Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 7 (1): 109-114, 2007
ISSN 1812-5654

Face Recognition System Based on Orthogonal Polynomials

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Abstract: A new computational model based face recognition system with edge extraction scheme is presented in this research. The proposed model has been built centering on some simple point spread operators, which are easily constructed from a set of orthogonal polynomials. One speciality of these point-spread operators is that they can be used in transforming vis-à-vis approximating 2D monochrome image regions. Also a complete set of difference operators are configured from these point-spread operators. Initially, we detect the face from the given input image using an edge extraction scheme, derived as maximizing the signal to noise ratio due to operator's response supported by the proposed orthogonal polynomials. Simple procedures are derived to compute characteristic subsets of coefficients of the proposed transformation that represent important features, are considered for face recognition on the face detected input image. The proposed face recognition system is tested with The Yale database and also compared with Discrete Cosine Transform based face recognition system, Principle Component Analysis based face recognition system and fisher face recognition system.

Key words: Edge extraction, face recognition, orthogonal polynomials, point-spread operators

INTRODUCTION

In recent years, automatic identification of human faces has gained popularity due to its application in many areas such as building-store access control, suspect identification and surveillance (Winkott *et al*., 1997; Liu and Weehsler, 2001). Basically there are two major approaches for face recognition (Chellappa *et al*., 1995; Brunelli and Poggio, 1993). The first approach is the feature based matching approach that uses the relationship between facial features such as eyes, mouth and nose (Brunelli and Poggio, 1993). The second approach is based on template matching technique that uses holistic features of the face image (Graham and Allinson, 1998). Feature based approaches to face recognition basically relay on the detection and characterization of individual facial features and their geometrical relationships. The detection of faces and their features prior to performing verification or recognition makes these approaches robust to positional variations of the faces in the input image. On the other hand, the holistic approaches to face recognition involve encoding the entire facial image and treating the resulting facial code as a point in a high dimensional space (Ziad and Levines, 2001).

In the literature, several classifiers are proposed for face recognition. It includes the minimum distance classification in the eigenspace (Turk and Pentland, 1991; Belhumeur *et al*., 1997), the independent face space based on Independent Component Analysis (ICA), the discriminative subspace based on Linear Discriminent Analysis (LDA) (Heseltine *et al*., 2003; Kong *et al*., 2005), neural networks based classifiers (Flemming and Cottrell, 1990) and probabilistic matching based on intrapersonal/ extra personal image difference (Teixeira and Beveridge, 2003).

Even though holistic approaches for face recognition system gained popularity, it needs some input parameters, in advance. For example, discrete cosine transform based face recognition system (Ziad and Levine, 2001) needs eye coordinates. Motivated by the fact that the system should take automatically certain features, without any input from the user, in this paper we present a face recognition system that uses a computational model based an orthogonal polynomials.

Proposed model: Since the face recognition system can be considered by extracting features from the given image based on the local properties, a local point spread operator is proposed which is a cartezian coordinate separable and deblurring from a set of orthogonal polynomials.

The two dimensional point-spread function M (x, y) can be considered to be a real valued function defined for (x, y) | X x Y where X and Y are ordered subsets of real values. In the case of a gray level image of size (n x n)

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where X (rows) consists of a finite set, which for convenience can be labeled as {0, 1,..., n-1}, the functions M (x, y) reduces to a sequence of functions.

$$M(i, t) = u_i(t), i= 0, 1,\ldots\ldots, n-1 \quad (1)$$

As shown in Eq. (2) the process of image analysis can be viewed as the linear two dimensional transformation defined by the point-spread operator

$$M (x, y)(M (i, t)= u_i (t))$$
$$\beta(\xi, \eta) = \int_{x\in X} \int_{y\in Y} M(\xi, x)\, M(\eta, y)\, I(x, y)dxdy \quad (2)$$

Considering both X and Y to be finite set of values {0, 1, 2, …., n-1} Eq. (2) can be written in matrix form as follows.

$$\left|\beta'_{ij}\right| = \left(|M| \otimes |M|\right)^t |I| \quad (3)$$

where the point spread operator |M| is

$$|M| = \begin{bmatrix} u_0(t_0) & u_1(t_0) & \cdots & u_{n-1}(t_0) \\ u_0(t_1) & u_1(t_1) & \cdots & u_{n-1}(t_1) \\ & & \vdots & \\ u_0(t_{n-1}) & u_1(t_{n-1}) & \cdots & u_{n-1}(t_{n-1}) \end{bmatrix} \quad (4)$$

is the outer product, $|\beta_{ij}|$ and $|I|$ are the n^2 matrices arranged in the dictionary sequence. |I| is the image and $|\beta_{ij}|$ s are the coefficients of transformation.

