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DISCRETE COSINE TRANSFORM BASED PALMPRINT VERIFICATION BY USING LINEAR DISCRIMINANT ANALYSIS

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ABSTRACT
In this paper a new method is proposed for palmprint verification using Linear Discriminant Analysis. The verification system is consists of two steps: One is enrolment step; the second one is verification step. In the enrollment step the palm is scanned and its region of interest (ROI) is extracted. After then ROI and it is owner’s name stored in the database. Several palm images are stored database like using same methods. In verification steps palm image is scanned for verification. The image’s ROI is extracted. The feature vector has been obtained by applying discrete cosine transform to a data extracted from ROI. The proposed method is tested with ORL database and the results are compared with palmprint verification using line edge maps and palmprint verification using linear discriminant analysis. Verification error rate obtained is approximately 3%, which is a significant result with respect to other available palm verification algorithms.

Keywords: Palmprint Verification, Linear Discriminant Analysis, Discrete Cosine Transform, Identification, Vector Field

1. INTRODUCTION
Recently biometrics is becoming a key for security replacing digit-password systems, since each person has different biometrics features such as iris, fingerprint, and face.
Golfarelli made a study about verifying personal identity. He used 17 hand shapes for this research [2]. Zunkel’s commercial product about hand-geometry-based recognition applied to the many access control. Jain also used hand shapes to verify the individuals. Sample hand shapes are stored in database, and a defined distance is calculated for the evaluation of similarity.96.5% accuracy rate and 2% false acceptance rate (FAR) are achieved in their approach [3].
In many researches two possible biometrics are used for human hands. Geometrical features of hand such as finger with , length, and thickness. Because of varying these features, using hand-shape feature for access control is not reliable but it can be used in the entry control systems with low security requirements and a low rejection rate to record the entry data of employees or users.
System is designed based on palm-print features. First of all some palm sample scanned with SCAN Express 12000P and their paths and owners name and surname stored in the ORL database. After this process, the palm, which is used for differentiation the salient points (Figure 1) are found. The roi is extracted. It is transform using digital cosine transform.
The performance of palm verification algorithm is based on the techniques used for dimensionality reduction and pattern classifiers for pattern separation.Hence as an alternative approach Discerete Cosine Transform is proposed for dimensionality reduction is proposed which extract features of palmobjects with enhanced discriminatory power. Selection of suitable pattern classifier is based on seperability criteria in the output space.Object classes that are closer in the output spae.The classification accuracy of traditional nearest neighbor classifier is degraded when the object classes in output space are overlapping with each other. Hence Linear Discriminant analysis is chosen for pattern classification.

In this approach the features extracted has good information packing ability which are subjected to classification using linear discriminant analysis.A verification rate of %97 is obtained which is comparatively higher than the existing palm verification approaches. The results are compared with the verification obtained from DF-LDA and LEM.

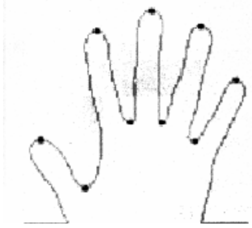

Figure 1. Salient Points

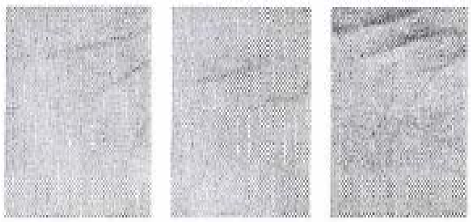

Figure 2. Sample Database Images

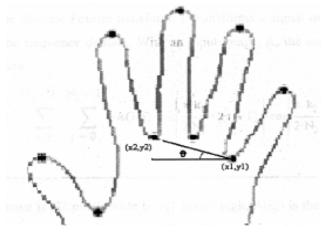

Figure 3. Finding Angle

2. DISCRETE COSINE TRANSFORM AND DATA COLLECTION

In this method DCT is used for feature extraction because it has been recognized as the world wide standard (JPEG) for image compression. In transform coding systems the mean square reconstruction error of DCT is relatively less with respect to other compression methods. Even though it is a glossy compression technique it has good compression ratio, information packing ability and reconstruction capability. Compared to other input independent transforms it has advantages of packing the most useful information into the fewest coefficients and minimizing the block like appearance called blocking artifact that results when boundaries between sub images become visible. These characteristics attracted in proposing this new approach. The DCT is an orthogonal transform [4] and consist of phase shifted cosine functions. It is calculated using the formula:

$$C(u,v)=\alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\left|\frac{(2x+1)u\pi}{2N}\right|\left|\frac{(2y+1)u\pi}{2N}\right| \qquad ...(1)$$

For u,v = 0,1,2,3,…..N-1 and

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

The images in the standard database (ORL database) are used to define the basis data set. The selection of training set should be representative of the expected classes of Palmprint features. The flatbed scanner is used for acquiring palm images because of its high availability and convenience. The printer, which is used in this work Mustek ScanExpress 12000P.The resolution of image, is chosen 2-2.5 Mp (Mega Pixel).To reduce the image size dimension being a little larger than of a person’s palm.

