tag{1}$$

where each sample $\mathbf{x}'_{i,j}$ is an image with n pixels.

At first, the brightness of each sample image is normalised by

$$\mathbf{x}_{i,j} = \frac{\mathbf{x}'_{i,j}}{\|\mathbf{x}'_{i,j}\|}. \tag{2}$$

After normalisation, the mean pixel value for the full image set is given by

$$\mathbf{m}_{\mathbf{x}} = \frac{1}{N_{\mathrm{T}}} \sum_{i=1}^{c} \sum_{j=1}^{N_i} \mathbf{x}_{i,j}. \tag{3}$$

By subtracting the mean from each image, the image set can be described by a $n \times N_T$ matrix $\mathbf{X}$, with each corrected image $\boldsymbol{\Psi}_i$, $i = 1, \ldots, N_{\mathrm{T}}$, forming one column of $\mathbf{X}$, that is

$$\mathbf{X} = [\mathbf{x}_{1,1} - \mathbf{m}_{\mathbf{x}}, \ldots, \mathbf{x}_{1,N_1} - \mathbf{m}_{\mathbf{x}}, \ldots, \mathbf{x}_{c,N_c} - \mathbf{m}_{\mathbf{x}}]$$

$$= [\boldsymbol{\Psi}_1, \ldots, \boldsymbol{\Psi}_{N_1}, \boldsymbol{\Psi}_{N_1+1}, \ldots, \boldsymbol{\Psi}_{N_{\mathrm{T}}}]. \tag{4}$$

2.1. Eigenspace transformation

EST is widely used in face recognition [7,8] and the recognition of human gait [6]. Basically it is used to reduce the dimensionality of an input space by mapping the data from a correlated high-dimensional space to an uncorrelated low-dimensional space whilst maintaining the minimum mean-square error for the information loss. EST uses the eigenvalues and eigenvectors generated by the data covariance matrix to rotate the original data coordinates along the direction of maximum variance.

If the rank of the matrix $\mathbf{XX}^{\mathrm{T}}$ is K, then the K nonzero eigenvalues of $\mathbf{XX}^{\mathrm{T}}$, $\lambda_1, \ldots, \lambda_K$, and their associated eigenvectors $\mathbf{e}_1, \ldots, \mathbf{e}_K$ satisfy the fundamental eigenvalue relationship

$$\lambda_i \mathbf{e}_i = \mathbf{R}\mathbf{e}_i, \qquad i = 1, \ldots, K, \tag{5}$$

where $\mathbf{R}$ is a square, symmetric and $n \times n$ matrix derived from $\mathbf{X}$ and its transpose $\mathbf{X}^{\mathrm{T}}$ by

$$\mathbf{R} = \mathbf{XX}^{\mathrm{T}}. \tag{6}$$

In order to solve Eq. (5), we need to calculate the eigenvalues and eigenvectors of the $n \times n$ matrix $\mathbf{XX}^{\mathrm{T}}$ which is computationally intractable for typical image sizes. Based on *singular value decomposition theory* [18], we can compute another matrix $\tilde{\mathbf{R}}$ instead, that is

$$\tilde{\mathbf{R}} = \mathbf{X}^{\mathrm{T}} X, \tag{7}$$

in which the matrix size is $N_{\mathrm{T}} \times N_{\mathrm{T}}$ that is much smaller than $n \times n$ in practical problems. Suppose the matrix $\tilde{\mathbf{R}}$ has nonzero eigenvalues $\tilde{\lambda}_1, \ldots, \tilde{\lambda}_K$ and associated eigenvectors $\tilde{\mathbf{e}}_i, \ldots, \tilde{\mathbf{e}}_K$ which are related to those in $\mathbf{R}$ by

$$\begin{cases} \lambda_i = \tilde{\lambda}_i \\ \mathbf{e}_i = \tilde{\lambda}_i^{-1/2} \mathbf{X} \tilde{\mathbf{e}}_i \end{cases}, \tag{8}$$

where $i = 1, \ldots, K$.