We consider a set of orthogonal polynomials $u_0(t)$, $u_1(t)$, ….. $u_{n-1}(t)$ of degrees 0, 1, 2,…..n-1, respectively.

The generating formula for the polynomials is as follows.

$$u_{i+1}(t) = (t-\mu)u_i(t) - b_i(n)u_{i-1}(t) \text{ for } i \geq 1,$$
$$u_1(t) = t-\mu, \text{ and } u_0(t) = 1, \quad (5)$$

where

$$b_i(n) = \frac{<u_i, u_i>}{<u_{i-1}, u_{i-1}>} = \frac{\sum_{t=1}^{n} u_i^2(t)}{\sum_{t=1}^{n} u_{i-1}^2(t)}$$

and

$$\mu = \frac{1}{n}\sum_{t=1}^{n} t$$

Considering the range of values of t to be t = i, i = 1, 2, 3, ….,n, we get

$$b_i(n) = \frac{i^2(n^2-i^2)}{4(4i^2-1)}, \quad \mu = \frac{1}{n}\sum_{t=1}^{n} t = \frac{n+1}{2}$$

We construct point-spread operators |M|s of different sizes from the above orthogonal polynomials as follows.

$$|M| = \begin{bmatrix} u_0(t_0) & u_1(t_0) & \cdots & u_{n-1}(t_0) \\ u_0(t_1) & u_1(t_1) & \cdots & u_{n-1}(t_1) \\ & & \vdots & \\ u_0(t_{n-1}) & u_1(t_{n-1}) & \cdots & u_{n-1}(t_{n-1}) \end{bmatrix} \quad (6)$$

for n≥2 and ti = i+1. For the convenience of point spread operations and for reducing the computational complexity, the elements of |M| are scaled to make them integers.

For computational simplicity, the finite Cartesian coordinate set X, Y are labeled as {1, 2, 3}. The point-spread operator in Eq. (4) that defines the linear transformation of images can be obtained as |M| |M| where |M| is computed and scaled from Eq. (5) as

$$|M| = \begin{bmatrix} u_0(t_0) & u_1(t_0) & u_2(t_0) \\ u_0(t_1) & u_1(t_1) & u_2(t_1) \\ u_0(t_2) & u_1(t_2) & u_2(t_2) \end{bmatrix} = \begin{vmatrix} 1 & -1 & \frac{1}{3} \\ 1 & 0 & -\frac{2}{3} \\ 1 & 1 & \frac{1}{3} \end{vmatrix} = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix} \quad (7)$$

The set of 9 two dimensional basis operators O_{ij}, (0 ˜ i, j ˜2) can be computed as follows.

$$O_{ij} = \hat{u}_i\, \hat{u}_j^t$$

where $\hat{u}_i$ is the (i+1)st column vector of |M|. Let the image under analysis be of size (NxN), |M| be the polynomial operator of size (3×3) and I be a small region of size (3×3) extracted from the image. β'_{ij}s are the coefficients of the linear transformations defined as follows.

$$\left|\beta'_{ij}\right| = |M|^t\, |I| \quad (8)$$

where |M| is the 2D point-spread operator defined as |M| = |M| |M|.

It is also proved that the orthogonal transformation defined by the orthogonal system |M| is complete (Krishnamoorthy and Bhattacharyya, 1998).

Edge extraction: Here we present an edge extraction scheme that uses statistical procedures to separate the proposed orthogonal polynomials operator's response towards noise from the responses towards edges. Measuring the significance of edge strength has been used for computing the Signal to Noise Ratio (SNR) and then edges are extracted by maximizing the SNR.