Totally 20 different person’s palm is scanned. Scanned images are cropped from wrists and their noise is removed using scanner program (iplus photo). An example of a subject with varying orientations is shown above in figure.2.

The block diagram of the proposed system is shown in figure.3. The images of ORL are of size “92x112”. For application of discrete cosine transform it is preferred to have the image sizes in powers of 2. So the images are resized to the sizes of “64x64”. The DCT array C(u,v) has frequency coordinates(u,v) and the original data sequence f(x,y) has space coordinates(x,y). The value N is the dimension of the image along the axis. The DCT coefficient matrix was calculated and the low frequency DCT coefficients were then extracted from the matrix and used as feature vectors. The input images are segmented into 8*8. When segmentation is applied 64 segments will be obtained. Discrete Cosine Transform is applied from which the feature vectors are extracted. During the experiment, the number of DCT coefficients extracted to form feature vector is varied from “1x1,2x2” and “3x3” per segment and as a result the size of feature vector will be 64, 256 and 526 respectively. The resultant feature vector will be normalized using the largest DCT coefficient. When DCT is applied for a given image, suitable quantization matrix is used so that most non-zero coefficients are clustered around the upper left corner. Since DCT has good information packing ability these coefficients store the characteristic feature of the images in the database.

3. PALM VERIFICATION

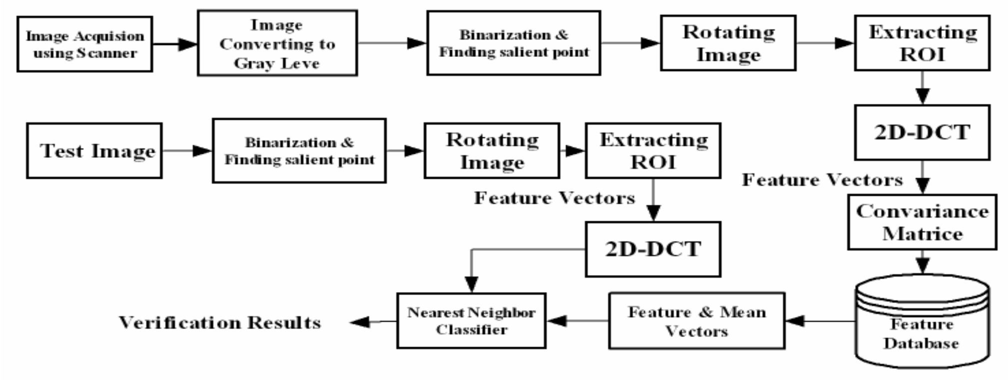

Figure 4. Block Diagram

4. LINEAR DISCRIMINANT ANALYSIS

There are many possible techniques for classification of data. The Principle component analysis (PCA) and Linear discriminant analysis(LDA) are two commonly used techniques for data classification and dimensionality reduction. 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. In PCA based techniques the shape and location of the original data set changes when transformed to a different space whereas LDA does not change the location but only tries to provide more class separability. The feature vectors can be transformed and test vectors can be classified in the transform space. The class dependent transformation involves maximizing the ratio of between class variance to within class variance. When the ratio is maximized adequate class seperability is obtained. The class specific type approach involves using two optimizing criteria for transforming the data sets independently. The class independent transformation involves maximizing the ratio of overall variance to within class variance. This uses only one optimizing criterion to transform the data sets and hence all data points irrespective of their class identity are transformed using this transform. In this type of LDA each class is considered as a separate class against all other classes. The within-class and between class scatter are used to formulate criteria for class separability. Within class scatter is the expected covariance of each of the classes. The scatter measures are computed using Where Sw is within scatter, pj is the priori probability of the class j and covj be the covariance of j class. The between class scatter is computed using the following equation

$$S_w = \sum_j p_j * (\mathrm{cov}_j) \qquad \text{...(3)}$$

$$S_b = \sum_j (\mu_j - \mu) * (\mu_j - \mu)^T \qquad \text{...(4)}$$

where Sb is the covariance of dataset whose members are the mean vectors of each class. The optimizing criteria in LDA is the ratio of between class scatter to the within class scatter. The solution obtained by maximizing this criterion defines the axes of transformed space.

