MULTIRESOLUTION EIGENFACE-COMPONENTS

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ABSTRACT

This paper presents a face recognition system that imitates the multiresolution processing technique employed by the human visual system. In the proposed system, a different degree of importance is assigned to each part of a face image, and each region of the face image is processed with a different resolution. This proposed system reduces the computational complexity of the eigenface method, and achieves higher compression ratios and higher recognition rates in comparison with the eigenface method. Experimental results are presented and discussed.

1. INTRODUCTION

It is known that the distribution of photoreceptors on the retina of the human eye is not uniform. The density of photoreceptors is greatest in the central area of the retina, where the visual acuity is at its highest, and tends to decrease proportionally with the distance from the retina centre, thereby causing a corresponding decrease in acuity. In visual perception, the central part of the retina is therefore focused on the most informative parts of an image while the lower resolution information gathered at the periphery of the retina is used to guide the eye movements [6]. For face recognition, the human visual system concentrates mostly on the eyes and mouth, since their shape and spatial relationships are unique to each person, rather than on other features.

In the case of artificial image recognition systems, multiresolution algorithms can be used to implement the search for important high resolution data [2]. The high resolution information is selectively considered depending on lower resolution processing. Therefore, only a small part of a uniform high resolution image is processed. Multiresolution search strategies depend on prior knowledge of the world.

Important advances in face recognition have employed forms of Principal Component Analysis (PCA) [1], [3], [8]-[11]. In PCA, the optimal basis is given by the eigenvectors of the correlation matrix. However, the algorithm to calculate the eigenvectors of a correlation matrix has cubic complexity. In PCA face recognition, an image is processed with uniform resolution. It is assumed that the information of different parts of the image has the same degree of importance for recognition.

This paper proposes a human face recognition system that imitates the multiresolution processing technique employed by the human visual system. In the proposed system, a different degree of importance is assigned to each part of a face image. Therefore, each region of the face image is processed with a different resolution.

The paper is organised as follows. Section 2 briefly describes the multiresolution analysis. In Section 3, an algorithm is explained for extraction of the eigenfaces from a set of training face images. Section 4 presents the proposed eigenface-components system. The experimental results are discussed in Section 5. Finally, the concluding remarks are given in Section 6.

2. MULTIRESOLUTION ANALYSIS

The theory of multiresolution analysis was originally developed by Mallat [7] to represent functions defined over $\Re^n$. In the case of images, a multiresolution pyramid computes the image approximation at a lower resolution 2^j for $j < 0$. Approximation of $f(x,y)$ at a resolution 2^j is defined as an orthogonal projection on a space V_j. This multiresolution space accepts orthogonal basis of V_j of dilated separable scaling functions

$$\{\sqrt{2^j}\Phi(2^j x - n)\sqrt{2^j}\Phi(2^j y - m) = \Phi_{j,n}(x)\Phi_{j,m}(y)\}_{(n,m)\in\Re^2} \tag{1}$$

The approximation at a resolution 2^j is characterised by the inner products

$$f^j[n,m] = \langle f(x,y), \Phi_{j,n}(x)\Phi_{j,m}(y)\rangle. \tag{2}$$

$f^0[n,m]$ is assumed to be the discrete image at the first resolution. Image approximation $f^j[n,m]$ at smaller resolutions are computed with an iteration of low-pass filtering and subsampling. Let $h[n]$ be the Conjugate Mirror Filter associated with the scaling function Φ_t and $h_2[n,m] = h[-n]h[-m]$. An image $f^j[n,m]$ at the resolution 2^j is obtained from a higher resolution image $f^{j+1}[n,m]$ with a low-pass filtering with $h_2[n,m]$ and a subsampling by two along the rows and columns

$$f^j[n,m] = f^{j+1}[n,m] * h_2[n,m]. \tag{3}$$

Figure 1. Multiresolution pyramid of a face image.

If $f^0[n,m]$ has N^2 nonzero samples, then $f^j[n,m]$ has $2^{2j}N^2$ nonzero pixels. Figure 1 shows an example of a multiresolution pyramid of a face image over four octaves.