The coefficients of the proposed transformation β_{ij} are approximating the partial derivatives of various order of the image region. For example, O_{01} denotes the first order differencing operation in y direction, $(\partial/\partial y)$ and O_{10} denotes the first order differencing operation in x direction, $(\partial/\partial x)$ etc. O_{00} is the local averaging operator. Excluding $O_{00,}$ the remaining operators can be considered for computing the gradient. Considering only the first order differences, namely β'_{01}, β'_{10} the gradient magnitude can be computed as:

$$\text{Gradient magnitude} = \sqrt{\beta_{01}'^{2} + \beta_{10}'^{2}}$$

By considering all the n^2-1 polynomial basis operators, the edge extraction criteria such as

$$\sqrt{\left(\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\beta_{ij}'^{2}\right) - \beta_{00}'^{2}}$$

where β_{00} is the averaging factor, can be used against a threshold 'T' for detection of edges. The (2×2) and (3×3) polynomial operators, except the local averaging operators O^2_{00} and O^3_{00} are considered to be the gradient edge detectors because of their large values in regions having prominent edges and small values on nearly uniform gray level regions.

In order to strengthen the gradient based edge detection, in the presence of noise, as suggested by Canny (1986), we propose a better criteria such as maximization of the operator's edge response compared to the responses towards noise, in terms of the proposed polynomial operators. For a given image region, a set of estimated variances Z^2 corresponding to the mean squared amplitude responses of the orthogonal polynomial operator is then computed and divided into 2 sets that correspond to edges and noise present in the image:

$$Z^2_{m,n} = \frac{\left([\beta']m,n\right)^2}{\left([W]m,m x[W]n,n\right)} \quad \text{where}$$

$$[w]=[M]^t[M]$$

and let A = $\{Z^2_{01}, Z^2_{02}, Z^2_{10}, Z^2_{21}\}$ and

$$B = \{Z^2_{11}, Z^2_{12}, Z^2_{21}, Z^2_{22}\}$$

We apply Bartlett statistical test (Roger *et al*., 1987) that tests the homogeneity of variances for the set A to be more divergent and B, to be more convergent. We then compute the mean square error variance msv,

$$msv = \frac{\sum Z^2_{m,n} \in B}{\|B\|} \quad \text{where } \|B\| \text{ is the cardinality of B.}$$

The significant mean square amplitude responses towards edges are added and their root mean square value (rms) is obtained amongst a significance level with f-ratio test (Fisher and Yates, 1997). Finally in order to maximize the SNR, the rms value is applied against a threshold T. If the rms value is greater than or equal to the threshold T, then the edge is assumed to be present.

Recognition based on the proposed model: In this section we present the selection of feature vector for face recognition by the proposed orthogonal polynomials based model. To recognize the face, first we detect the presence of face from the given input image using background subtraction and edge extraction. In this study, we follow the background subtraction proposed by Tian *et al*. (2003). We then apply the proposed edge extraction scheme and hence detect the face present in the given image.

In our scheme, the face detected image is subjected to extract only face features that correspond to low level properties of the image. The proposed system also does not need any input parameters such as eye-coordinates as used by Ziad and Leine (2001). If the entire face detected image is (of size N x N) considered, the face recognition system shall be a time consuming process. Hence, a subset of the image under analysis as a characteristic feature image is considered. This subset is then transformed to the frequency domain by applying the proposed Orthogonal Polynomials based Transformation (OPT) 2. In the transformed domain, for each element of the subset, we find the feature vector that can effectively be used for face recognition. Since the orthogonal polynomials based transform coefficients, β_{ij}, $0 \le i$, $j \le n$ where $n \le N$, of each element of the characteristic subset represent the low level features such as texture and edges and by applying statistical design of experiments approach, we obtain the following orthogonal effects such as main effects and interaction effects (Ganesan and Bhatlacharyya, 1995; Krishnamoorthy and Bhattacharyya, 1997). The transform coefficients due to main effects β'_{ij}s at I = 0, $0<j\le 2$ and j = 0, $0<i\le 2$ the transform

coefficients due to interaction effects, β'_{ij} at $i \neq 0$, $j = 1,2$ and $j \neq 0$, $i = 1, 2$ that are linear contrasts considered along both the directions x and y at a time, are obtained. The mean and standard deviation of these orthogonal effects along with the averaging factor of the orthogonal polynomial coefficients are selected as the feature vector in our proposed model.