The K eigenvectors are used as an orthogonal basis to span a new vector space. Each image can be projected to a single point in this K-dimensional eigenspace. According to the theory of PCA [19], the image data can be approximated by taking only the $k \le K$ largest eigenvalues $|\lambda_1| \ge |\lambda_2| \ge \cdots \ge |\lambda_k|$ and their associated eigenvectors $\mathbf{e}_1, \ldots, \mathbf{e}_k$. This partial set of k eigenvectors spans an eigenspace in which $[\mathbf{y}_{1,1}, \ldots, \mathbf{y}_{c,N_c}]$ are the points in the eigenspace that are the projections of the original images $[\mathbf{x}_{1,1}, \ldots, \mathbf{x}_{c,N_c}]$ given by

$$\mathbf{y}_{i,j} = [\mathbf{e}_1, \ldots, \mathbf{e}_k]^{\mathrm{T}} \mathbf{x}_{i,j}. \tag{9}$$

We called this matrix $[\mathbf{e}_1, \ldots, \mathbf{e}_k]^{\mathrm{T}}$ *EST matrix*. After this transformation, each original image $\mathbf{x}_{i,j}$, can be approximated by the linear combination of these k eigenvectors and $\mathbf{y}_{i,j}$ is an one-dimensional vector with k elements which are their associated coefficients. We call these eigenvectors *eigengaits* in gait analysis.

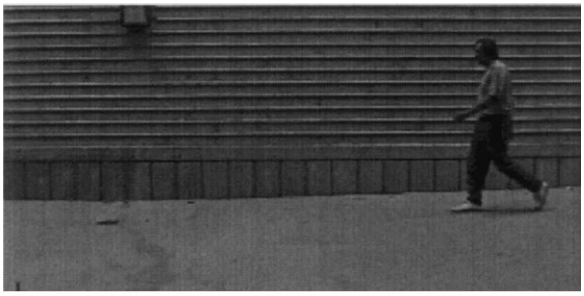
2.2. Canonical space transformation

Based on the theory of CA [19], CST is presented in the ensuing paragraphs. Suppose $\{\Phi_1, \Phi_2, \ldots, \Phi_c\}$ represents the classes of transformed vectors by EST and $\mathbf{y}_{i,j}$ is the jth vector in class i. The mean vector of the entire set is given by

$$\mathbf{m}_{\mathbf{y}} = \frac{1}{N_{\mathrm{T}}} \sum_{i=1}^{c} \sum_{j=1}^{N_i} \mathbf{y}_{i,j} \tag{10}$$

and the mean vector of the ith class is represented by

$$\mathbf{m}_i = \frac{1}{N_i} \sum_{\mathbf{y}_{i,j} \in \Phi_i} \mathbf{y}_{i,j}. \tag{11}$$



(a) Original image

(b) Background image

(c) Preprocessed image

Fig. 3. Human silhouette extraction.

Let $\mathbf{S}_\mathrm{w}$ denote *within-class matrix* and $\mathbf{S}_\mathrm{b}$ denote *between-class matrix*, then

$$\mathbf{S}_\mathrm{w} = \frac{1}{N_\mathrm{T}} \sum_{i=1}^{c} \sum_{\mathbf{y}_{i,j} \in \Phi_i} (\mathbf{y}_{i,j} - \mathbf{m}_i)(\mathbf{y}_{i,j} - \mathbf{m}_i)^\mathrm{T}, \quad (12)$$

$$\mathbf{S}_\mathrm{b} = \frac{1}{N_\mathrm{T}} \sum_{i=1}^{c} N_i (\mathbf{m}_i - \mathbf{m}_\mathbf{y})(\mathbf{m}_i - \mathbf{m}_\mathbf{y})^\mathrm{T}, \quad (13)$$

where $\mathbf{S}_\mathrm{w}$ in Eq. (12) represents the mean of within-class vectors distance and $\mathbf{S}_\mathrm{b}$ in Eq. (13) represents the mean of between-class vectors distance. The objective is to minimise $\mathbf{S}_\mathrm{w}$ and maximise $\mathbf{S}_\mathrm{b}$ simultaneously, that is to maximise the criterion function known as the *generalisd Fisher linear discriminant function* and given by

$$\mathbf{J}(\mathbf{W}) = \frac{\mathbf{W}^\mathrm{T}\mathbf{S}_\mathrm{b}W}{\mathbf{W}^\mathrm{T}\mathbf{S}_\mathrm{w}W}. \quad (14)$$

