Face Recognition Using Legendre Moments

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Abstract

The wide range of variations in human face due to view point, pose, illumination and expression deteriorate the recognition performance of the existing Face recognition systems. This paper proposes a new approach to face recognition problem using Legendre moments for representing features and nearest neighbor classifier for classification. The Legendre moments are orthogonal and scale invariant in its characteristics and hence it is suitable for representing the features of the face images. The obtained feature vectors are transformed using Linear Discriminant Analysis and stored in the database and are compared using Nearest neighbor classifier during testing. For testing the proposed approach, Legendre feature vector of size 12 is used for the images of ORL (Olivetty Research Laboratories) database with 40 subjects and each of them having 10 orientations. Similarly the Hu moments, Discrete Cosine Transforms (DCT) are also used for feature extraction. The recognition percentage is compared with the proposed approach. The recognition percentage of 98.25% is achieved using Legendre moments which are comparatively superior than other Face recognition approaches using central moments (Hu), DCT or other statistical approaches.

Keywords: Hu moments, orthogonal Legendre moments, Discrete Cosine Transform (DCT), Linear Discriminant Analysis (LDA) and nearest neighbor classifier.

1. Introduction

In recent years, there has been a growing interest in machine recognition of faces due to potential commercial applications such as film processing, law enforcement, person identification, access control systems etc. Face recognition may appear to be easy for human and yet computerized face recognition system cannot achieve a completely reliable performance. The difficulties arise due to large variation in illumination, facial appearance, head size, orientation and change in environment conditions. Such difficulties make face recognition one of the fundamental problems in pattern analysis. In general, A.Saradha² Research scholar in CSE Government College of Technology, Coimbatore, Tamilnadu, India. Email : <u>saradha_irtt@yahoo.com</u>

feature extraction. discriminant analysis and classification rule are the three important basic elements of the face recognition system. The robustness of face recognition system could be improved by treating variations in these elements. Many researchers attempted this problem and could not achieve 100% recognition for face data bases. The popular approaches used for face recognition are based on i) structural ii) statistical and iii) neural networks. The first one is based on extracting structural facial features such as eyes, nose, mouth and chin with their areas, distances, and angles and is popular in literature [2]. It deals with local information rather than global information. The second approach is based on statistical approaches using image transforms where features are extracted from the whole image and therefore using global information instead of local information. The Eigen face [2] derived from a set of face images by applying the Principal Component Analysis (PCA) is an example for statistical approach. The third approach using neural networks was also employed for feature extraction as well as recognition but the training time needed was very high.

Moment based feature extraction is proposed in this paper. Moment functions of the twodimensional image intensity distribution are used in a variety of applications like visual pattern recognition, object classification, template matching, edge detection, pose estimation, robotic vision and data compression. Image moments that are invariant with respect to the transformations of scale, translation and rotation find applications in areas such as pattern recognition, object identification and template matching. Orthogonal moments have additional properties of being robust in the presence of image noise and have a near zero redundancy measure in a feature set.

The efficiency of face recognition algorithm depends on two parameters (i) an efficient and invariant feature representation with respect to illumination, scaling, rotation etc. (ii) classification technique that will map the feature vectors into their appropriate classes without any misclassification. Considering above said facts a novel approach is proposed and it uses orthogonal moments called Legendre moments [1],[5] and [3] which is invariant to scaling as feature extraction approach. The moments of order 4 which constitute the feature vector of size 12 and is used in the experiments conducted. The proposed approach must be tested with a standard face database in order to prove its efficiency. Hence ORL data base is used which is one of the popular face database used for performance comparison. The extracted features are transformed using Linear Discriminant Analysis (LDA) and nearest neighbor classifier is used for classification. A very high recognition rate of 98.25% is achieved. The results are compared with the recognition performance using features obtained from Hu moments and DCT coefficients.