3. THE EIGENFACES

The eigenfaces are calculated using PCA. Let the training set of face images be $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$. Each face image is represented by a vector of N^2 pixels. The average face of the set is defined by $\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$. Each face differs from the average by the vector $\Phi_i = \Gamma_i - \Psi$. A set of M orthonormal vectors, $\boldsymbol{u}_n$, is sought to best describe the distribution of the data. The kth vector $\boldsymbol{u}_k$ is chosen such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(\boldsymbol{u}_k^T\Phi_n)^2 \tag{4}$$

is a maximum. The vectors $\boldsymbol{u}_k$ and scalars λ_k are the eigenvectors and the eigenvalues of the covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T \tag{5}$$

where the matrix $A = [\Phi_1\Phi_2\ldots\Phi_M]$. To simplify the computations, a $M \times M$ matrix $L = A^TA$ is constructed where $L_{mn} = \Phi_m^T\Phi_n$. Then M eigenvectors, $\boldsymbol{v}_l$, are found. The eigenfaces can be calculated from

$$\boldsymbol{u}_l = \sum_{k=1}^{M}\boldsymbol{v}_{lk}\Phi_k, \quad l = 1,\ldots,M \tag{6}$$

A face image is represented as

$$w_k = \boldsymbol{u}_k^T(\Gamma - \Psi) \tag{7}$$

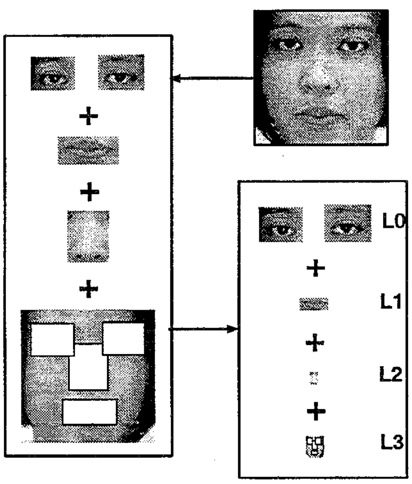

Figure 2. A face image is divided into different regions according to their degrees of importance. Each region is then processed at different levels of resolutions.

4. MULTIRESOLUTION EIGENFACE-COMPONENTS

In this section, the theory of multiresolution analysis and the eigenface method are employed to develop a face recognition system. In the proposed system, a different degree of importance is assigned to each part of a face image. Therefore, each region of the face image is processed with a different resolution. The left and right eyes are assigned the highest degree of importance. Thus, they are processed at the highest resolution (the first level). The mouth part is taken as the second important part. The information of this part is processed at the second level of resolution. The nose forms the next most significant part of a face image and is dealt with at the third level of resolution. Finally, the information contained within the other parts of a face image, such as forehead, chin, and cheeks is processed at the lowest resolution (the fourth level). Figure 2 shows the face regions and their representation in different resolutions.

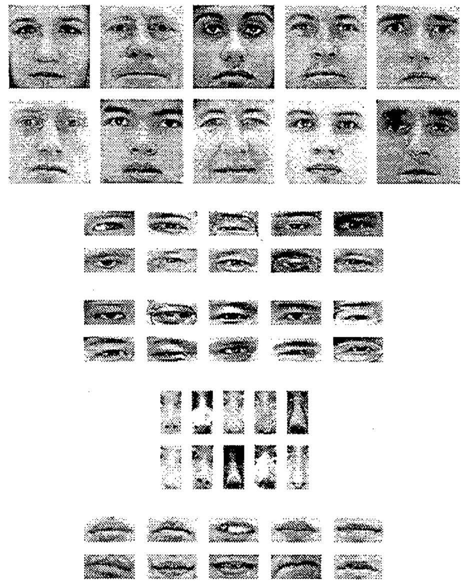

Figure 3. Samples of face-components databases used in this work.

At each resolution level, the related face region is decomposed into a small set of characteristic features which can be thought of as the principal components of a corresponding training set. To build the training sets, a database of 200 gray-scale front-view 128 × 128 face images was used. From this database, five face-components databases (left eye, right eye, mouth, nose, and others) were constructed and transfered into the corresponding resolution levels. The size of images within these databases are $32 \times 48, 32 \times 48, 16 \times 34, 14 \times 10$, and 16×16 for the left eye, right eye, mouth, nose, and others databases, respectively. It should be noted that the others database is built using the resized original face images and the components regions are not removed from these face images. Figure 3 illustrates samples of the face-components databases used in this work. The images have been enlarged for a better visualisation.

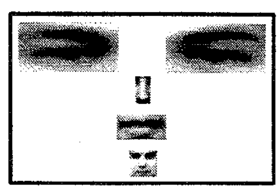

Figure 4. Average face-components.