The ratio of variances in the new space is maximised by the selection of feature $\mathbf{W}$ if

$$\frac{\partial \mathbf{J}}{\partial \mathbf{W}} = \mathbf{0}. \quad (15)$$

This equation can be solved and represented as [20]

$$(\mathbf{S}_\mathrm{b} - \mathbf{J}\mathbf{S}_\mathrm{w})\mathbf{W} = \mathbf{0}. \quad (16)$$

Eq. (16) is called the *generalised eigenvalue equation* and must be solved for the unknowns $\mathbf{J}$ and $\mathbf{W}$. The first canonical axis will be in the direction of first eigenvector in $\mathbf{W}$, and $\mathbf{J(W)}$ will give the associated ratio of between-class to within-class variance along that axis. Suppose $\mathbf{W}^*$ be the optimal solution and $\mathbf{w}_i{}^*$ be its column vector which is a generalised eigenvector and corresponds to the ith largest eigenvalue λ_i. Eq. (16) can be written as

$$\mathbf{S}_\mathrm{b}\mathbf{w}_i{}^* = \lambda_i \mathbf{S}_\mathrm{w}\mathbf{w}_i{}^*. \quad (17)$$

After the *generalised eigenvalue equation* is solved, we will obtain $(c-1)$ nonzero eigenvalues and their corresponding eigenvectors $[\mathbf{v}_1, \ldots, \mathbf{v}_{c-1}]$ that create another orthogonal basis and span a $(c-1)$-dimensional canonical space. By using this basis, each point in eigenspace can be further projected to another point in this canonical space by

$$\mathbf{z}_{i,j} = [\mathbf{v}_1, \ldots, \mathbf{v}_{c-1}]^\mathrm{T}\mathbf{y}_{i,j}, \quad (18)$$

where $\mathbf{z}_{i,j}$ represents the new point and $[\mathbf{z}_{i,1}, \ldots, \mathbf{z}_{i,N_i}]$ is the new trajectory of class $i, i = 1, \ldots, c$, in canonical space. We called this orthogonal basis $[\mathbf{v}_1, \ldots, \mathbf{v}_{c-1}]^\mathrm{T}$ *CST matrix*. Following this analysis, different classes will be better separated which means that CA is useful to separate different classes of human gait even when the number of classes for different gait sequence is increased.

By merging Eqs. (9) and (18), each image can be directly projected into one point in the new $(c-1)$-dimensional space by

$$\begin{aligned}\mathbf{z}_{i,j} &= [\mathbf{v}_1, \ldots, \mathbf{v}_{c-1}]^\mathrm{T}\mathbf{y}_{i,j} \\ &= [\mathbf{v}_1, \ldots, \mathbf{v}_{c-1}]^\mathrm{T}[\mathbf{e}_1, \ldots, \mathbf{e}_k]^\mathrm{T}\mathbf{x}_{i,j} = \mathbf{H}\mathbf{x}_{i,j}, \quad (19)\end{aligned}$$

in which $\mathbf{H} = [\mathbf{v}_1, \ldots, \mathbf{v}_{c-1}]^\mathrm{T}[\mathbf{e}_1, \ldots, \mathbf{e}_k]^\mathrm{T}$. The centroid vector of each class in the canonical space can be given by

$$\mathbf{C}_i = \frac{1}{N_i} \sum_{j=1}^{N_i} \mathbf{z}_{i,j}, \quad (20)$$

where $i = 1, \ldots, c$.

3. Preprocessing

Preprocessing of image data is necessary before we can apply the EST and CST to the training database and test