2. Related Techniques

2.1 Moments for Image Analysis

The region based moments interpretations interpret a normalized gray level image function as a probability density function of a random variable. Properties of this random variable can be described using statistical characteristics called moments [6]. A moment of order (p+q) independent of scaling, translation and rotation on gray level transformations and is given by

$$M_{pq} = \int_{-1-1}^{1} \int_{-1-1}^{1} x^{p} y^{p} f(x, y) dx dy$$
(1)
x, y \le \{-1,1\}

In digitized images the translation invariant central moments are calculated using the following equation

$$\mathbf{m}_{pq} = \sum_{x} \sum_{y} f(x, y) (x - x_0)^p (y - y_0)^q$$
(2)

$$X_0 = M_{10} / M_{00} \tag{3}$$

$$Y_0 = M_{01} / M_{00} \tag{4}$$

The Hu moments which are invariant to translation, rotation and scaling are calculated using the following formula

$$\boldsymbol{j} \, \boldsymbol{1} = \boldsymbol{m}_{20} + \boldsymbol{m}_{02} \tag{5}$$

$$\mathbf{j} \, 2 = (\mathbf{m}_{20} - \mathbf{m}_{02})^2 + 4\mathbf{m}_{1}^2 \tag{6}$$

$$\mathbf{j} \, 3 = (\mathbf{m}_{30} - 3\mathbf{m}_{2})^{2} + (3\mathbf{m}_{21} - \mathbf{m}_{03})^{2} \tag{7}$$

$$j 4 = (\mathbf{m}_{50} + \mathbf{m}_{12})^{2} + (\mathbf{m}_{21} - \mathbf{m}_{03})^{2}$$

$$j 5 = (\mathbf{m}_{50} - 3\mathbf{m}_{23})(\mathbf{m}_{50} + \mathbf{m}_{33})[(\mathbf{m}_{50} + \mathbf{m}_{32})^{2} - 3(\mathbf{m}_{51} + \mathbf{m}_{22})^{2}]$$
(8)

+
$$(3\boldsymbol{m}_{21} - \boldsymbol{m}_{03})(\boldsymbol{m}_{21} + \boldsymbol{m}_{03})[3(\boldsymbol{m}_{50} + \boldsymbol{m}_{12})^2 - (\boldsymbol{m}_{21} + \boldsymbol{m}_{03})^2]$$
 (9)
 $\boldsymbol{j} \, \boldsymbol{6} = (\boldsymbol{m}_{50} - \boldsymbol{m}_{12})[(\boldsymbol{m}_{50} + \boldsymbol{m}_{22})^2 - (\boldsymbol{m}_{21} + \boldsymbol{m}_{03})^2]$

$$+4\boldsymbol{m}_{1}(\boldsymbol{m}_{50}+\boldsymbol{m}_{2})(\boldsymbol{m}_{21}+\boldsymbol{m}_{03})$$
(10)

$$\mathbf{j} \, 7 = (3\mathbf{m}_{21} - \mathbf{m}_{03})(\mathbf{m}_{50} + \mathbf{m}_{22})[(\mathbf{m}_{50} + \mathbf{m}_{22})^2 - 3(\mathbf{m}_{21} + \mathbf{m}_{03})^2]$$

$$-(\mathbf{m}_{30} - 3\mathbf{m}_{2})(\mathbf{m}_{21} + \mathbf{m}_{03})[(3(\mathbf{m}_{30} + \mathbf{m}_{12})^{2} - (\mathbf{m}_{21} + \mathbf{m}_{03})^{2})] \quad (11)$$

2.2. Legendre Moments

The moments with Legendre polynomials as kernel functions denoted as Legendre moments were introduced by Teague [1] and [4]. Legendre moments belong to the class of orthogonal moments and they were used in several pattern recognition applications. They can be used to attain a near zero value of redundancy measure in a set of moment functions so that the moments correspond to independent characteristics of the image. The definition of Legendre moments has a form of projection of the image intensity function into Legendre polynomials.

The two-dimensional Legendre moments of order (p+q), with image intensity function f(x,y), are defined as

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \iint_{-1-1}^{1} P_p(x) P_q(y) f(x,y) dx dy \qquad (12)$$
$$x, y \in \{-1,1\}$$

Where Legendre polynomial, $P_p(x)$, of order p is given by $P_p(x)$

$$=\sum_{k=0}^{p} \left\{ (-1)^{\frac{p-k}{2}} \frac{1}{2^{p}} \frac{(p+k)! x^{k}}{\left[\frac{p-k}{2}\right]! \left[\frac{p+k}{2}\right]! K!} \right\}_{p-k=even}$$
(13)