In the next step, the principal components of each training set were calculated using the algorithm described in Section 2. First the average face-components were computed (see Figure 4). Then, the eigenvectors of the covariance matrix for each training set were obtained. Since each eigenvector looks like the images used for training, the five different sets of eigenvectors are called eigenface-components (eigenlefteyes, eigenrighteyes, eigenmouths, eigennoses, and eigenothers). Figure 5 displays the eigenface-components. The best ten eigenlefteyes, eigenrighteyes, eigenmouths, eigennoses, and eigenothers, are shown from top to bottom of Figure 5. Some eigenface-components have been enlarged for a better visualisation.

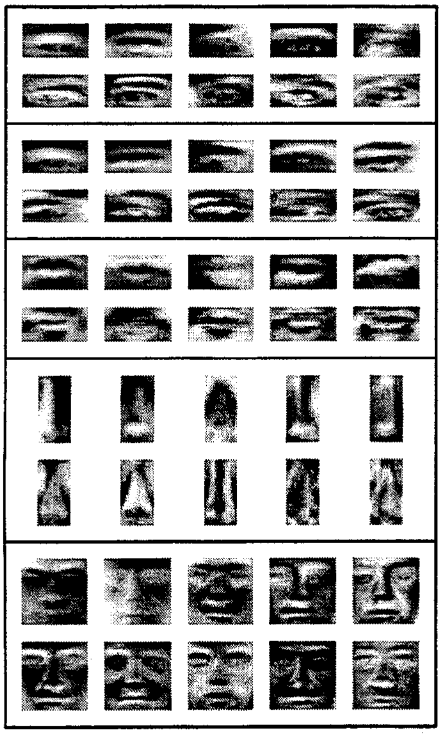

Figure 5. Ten best eigenface-components. From top: eigenlefteye, eigenrighteyes, eigenmouths, eigennoses, and eigenothers.

Each individual face image can be represented exactly in terms of a linear combination of the $M = 200$ eigenface-components. However, each face can be also approximated using only $M' \ll 200$ best eigenface-components; the eigenface-components with the highest eigenvalues.

4.1. Compression Rate

In the eigenface method, for an ensemble of M known face images of N^2 pixels, the best M' eigenfaces of the same size as the face images, and a weight vector of size M' (see Equation 7) are stored. M' is the minimum number of the best eigenfaces that can be used for a successful recognition of all known faces. Based on the experiments, for a set of 200 face images of 128×128 pixel intensities, the best 70 eigenfaces are sufficient for a good description of the set of face images. Therefore, a total of $(128 \times 128 \times 70) + (200 \times 70) = 1.16 \times 10^6$ numbers have to be stored. In the proposed approach, however, for the same ensemble of face images, the eigenface-components require only 25% of the storage needed by the eigenface method. Therefore for the set of 200 face images of 128×128 pixel intensities, only a storage of $(4012 \times 70) + (200 \times 70) = 0.29 \times 10^6$ is required. Even if one requires describing the set of face images with all 200 eigenface-components, the required storage (0.84×10^6) is still less than the space needed for the representation of the face images with the eigenface method using only the best eigenfaces.

4.2. Recognition

For face recognition, an input image is first presented to an intelligent face detection system [4]-[5] that is used to detect the location of faces within the image. Then, centred face images are extracted from the input image and are provided to the face recognition system. The centred face image is resized to 128×128 pixels and preprocessed. Next, the face image is represented using four different levels of resolutions ($128 \times 128, 64 \times 64, 32 \times 32$, and 16×16). In each resolution level, the related part of the face image is extracted. For example, from the face image in the third resolution level, the region 18×13 is extracted from the middle of the image and resized to 14×10. This region represents the nose. After extracting the face components from each respective resolution level, each component is projected onto the related eigenface-components. Then each component is classified using the principal components of the training sets for known individuals. The results of the classifications, obtained for all the components, are processed to decide whether the input face image is known.

5. RESULTS

In this section, the preliminary results obtained for experiments on the eigenface system and the proposed eigenface-components system are presented. Using the database of 200 face images of 128×128 pixels of known individuals, and 36 face images of unknown individuals, the following experiments were carried out.

In the first experiment, the recognition was performed using all 200 eigenfaces and eigenface-components. Full recognition were obtained for known face images. Figure 6 displays the recognition results for the known face No. 160 using the eigenface method (left) and the eigenface-components method (right).

