Paper:

New Fast Principal Component Analysis for Face Detection

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Principal component analysis (PCA) has different important applications, especially in pattern detection such as face detection and recognition. In real-time applications, response time must be as fast as possible. For this, we propose a new PCA implementation for fast face detection based on the cross-correlation in the frequency domain between the input image and eigenvectors (weights). Simulation results demonstrate that our proposal is faster than the conventional one, and experimental results for different images show good performance.

Keywords: fast PCA, face detection, cross correlation, frequency domain

1. Introduction

Principal component analysis (PCA), or Kahunen-Loeve expansion, is applied to find facial aspects important in identification. Facial eigenvectors or, as they are sometimes called, eigenpictures or eigenfaces, compactly represent whole faces, which is optimal for face reconstruction. Sirovich and Kirby [1, 2] first applied PCA in efficient face representation in which new coordinates are created for faces where coordinates are part of the eigenvectors of a set of face images. New faces are roughly reconstructed using only part of their projection onto new low-dimensional space. Matthew Turk and Alex Pentland [3] expanded this idea to face recognition by encoding faces using a small set of weights corresponding to their projection onto new coordinates and are recognized by comparing them to those of known individuals. Eigenfaces work well in different expression changes [22].

Improving PCA speed in face detection is required in real-time applications such as covert criminal surveillance. Here, we focus on increasing PCA speed during detection while maintaining conventional implementation (detection rate). The PCA algorithm is applied to check for a face at each pixel in the input image. This search is realized using cross-correlation in the frequency domain between the entire input image and eigenvectors. This increases detection speed over normal PCA algorithm implementation in the spatial domain.

Cross-correlation in the frequency domain is faster than in the time domain [19]. By "fast cross-correlation" we mean that cross-correlation is done in the frequency domain. Among the many applications involving fast cross-correlation are a general fast pattern detection model [7–18]; fast subimage detection involving a fast search algorithm for face/object detection using neural networks [8, 16, 17]; very fast iris detection [14]; a faster algorithm for pattern detection using image decomposition [8, 10, 14, 17]; real-time fast code detection for communication applications; a new time-delay artificial neural network [9, 23]; an interesting mathematical application [18]; an Internet application for the fast search of web pages [15]; and high-speed data processing [13].

In the previous work, neural networks were used for pattern detection speeded up by applying cross-correlation in the frequency domain between the input data and neural network weighting. Here, we apply cross-correlation in the frequency domain to increase PCA speed in face detection by reducing the number of PCA calculation steps between the input image and eigenvectors.

This paper is organized as follows: section 2 discusses PCA principles and training and detection phases. Section 3 presents fast PCA for pattern detection in fast PCA complexity, giving the speed-up ratio for pattern detection and simulation results. Section 4 presents conclusions.

2. PCA Theory

Our proposal takes advantage of face structure by proposing recognition based on information theory and encoding the most relevant information in a group of faces to best distinguish between them. Our approach transforms face images into a set of characteristic feature images (eigenfaces) forming the principle components of the initial training set of face images. Recognition involves projecting a new image into the subspace spanned by eigenfaces (face space) and classifying a face by comparing its position in face space with positions of known individuals [3]. Eigenspace representation is based on the earlier work [5] on autoassociative memory. Autoassociative memory is a special case of associative memory in which input patterns are mutually self-associated. The goal of autoassociative memory is to find values or weights for connections between input units so when a portion of an input is presented as a memory key, memory retrieves the complete pattern, filling in missing components. Kohonen [6] used faces as stimuli to demonstrate properties of autoassociative memory. Specifically, he showed that autoassociative memory acts as content-addressable memory of faces. Kohonen and Anderson et al. pointed out that using autoassociative memory to store a pattern set is equivalent to comparing the eigen decomposition of the cross-product matrix created from the set of features describing these patterns, or, in other words, principle component analysis of the pattern set. We first present the model and then the interpretation of eigenvectors as macrofeatures.

Training is done in the spatial domain as follows: Let face image $\mathbf{\Gamma}$ be two-dimensional n by an n array of intensities. An image may also be considered as a vector of dimensions $n \times n$, so a typical 20 by 20 image (as in our experiments) becomes a vector with dimension 400. The main idea of principle component analysis is to find vectors best accounting for the distribution of face images within the entire image space. These vectors determine the subspace of face images, i.e., face space. Each vector is of length $n \times n$, describes an n by n image, and is a linear combination of original face images. Because these vectors are eigenvectors of the covariance matrix corresponding to original subimages and because they are face-like in appearance, we refer to them as eigenfaces. Let a set of face images be $\mathbf{\Gamma}_1, \mathbf{\Gamma}_2, \mathbf{\Gamma}_3, \ldots, \mathbf{\Gamma}_M$. Average image $\boldsymbol{\beta}$ of the set is defined by [3]:

$$\boldsymbol{\beta} = \frac{1}{M}\sum_{t=1}^{M}\mathbf{\Gamma}_t. \qquad (1)$$

Each image differs from the average by the vector [3]:

$$\boldsymbol{\phi}_i = \mathbf{\Gamma}_i - \boldsymbol{\beta}. \qquad (2)$$

This set of very large vectors is then subject to principle component analysis, which seeks a set of M orthonormal vectors, $\mathbf{u}_t$, which best describes the data distribution. The k^{th} vector, $\mathbf{u}_k$, is chosen so [3]:

$$\lambda_k = \frac{1}{M}\sum_{t=1}^{M}(\mathbf{u}_k^T\boldsymbol{\phi}_t)^2 \qquad (3)$$

is a maximum, subject to:

$$\mathbf{u}_\ell^T\mathbf{u}_k = \delta_{\ell k} = \begin{cases} 1 & \text{if } \ell = k \\ 0 & \text{if } \ell \neq k. \end{cases} \qquad (4)$$

Vectors $\mathbf{u}_k$ are significant M eigenvectors and scalars λ_k eigenvalues of the covariance matrix

$$C = \frac{1}{M}\sum_{t=1}^{M}\boldsymbol{\phi}_t\boldsymbol{\phi}_t^T = AA^T \qquad (5)$$

where matrix $A = [\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots, \boldsymbol{\phi}_t]$. Matrix C, however, is n^2 by n^2, and determining n^2 eigenvectors and eigenvalues is difficult for typical image sizes. We need a calculationally feasible way to find these eigenvectors [3]. If the number of data points in image space is less than the dimension of space ($M < n \times n$), there are only M, rather than n^2, meaning eigenvectors. Remaining eigenvectors have associated eigenvalues of zero. We thus solve for n^2 dimensional eigenvectors by first solving for eigenvectors of an M by M matrix. Solving a 10×10 matrix rather

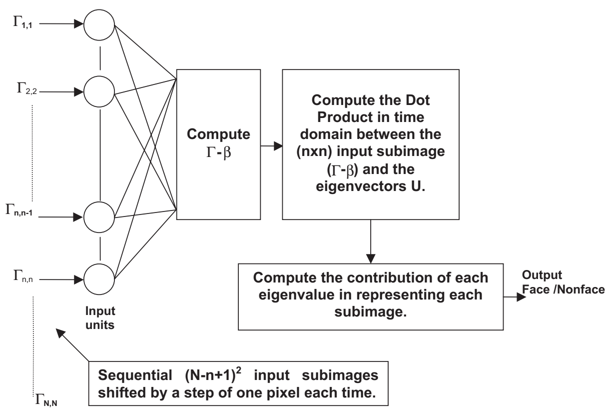

Fig. 1. Classical implementation of PCA.

than a 400×400 matrix, for example, and taking appropriate linear combinations of images $\boldsymbol{\phi}_t$ is thus feasible. Consider eigenvectors $\mathbf{v}_i$ of A^TA so [3]:

$$A^TA\mathbf{v}_i = \lambda_i\mathbf{v}_i. \qquad (6)$$

Pre-multiplying both sides by A, from the left, we have [3]:

$$AA^TA\mathbf{v}_i = \lambda_iA\mathbf{v}_i \qquad (7)$$

from which we see that $A\mathbf{v}_i$ are eigenvectors of $C = AA^T$.

Following this analysis, an M by M matrix called $L = A^TA$ is constructed and M eigenvectors $\mathbf{v}_\ell$ of L are calculated. These vectors determine the linear combination of M training set face images to form eigenspace $\mathbf{u}_\ell$ [3]:

$$\mathbf{u}_\ell = \sum_{k=1}^{M}\mathbf{v}_{\ell k}\boldsymbol{\phi}_k. \qquad (8)$$

This analysis greatly reduces calculation from the order of the number of pixels in images (n^2) to the order of the number of images in training set (M). In practice, the training set of face images is relatively small ($M \ll n^2$) and calculation is quite manageable. Associated eigenvalues enable us to rank eigenvectors based on their usefulness in characterizing variation among images [3].

In detection phase, new subimage $\mathbf{\Gamma}$ is transformed into eigenspace components w_k (projected into face space) by a simple operation [3]:

$$w_k = \mathbf{u}_k^T(\mathbf{\Gamma} - \boldsymbol{\beta}) \qquad (9)$$

for $k = 1, \ldots, M$. Average image $\boldsymbol{\beta}$ is subtracted and the reminder projected onto eigenspace $\mathbf{u}_k$. Weights form vector $\mathbf{\Omega}^T = [w_1, w_2, \ldots, w_M]$ that describes the contribution of each eigenvalue in representing the subimage, treating eigenfaces as a basic face image set. Classical implementation of PCA is shown in **Fig. 1**.

3. Fast PCA for Pattern Detection Using Cross-Correlation in the Frequency Domain

Here, we are interested in increasing the speed of detection using PCA during detection. By "Fast PCA" we