The recurrence relation of Legendre polynomials, $P_p(x)$, is given as follows;

$$P_{p}(x) = \frac{(2p-1) \times P_{p-1}(x) - (p-1)P_{p-2}(x)}{P}$$

Where $P_0(x) = 1$, $P_1(x) = x$ and p > 1. Since the region of definition of Legendre polynomials is the interior of $\{-1,1\}$, a square image of NxN pixels with intensity function f(i,j), $0 \le i$, $j \le (N-1)$, is scaled in the region of -1 < x, y < 1. as a result of this, equation (12) can now be expressed in discrete form as

$$L_{pq} = \boldsymbol{I}_{pq} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_p(x_i) P_q(y_j) f(i,j)$$
(14)

Where the normalizing constant,

$$\boldsymbol{I}_{pq} = \frac{(2p+1)(2q+1)}{N^2}$$

 x_i and y_j denote the normalized pixel coordinates in the range of $\{-1,1\}$, which are given by

$$x_i = \frac{2i}{N-1} - 1$$
 and $y_i = \frac{2i}{N-1} - 1$

2.3 Discrete Cosine Transform

DCT is a popular technique in transform coding systems and the mean square reconstruction error is less and it has good reconstruction capability. It is also having a good information packing ability. Compared to other input independent transforms it has advantages of packing the most information into the fewest coefficients and hence used for representing the features of the images. A subset of extracted coefficients forms the feature vector and is compared with nearest neighbor classifier. DCT is an orthogonal transform [4][6] and consists of phase shifted cosine functions. It is calculated using the formula

$$C(u,v) = \mathbf{a}(u)\mathbf{a}(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\left|\frac{(2x+1)u\mathbf{p}}{2N}\right| \frac{(2y+1)u\mathbf{p}}{2N} \cdots (15)$$

For u,v = 0,1,2,3,....N-1 and

$$a(u) = \begin{cases} \sqrt{1/N} & \text{for } u = 0 \\ \sqrt{2/N} & \text{for } u = 1,2,....N-1 \end{cases}$$

2.3. Linear Discriminant Analysis

Discriminant analysis is used to classify cases into one of several known groups on the basis of various characteristics. It can also identify the variables that are good predictors of group membership by using the stepwise method of variable selection.

Available at each step are F statistics for evaluating the usefulness of variables in and out of the equation, Wilk's lambda or U statistics and F statistics for testing pair wise differences between group means. For the final equation, coefficients are displayed for the classification functions (Fisher's linear discriminant function) which provide the best discrimination between the groups. The functions are generated from a sample of cases for which group membership is known; the functions can then be applied to new cases with measurements for the predictor variables with unknown group membership.

Linear discriminant analysis easily handles the case where the within-class frequencies are unequal. It maximizes the ratio of between class variance to the within class variance in any particular data set thereby guaranteeing maximal separability.

3. Proposed Face Recognition System

The proposed face recognition system shown in Figure-1 consists of 4 major modules. They are 1) Image normalization 2) Feature Extraction 3) Linear discriminant analysis 4) nearest neighbor classifier.

3.1 Image Normalization

The ORL database consists of images of 40 subjects and each subject consists of 10 orientations. Each image is a gray scale image consists of pixel values ranges from 0 to 255. In order to reduce the computational overhead it is normalized by its maximum pixel value.

3.2 Feature Extraction

The next process of face recognition is to extract the invariant features from the normalized images of the database. Three feature extraction approaches are used and the extracted features are subjected to classification. DCT, Hu moments and Legendre moments are used as feature extraction approaches in the experiment. DCT feature vectors are of size 8x8, 16x16 and 24x24. Hu moments contribute a feature vector of size seven and Legendre moments contribute the feature vector of size 12.



Figure 1 - Block Diagram of Face Recognition System

Results



Figure-2 40 subjects of ORL Database

3.3 LDA

The extracted features are invariant features of the images under consideration and are subjected to transformation in order to improve discriminality. These transformed feature vectors are classified with nearest neighbor classifier.

3.4 NN Classifier

The features of the images of the database are extracted, transformed using Linear Discriminant Analysis and stored in the feature database. Similarly during testing the feature vectors of the test image are extracted using DCT, Hu and Legendre moments and transformed using discriminant function. The transformed vector is compared with the respective feature vectors stored in the database by measuring Euclidean distance between the test vector and the feature vectors of the database. A comparative study is performed and the results are tabulated. The experiment is repeated by increasing the number of images of the database from 5 to 40 in steps of 5 and the recognition percentage is calculated and recorded.