An Eigen vector of a transformation represents a 1-D invariant subspace of the vector space in which transformation is applied. A set of these Eigen vectors whose values are non-zero are all linearly independent and are invariant under transformation. Thus any feature in vector space can be represented in terms of linear combinations of these Eigen vectors. A linear dependency between features is indicated by a zero Eigen value. To obtain a non redundant set of features all Eigen vectors corresponding to zero Eigen values are neglected. For any L class problem L1 non zero Eigen values are obtained. The Eigen vectors corresponding to the non zero Eigen values are used for transformation. The transformation along the largest Eigen vector axis provides a boundary for proper classification and has maximum discrimination information. Once the transformations are completed using LDA transforms, Euclidean distance or RMS distance is used to classify the data points.

The feature vector obtained in the previous step is of size “8x8” or “16x16” or “24x24” depending upon the number of coefficients extracted from each segment. For every subject 10 images are considered and there are 10 feature vectors. In the experiment 20 subjects are used and hence 200 feature vectors are obtained. Using these feature vectors the covariance matrices are found out based on the following principle. For M vector samples from random population, the covariance matrix can be approximated from the samples by

$$C_x = \frac{1}{M}\sum_{k=1}^{M} x_k\, x_k^T - m_x\, m_x^T \quad ...(5)$$

For the feature vectors of images in the database Sw and S b are calculated. The optimizing criterion is obtained and maximized which defines the axes of the transformed space. The Eigen vectors are calculated for these criterions and classification is performed.

4.1 Example

In this test for every image segment the dc coefficient is alone considered to form feature vector. For a given image size of “64x64” after segmentation 64 segments are obtained and each segment contribute one dc coefficient which constitute “8x8” feature vector . The feature vector is normalized using maximum magnitude of DCT coefficient. In ORL database for every person 10 images with different orientations and postures are available and hence 10 feature vectors are obtained. These feature vectors are used for finding the mean and covariance matrices. 200 images of 20 subjects are considered for the calculation of mean, covariance matrices, within and between class scatter. The feature vectors for some images are given below.

-39	-34	-15	-12	-10	-22	-28	-39
-36	0	14	24	24	16	-11	-39
-31	14	20	28	22	21	1	-41
-11	13	2	18	11	2	5	-14
12	21	17	17	17	15	16	7
-30	22	25	18	14	25	10	-36
-41	-3	27	11	8	20	-8	-44
-40	-15	23	20	13	9	-6	-43

Table 1. “8x8” Feature vector of 1-1.bmp

5. COMPARISION

The results obtained from the above experiments are tabulated and compared with the results obtained from LEM and Direct fractional step LDA [1]-[3]. The recognition rates obtained for different vector sizes are tabulated in table.2.

Results of DCT – LDA				FD-LDA	LEM
No. Sub	Feature vector size				
	8*8	16*16	24*24		
5	88%	100%	100%	98%	98%
10	84%	98%	98%	97%	96%
20	80%	96%	97.15%	96%	86.6%

Table 2. Performance Comparison

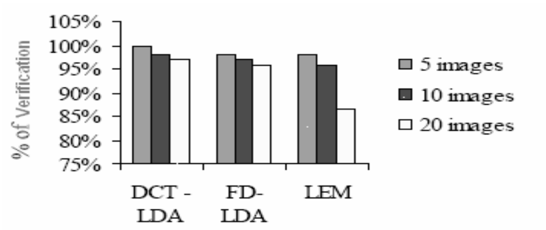

Chart.1 Performance Analysis

The above chart.1 represents the performance analysis of different recognition methods. From the experimental results it is found that the proposed approach out performs the other two approaches.

6. CONCLUSION

From the above results it is observed that DCT based feature extraction LDA base classification out perform LEM and DF-LDA methods. It also shows that discrete cosine transform is well suited for feature extraction with high percentage of dimensionality reduction. For every segment only 1/16 th of the dct coefficients are used which is less than 7%. The classifier LDA is well performing due its discriminatory power on the data on which it is applied. Even the increase in feature vector size does not make much difference in recognition. The face database consists of different images obtained at different orientations, illumination, lighting conditions. Still the proposed method is capable of giving better recognition. As an extension of this work the same experiment can be performed with more dct coefficients. Image database can also be increased in order to verify the feasibility of this approach.

7. REFERENCES

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