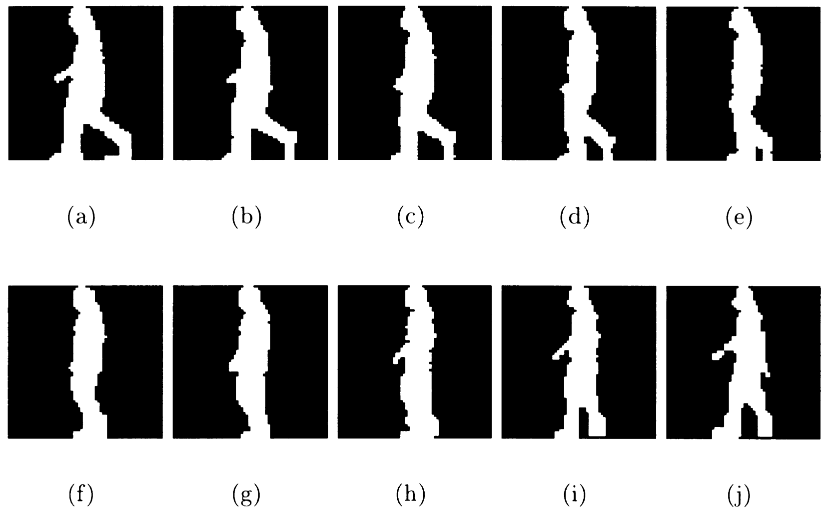


Fig. 4. Image templates of a walking person.

sequences. As mentioned earlier, the intensity of each input image must be normalised using Eq. (2). For human gait analysis, it is essential to extract the required human silhouettes by eliminating irrelevant background from each image. For human walking sequences, the preprocessing steps are described as follows.

We make two assumptions for the human walking sequences. Firstly individuals are walking laterally before a static camera, and secondly, that the body is not occluded. Naturally, to isolate the human silhouette, we can simply subtract the background from each image. To obtain an approximate background image of a walking sequence, a mean image is computed by averaging grey-level values for each pixel position over the entire image sequence. After which this mean image is subtracted from each image to extract the desired silhouette. Obviously, the difference image thus obtained is not binarized. To simplify the representation, a binary image (e.g. 0 for background and 1 for foreground) is obtained by means of region growing technique [21]. Fig. 3 shows an original human walking image in a sequence, background image and the preprocessed image.

In order to eliminate redundancies, each extracted human silhouette is fitted into a fixed 64×64 image template [6] which is illustrated in Fig. 4.

4. Experimental results

To recognise the unknown sequences, the new approach is applied to project each image template of gait sequences onto one point in the canonical space. By using different distance measures in pattern recognition, the recognition can be achieved easily in the canonical space. Experimental results of one biometric application — gait recognition, are presented here using the proposed technique for the feature extraction.

4.1. Test data

The sample human gait data came from the Visual Computing Group, University of California, San Diego [5] and had been augmented 5 subjects and 5 sequences of each to 6 subjects and 7 sequences of each. To acquire these images, a Sony Hi8 video camera was pointed at a concrete wall in a courtyard. A number of students walked in a circular path around the camera so that only one person at a time was in the camera's field of view. The original digitized 640×480 full color images were then translated to black and white, cropped and sub-sampled to a resolution of 320×160. We make two assumptions in the human walking sequences. The first is that individuals are walking laterally before a static camera, and secondly, that the body is not occluded. One walking sequence is selected from each subject as the training sequence and remaining 36 sequences serve as test sequences. Fig. 3(a) shows one sample image from a walking sequence.

4.2. Results

Let a test gait sequence be $\mathbf{g}(t)$, in which $t = 1,\ldots,T$. Before recognition, spatial templates are extracted from this test sequence and projected into a trained eigenspace and a canonical space by Eq. (19), given one vector sequence $\mathbf{k}(t)$ after EST projection and $\mathbf{h}(t)$ after CST projection by

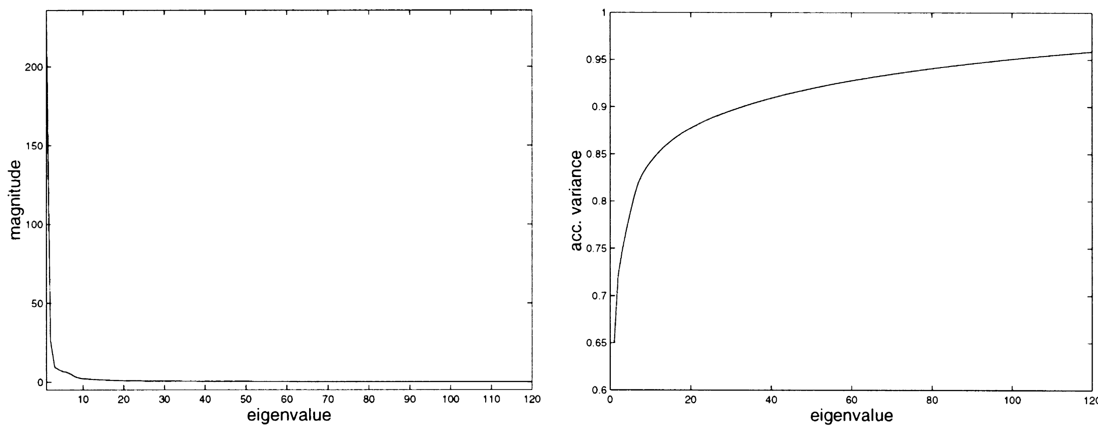
$$\mathbf{k}(t) = (u_1(t), \ldots, u_k(t))$$