4. Experimental Results

The experiments are conducted by extracting the features using the approaches of Hu moments, Legendre moments and DCT. The ORL database is used for experimentation. The ORL database consists of images of 40 subjects of size 92x112 as shown in figure-2 and each subject has 10 orientations. Some orientations of sample image is shown in figure 3. They are resized to 64x64 in order to reduce the computational complexity.



Figure – 3 Different Orientations of Subject

4.1 Experiment 1

The Hu moments are calculated up to third order which results in a feature vector of size 7. Table.1 consists of 10 feature vectors for 10 orientations of the subject shown in figure.3. Feature vectors obtained are subjected to Linear Discriminant Analysis and transformed. The number of subjects used for the analysis is increased from 5-40 in steps of 5 and the recognition percentage is tabulated. Only 40% of recognition percentage is observed.

4.2 Experiment 2

The Legendre moments of order four is considered for the calculation of moments. The extracted feature vectors are subjected to Linear Discriminant Analysis which increases the

IMAGE	Hu Moments of order 3							
No.	φ1	φ ₂	φ3	φ4	φ5	φ ₆	φ ₇	
2-1	0.321206	0.000697	0.642788	0.075973	0.016117	-0.00132	0.004703	
2-2	0.31817	0.000378	5.430554	0.290175	0.252781	0.000464	0.262275	
2-3	0.333391	0.000829	3.87237	0.25416	-0.09985	-0.00731	0.231532	
2-4	0.323398	0.000291	2.938581	0.088474	0.020075	0.000133	0.040399	
2-5	0.328096	0.000562	2.368621	0.088565	-0.02353	0.000306	-0.03304	
2-6	0.31771	0.000067	2.95772	0.398794	0.368927	0.00128	-0.22689	
2-7	0.332101	0.001394	9.402906	0.371977	0.473293	-0.00959	0.509858	
2-8	0.338357	0.000946	2.529241	0.010237	-0.00148	-0.0002	-0.00072	
2-9	0.330197	0.000017	6.276105	0.631597	1.255381	-0.00252	0.072834	
2-10	0.324126	0.000354	2.406464	0.2113	0.150603	-0.00145	-0.00463	

Table-1 Feature vectors of sample image using Hu moments

Table.2 Feature vector of sample image using Legendre moments of order 4

Image	Legendre Moments of Order 3							
No	L_{20}	L ₀₂	L ₁₁	L ₂₁	L ₁₂	L ₃₀	L ₀₃	L_{40}
2-1	0.630146	0.576177	1.016352	-1.02772	-0.97946	-1.52283	-1.50392	2.745453
2-2	0.591155	0.689645	0.997223	-0.88384	-0.94851	-1.4879	-1.62490	2.712697
2-3	0.655017	0.661265	1.055558	-1.04319	-1.03285	-1.54638	-1.59680	2.757582
2-4	0.592927	0.6204	0.957181	-0.87709	-0.88653	-1.47573	-1.53728	2.684474
2-5	0.575116	0.676499	1.019936	-0.90916	-1.00164	-1.49895	-1.62664	2.741392
2-6	0.567606	0.70133	0.955957	-0.79248	-0.90876	-1.46515	-1.62683	2.705298
2-7	0.753609	0.669043	1.116487	-1.18364	-1.10983	-1.65188	-1.61243	2.889758
2-8	0.686332	0.607345	1.028329	-1.05051	-0.97669	-1.57214	-1.53227	2.798169
2-9	0.652628	0.749567	1.026864	-0.92732	-0.98328	-1.52831	-1.68223	2.769508
2-10	0.713316	0.681758	1.101063	-1.11991	-1.10409	-1.63034	-1.63367	2.893186

discriminatory power of feature vectors. The transformed vectors are stored in the database. The number of subjects used for testing is increased from 5 to 40 in steps of 5 and the results are tabulated. A Good recognition percentage of 98.25% is achieved.