RESULT AND DISCUSSION

Here, we present and discuss the experimental results of the proposed orthogonal polynomials based Face recognition system, using the standard Yale database. One such sample input test image used for face recognition system is of size 146×111 with pixel values in the range 0 to 255 and is shown in Fig. 1. This image is first subjected to presence of face detection scheme using the proposed edge extraction scheme and the output is shown in Fig. 2. If the output is positive we extract characteristic subset of this image and are then subjected to the proposed orthogonal polynomial based transformation as earlier. In the transformed domain, we extract the mean and standard deviation of the orthogonal coefficients due to main and interaction effects, along with the averaging factor of the transformation, as feature vector. This experiment is conducted for each element of the characteristic subset of the face detected test image. This feature vector is then obtained for each images of the database. Sample images that are considered in our experiment, taken from The Yale database is shown in Fig. 3. The exact match of feature vectors of the test image with the database image is then obtained using Euclidean distance.

Fig. 1: Input image

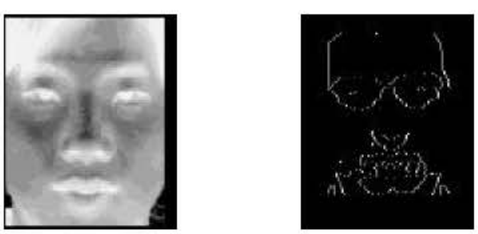

Fig. 2: Background subtraction and edge detected output for the Fig. 1

Fig. 3: Sample images from the Yale database

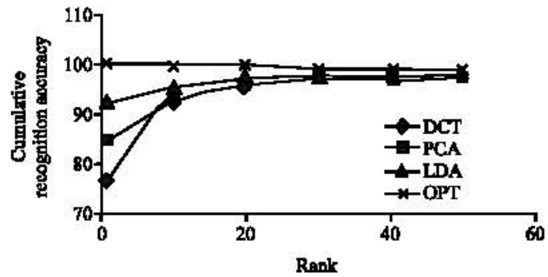

Fig. 4: Cumulative recognition accuracy as a function of rank for the Yale face database

In order to measure the efficiency of our proposed face recognition system and to compare with Principle component Analysis based, Discrete Cosine transform based and Linear discriminent analysis based face recognition systems, we conduct additional experiments performed on the Yale database. These experiments were intended to further highlight the face recognition capabilities of the orthogonal polynomials based face recognition system. The results obtained are summarized. The Fig. 4. shows that the cumulative recognition accuracy as a function of rank for a variety of conditions, as introduced in Ziad and Levine (2001). In DCT method we obtain the cumulative recognition accuracy of 77 to 98% of the first 50 ranks. In the PCA method we obtain the cumulative accuracy of 85 to 97% of the first 50 ranks, whereas in LDA method the cumulative accuracy was 92 to 98% for the first 50 ranks. Using our proposed method we obtain the recognition accuracy 98 to 99.98% for the first 50 ranks. The basic idea behind this is to show that the correct match always appears in the top 60 matches (or ranks). That is if a particular experiment results in a cumulative recognition accuracy of 99.98% at rank 20, then the correct match is among the closest 20 matches always.

Table 1: Comparison of different methods in term of recognition rate

Method	DCT	PCA	LDA	Proposed method
Recognition rate (%)	84.58	88.92	92.50	99.98

The result of this face recognition system experiment based on the proposed orthogonal polynomials based transformation as well as those obtained using the DCT, PCA and LDA are shown in Fig. 4. We also notice slightly inferior performance of the DCT when compared with PCA. It is also evident from this output that the proposed orthogonal polynomials transformation based face recognition system is comparable and superior to discrete cosine transformation, principle component analysis and linear discriminent analysis based face recognition systems.

We also conduct experiments for recognition accuracy on the images using DCT, PCA, LDA and OPT based schemes and the results are presented in Table 1. It is evident from the table that the proposed orthogonal polynomials based face recognition system could achieve the recognition rate of 99.98%.

CONCLUSIONS

Real time security and surveillance due to certain limitations and restrictions have made this area of research more attractive and challenging for Biometric researchers. In this study a new computational framework has been proposed for automatic face recognition system. The proposed framework is designed from a set of orthogonal polynomials. An edge extraction scheme has been presented by maximizing SNR due to the operators' response of the proposed orthogonal polynomials. Simple procedures are then derived to compute the characteristic subsets of the coefficients of the proposed transformation that represent important features for face recognition. The face recognition results of the proposed framework have been compared with few existing face recognition systems.

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