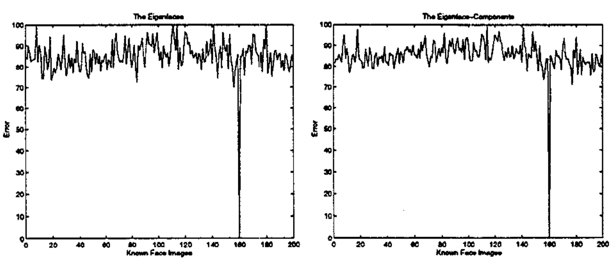

Figure 6. Recognition results for known face No. 160 using all 200 eigenfaces (left) and eigenface-components (right).

In the second experiment, the recognition was also performed using all 200 eigenfaces and eigenface-components. In this experiment unknown face images were presented to the systems and none of the images was recognised. Figure 7 displays the recognition results for an unknown face image, using the eigenface method (left) and the eigenface-components method (right).

In the third experiment, the recognition was carried out using only the best 10 eigenfaces and eigenface-components.

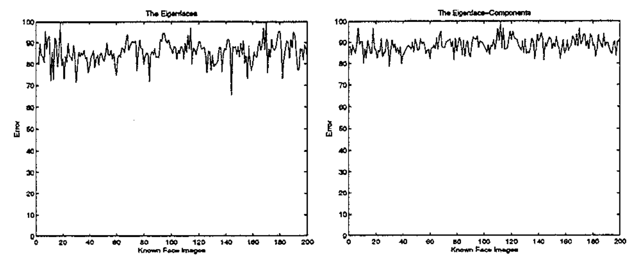

Figure 7. Recognition results for an unknown face using all 200 eigenfaces (left) and eigenface-components (right).

Known faces were presented to the systems and the eigenface method achieved 83% recognition success, whereas the eigenface-component method obtained 91% recognition success. Figure 8 displays the recognition results for the known face image No. 160, using the eigenface method (left) and the eigenface-components method (right).

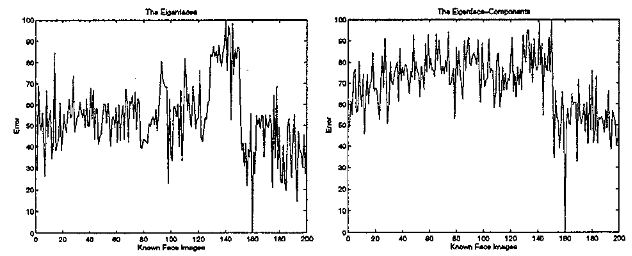

Figure 8. Recognition results for known face No. 160 using only the best 10 eigenfaces (left) and eigenface-components (right).

In the fourth experiment, the recognition was also performed using only the best 10 eigenfaces and eigenface-components. In this experiment unknown face images were presented to the systems. The recognition success was 93% for the eigenface method but 100% for the eigenface-components method. Figure 9 displays the recognition results for an unknown face using the eigenface method (left) and the eigenface-components method (right).

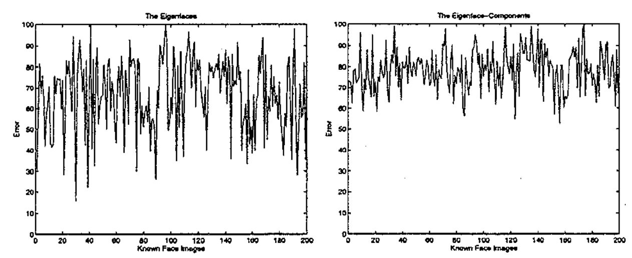

Figure 9. Recognition results for an unknown face using only the best 10 eigenfaces (left) and eigenface-components (right).

As it can be seen from the figures, the recognition is still performed more accurately by the eigenface-components method when using only about 25% of information used by the eigenface method. Therefore, if the same amount of information is used, the performance of the eigenface-components method will be higher than that of the eigenface method. The proposed system also reduces the computational complexity of the eigenface method by calculating the principal components of the lower-dimensional face-componets training sets.

6. CONCLUSIONS

A face recognition system was presented to imitate the multiresolution processing technique of the human visual system. In the proposed system, each part of a face image is assigned a different degree of importance and processed with a different resolution. The experimental results demonstrate that the proposed system reduces the complexity of the eigenface method, achieves higher compression ratios and higher recognition rates than the eigenface method.

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