and

$$\mathbf{h}(t) = (v_1(t), \ldots, v_{c-1}(t)),$$

in which k represents the number of principal eigenvectors after PCA and c depicts the number of subjects.

There are six walking sequences in our training database. Fig. 5(a) shows the magnitudes of eigenvalues in the



(a) Magnitude (b) Accumulated variance

Fig. 5. Eigenvalues in the eigenspace.

eigenspace and Fig. 5(b) represents the accumulated variance of these eigenvalues after PCA. We choose the first 110 eigenvalues which will accumulate 95% of the total signal energy and their corresponding eigenvectors as the EST matrix.

Fig. 6 shows the first six eigenvectors of 110 eigenvectors which we called *eigengaits* used to approximate each walking template in the experiments.

Fig. 8(a) shows the trajectories in the eigenspace that represent training gait sequences of six subjects projected into the eigenspace. For visualisation purposes, we only show the first three dimensions spanned by the first three principal eigenvectors in the eigenspace. From this figure, it is obvious that all the trajectories of six different subjects overlapped and their centroids are close to each other. The *spatio-temporal correlation* [6] is used here to recognise an input gait sequence in the eigenspace and is given by

$$d_e^2(i) = \min_{\delta} \sum_{t=1}^{T} \|\mathbf{k}(t) - \mathbf{y}_{i,t+\delta}\|^2, \tag{21}$$

in which δ represents the phase difference and is an integer here. To match a test sequence $\mathbf{k}(t)$ after EST to a training sequence can be accomplished by choosing i which minimises $d_e^2(i)$.

Fig. 7 shows the eigenvalues after CA and all the signal energy is represented by the accumulated variance over the first five eigenvectors. The first five eigenvectors will be used as the transformation matrix of canonical space.

Fig. 8(b) shows the trajectories in the canonical space that represent the training sequences of six subjects after projecting their transformed vectors to the canonical space. For visualisation purposes, we only show the first three dimensions spanned by the first three principal eigenvectors in the canonical space. As we can see from this figure, all the six trajectories are widely separated into six different clusters.

To recognise a gait sequence from a database in the canonical space, the *accumulated distance to each centroid* is used. This will eliminate matching problems caused by velocity changes and phase shifts. The distance between the test vector sequence, $\mathbf{h}(t)$, and training vector sequences, $\mathbf{z}_{i,j}$, is

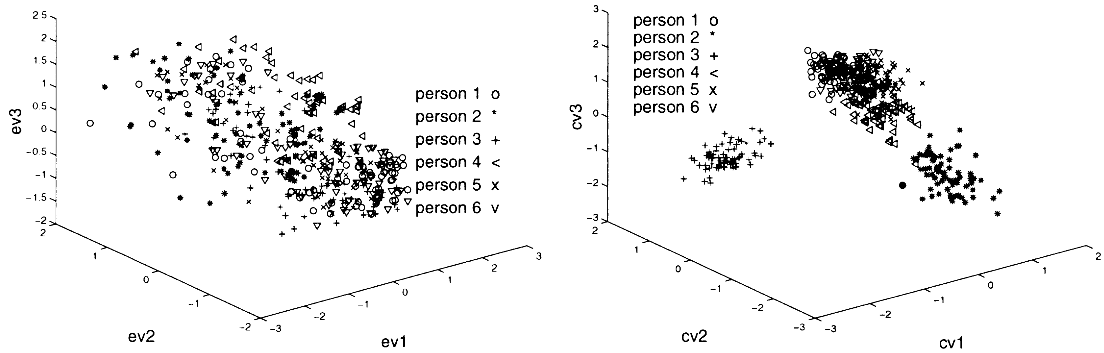
$$d_c^2(i) = \sum_{t=1}^{T} \|\mathbf{h}(t) - \mathbf{C}_i\|^2, \tag{22}$$

where $\mathbf{C}_i$ is the centroid of class i in the canonical space and $i = 1,\ldots,c$. To match a test sequence $\mathbf{h}(t)$ to a training sequence i can be accomplished by choosing the *minimum* $d_c^2(i)$.