4.3 Experiment 3

In this experiment the images are segmented into 8x8. Discrete cosine transform is applied on these segments. For every image segment 2x2 DCT coefficients of DCT matrix is selected which constitutes a feature vector of 16x16 in size. An example 16x16 feature vector of image 1-1.bmp is shown in table.3. For all the images feature vectors of size 16x16 are used for calculating mean and covariance matrices. Testing is done by comparing the covariance matrices of test image with that of images in data base. A recognition percentage of 100% is achieved for 5 subjects. When the number of subjects is increased from 5 to 40 in steps the recognition percentage is slightly degraded and for 40 subjects it is



Figure 4. Image 1-1.bmp

Table.3. 16x16	Feature	vector	of	1-1	l.bmp
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-39 -1 -34 -5 -15 -7 -12 -5 -10 2 -22 3 -28 0 -39 3
-1 0 - 3 5 -8 -2 -16 2 -21 0 -13 -4 0 -5 0 0
-36 -5 0 -13 14 -1 24 -4 24 0 16 7 -11 19 -39 4
0 3 -10 -1 -7 -1 -1 -1 2 -1 -7 5 -13 -6 0 0
-31 -13 14 -6 20 -1 28 -2 22 3 21 0 1 22 -41 2
0 1 -2 -3 0 0 0 0 0 0 0 0 -2 1 0 0
-11 -2 13 2 2 0 18 -6 11 12 2 -3 5 4 -14 -4
-25 -7 -1 -4 3 -1 5 3 3 0 -1 -2 -4 8 -28 2
12 2 21 0 17 1 17 -1 17 6 15 -2 16 4 7 0
-1 0 - 2 0 -5 2 0 0 -4 2 -4 -1 0 -1 0 -9
-30-11 22 -13 25 4 18 -1 14 0 25 -1 10 20 -36 8
20-12 3 7-1-1 2 -3 0 2-1 0 7-8 11 10
-41 1 -3 -41 27 6 11 6 8 -4 20 0 -8 33 -44 0
-1 0 12 0 -3 3 -11 0 -9 -1 2 -4 3 4 0 0
-40 0-15 -42 23 0 20 4 13 0 9 0 -6 35 -43 -2
0 0 0 3 0 -5 2 2 3 -3 0 7 0 -3 0 0

90%. The same experiment is repeated for different sizes of feature vectors formed by extracting 1x1 and 3x3 coefficients of DCT matrix.

5. Performance Comparison

Using the above experiments the invariant features (Hu and Legendre moments) and DCT coefficients are extracted for the images in the ORL database. The experiments are conducted with varying sizes of data set. The number of subjects considered is increased from 5 to 40 in steps of 5 where each subject contains 10 images. The classification accuracy obtained using both the moments and DCT feature vectors are tabulated in Table.4. It is observed that the Hu moments which are efficient in handling binary images when used for feature representation it is found that it is not an appropriate feature representation method for such a complex face recognition problems. It is also found that the recognition percentage of the face recognition system using orthogonal moments (Legendre moments) is found superior to other feature extraction techniques such as DCT and Hu moments and shown in Figure.5

No of	% of Recognition				
subjects	Hu	Legendre	DCT		
5	96%	100%	100%		
10	72%	100%	96%		
15	61.37%	100%	95%		
20	55%	98%	94%		
30	51%	97.36%	93%		
35	50.01%	96.32%	91.03%		
40	46.8%	98.25%	90.01%		

Table . 4 Performance Analysis



Figure.5 Chart for Performance comparison

5.1 Observations from the chart

- The chart represents the recognition percentage using Legendre and Hu moments.

- Using Legendre moments there is no much degradation in recognition percentage with increasing in the number of images

- Using DCT the recognition percentage is good when the number of images is less and degraded as the number of images increased.

6. Conclusion

In this paper a new method for face recognition is presented. From the experimental results it is observed that the feature representation using DCT provides a maximum recognition rate of 90% and the size of feature vector is also very large. Orthogonal moments that are invariant in nature are capable of representing the images with minimum number of coefficients and the recognition percentage is also superior. Hence it is found very much suitable for feature representation of complex face images which are almost similar in nature with variations size, pose, illumination and orientation within a smaller area. It is also superior over the conventional central moments based recognition system. A good recognition percentage of 98.25% is achieved using Legendre moments. It is also found that it is superior over other statistical approaches like PCA analysis [2] and Line edge map method [7].

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