Murase and Sakai's approach [6] is actually the EST method. Little and Boyd [5] used feature vectors generated from frequency characteristics of optical flow for gait recognition. Our approach improved EST method by combining with CST for increasing class separability. All three different

(a) $\mathbf{e}_1$ (b) $\mathbf{e}_2$ (c) $\mathbf{e}_3$ (d) $\mathbf{e}_4$ (e) $\mathbf{e}_5$ (f) $\mathbf{e}_6$

Fig. 6. The first six eigengaits.



(a) Eigenspace (b) Canonical Space

Fig. 8. Trajectories in two spaces.

approaches had applied to the same test data in this article for comparison. The comparison of three different approaches is shown in Table 1. For Little and Boyd's method [5], we selected the best performance. Clearly, the feature vectors generated by the combined EST and CST yields the best result, since the classes do not overlap and a high recognition rate can be achieved.

4.3. Discussion

We have proposed a statistical approach for feature extraction which can reduce dimensionality and increase separability of gait recognition by template matching. The promising recognition results and strong statistical evidence of variation between subjects reveal the value of template matching. The computation complexity of template matching was greatly reduced from $n^2 \times T \times c$ to $(c-1) \times T \times c$ where $n = 64$ and $c = 6$ in this article. Although there are six subjects with 42 sequences in the test data which is larger than previous data which had five subjects and 25 sequences only, we still need more data to evaluate the accuracy and robustness of our approach. In this article, we only considered the spatial changes of human silhouettes but ignored the temporal information between silhouettes. Since gait is one kind of articulated motion, an appropriate method for incorporating temporal information into spatial features is our next objective. The assumption we made about the test data is that individuals are walking laterally before a static camera. Accordingly, it appears that our approach is invariant to slight but not drastic changes of viewing angles, and we intend to investigate this further.

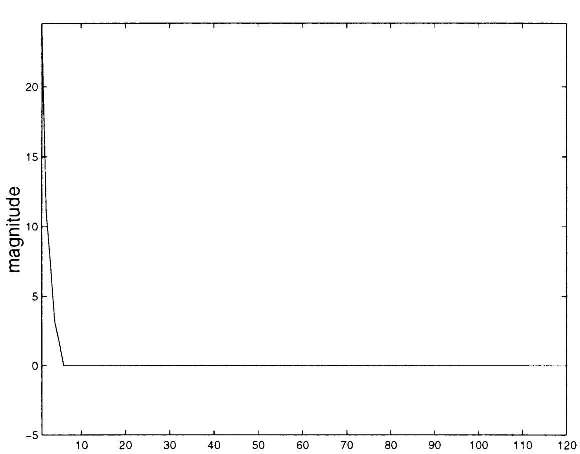


Fig. 7. Eigenvalues in the canonical space.

5. Conclusion

Gait is an emergent biometric aimed to recognise people by the way they walk. Extant approaches do not capitalise on the power of established statistical pattern recognition paradigms. In this article we propose a new approach for gait recognition via template matching by combining CST with EST to reduce data dimensionality and to optimise the class separability of different classes, simultaneously. The projection and recognition algorithms proposed are simple to implement. Experimental results show that 6 training gait sequences are transformed into six widely separated clusters in the new space. The recognition rate for 36 test gait sequences is 100%. In comparison with the results of two other independent approaches, our new approach appears to provide better results. In solving the recognition problem of human gait which is a complicated articulated-motion, template matching shows its simplicity, accuracy and robustness. As such, this article describes a potentially effective approach for gait recognition. We are currently working on extension of the test environment. In addition

Table 1
Comparison of different approaches in gait recognition

Recognition results for 36 testing sequences		
Method	Recognition rate (%)	Class separability
Murase and Sakai's	100	Overlapped
Little and Boyd's	95.2	–
EST + CST	100	Widely separated

to evaluation on a larger database, we are considering use of temporal features of human gait. Future work will also concentrate on establishing more precisely the attributes and ramifications of this work.

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