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Face Recognition Using Improved Principal Component Analysis with Different Transforms

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Abstract: *Most of the face recognition algorithms concentrate on the transformations (like DCT, FFT, etc.) for recognition of face images. These transformations concentrate on the global information of the face images and they miss the local information i.e. the relationship with the neighboring pixels. So, here, we considered the local matching method (local binary pattern) for considering the local information of the face images. For better recognition is obtained by combining the local as well as global information of the face image. So, for effective face recognition system, we combined the local binary patterns with the DCT. In this paper, we proposed a face recognition system with local binary pattern with DCT using doubly truncated multivariate Gaussian mixture model. By using EM algorithm with K-means or hierarchical clustering, the model parameters are estimated. The experimentation is carried with two face image databases, namely, Jawaharlal Nehru Technological University Kakinada (JNTUK) and Yale. The proposed system was found to be efficient compared to the existing system using GMM. The effect of the number of DCT coefficients on the recognition rate is also studied and found efficient recognition rate for 15 DCT coefficients. We also studied the recognition rate by varying the number of training images for each person.*

Keywords: *Local binary pattern; EM algorithm; doubly truncated multivariate Gaussian mixture model; DCT coefficients.*

1. INTRODUCTION

In recent days, face recognition system has gained its popularity due to its importance in security and surveillance. This system is useful in computer vision and biometric authentication. So, there is a need of automation of this face recognition system. So many no of researchers are worked on this face recognition system by using different techniques and transformations like DCT, FFT, GMM, HMM etc. In all these holistic methods they concentrated on the global information of the face images. Only the pixel information is considered and the relation with the neighboring pixels is missed. In order to incorporate the relations with the neighboring pixels they introduced the local matching methods. In this local matching method, it considers only local information but it misses the global information of the face images. To fill the gap, we incorporate both features by considering both local matching method (Local binary pattern) with DCT. Hence a face recognition system based on doubly truncated multivariate Gaussian mixture model with LBP and DCT as feature vector is developed and analyzed. (Md jan Nordin et al., (2011), Hazim et al., (2007), Pei-zhi-chen et al., (2010), Satyanarayana et al., (2007)). In model based face recognition systems, it is customary to assume that the feature vector associated with each individual face in the database follows a finite K component multivariate Gaussian mixture model. Since they assume each face is a collection of K-different components like eyes, nose, chins, cheeks, forehead etc., each represented by a Gaussian distribution, the mixture model is considered. But, the Gaussian mixture model has certain drawbacks such as the feature vector in each component is symmetric, meso kurtic and should have infinite range. However, in many face recognition problems, the feature vector of each individual face may not be distributed as meso kurtic and symmetric. Also, it has finite range bounded by two finite values, i.e., in many face images, the feature vector lies between two finite values. Ignoring the nature of finite range and asymmetrically distributed feature of the feature vector in each component may bring falsification in the face recognition model and may not be accurate. The probability density function of the doubly truncated multivariate normal is $\frac{\varphi(\vec{z})}{\int \int_{\vec{z_L}}^{\vec{z_M}} \dots \int \varphi(\vec{z}) dz_1, dz_2 \dots dz_K}$ Where, J is the Joint probability density function of multivariate ormal distributions. The value of is significant based on the values of the mean vector and variance covariance matrix . The doubly truncated multivariate Gaussian distribution includes several asymmetric / symmetric, lepto kurtic / meso kurtic/ platy kurtic distributions with finite range. It also includes Gaussian distribution as a limiting case when the truncating parameters tend to infinite. The effect of transformation on multivariate Gaussian distributions is highly influenced by and . Hence, to have an accurate face recognition system it is needed to characterize the feature vector of each component in each individual face is to be characterized by a doubly truncated multivariate Gaussian distribution and the whole face image is to be characterized by K-component doubly truncated multivariate Gaussian mixture model (Norman et al., (1995), Sailaja et al., (2010), Haritha et al., (2012)). Very little work has been reported in the literature regarding utilizing doubly truncated multivariate Gaussian mixture distribution in face recognition systems. Here, it is to be mentioned that, even though, several systems have been developed for face recognition, there doesn't exist a unique face recognition system which is capable of recognizing all faces in different conditions of image. This stresses the need for developing new face recognition system with plausible assumptions, which provide accurate recognition. Therefore, in this paper, we fill the gap in this area of research by developing and analyzing face recognition system based on doubly truncated multivariate Gaussian mixture model. Basics related PCA and Transforms are discussed in section II. Proposed method is discussed in section III. Experimental results are presented in section IV. Concluding remarks are discussed in section V.

2. PCA AND TRANSFORMS

In this section, we briefly review some important contributions in the face recognition system based on local binary patterns (LBP). Timo Ahonen et al., (2003) studied a face recognition system based on LBP. They divided the face area into small regions and applied LBP. The histograms of LBP are extracted and concatenated, the resultant histogram represent the feature vector. The nearest neighbor classifier used for classification.

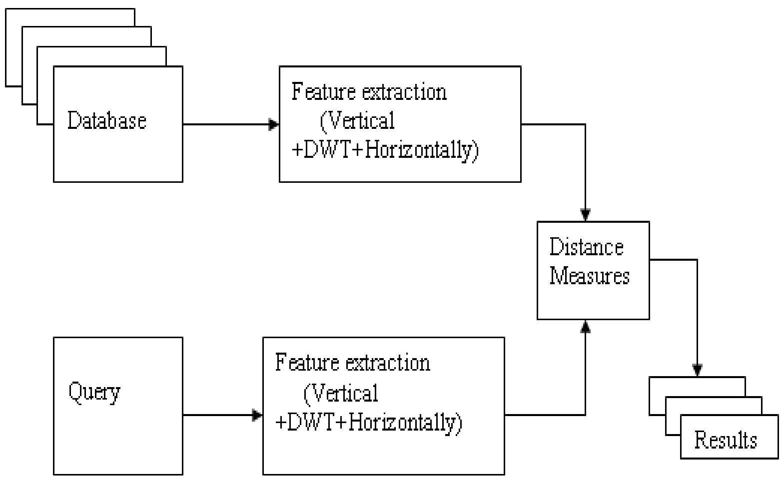
Yann Rodriguez et al., (2006) analyzed an approach for face authentication, based on a LBP description of the face. A collection of LBP-histograms are considered for a generic face model. From this generic model, a client-specific model is obtained by an adaptation technique under a probabilistic framework. Yann Rodriguez et al., (2006) analyzed a face authentication experimental protocol. They compared their approach with the two approaches: LBP-b, LBP description of the face. This generic face model is derived by the collection of LBP-histograms. Hazim et al., (2007) studied a face recognition system with DCT and LBP. They divided the face image into several blocks. For each block of the face image LBP is applied. The obtained LBP representation is then decomposed into non-overlapping blocks and on each local block the DCT is applied to extract the local features.

The extracted local features are then concatenated to construct the overall feature vector. Qian et al., (2007) considered a face authentication algorithm based on LBP. They applied the LBP for each block of the face image after dividing the face image into several blocks. After obtaining the LBP image, they applied likelihood ratio classifier. Xiaoyang Tan et al., (2007) studied a face recognition system with Gabor Wavelets and LBP. LBP concentrate on the textual features of the face image and Gabor features encode facial shape over a broader range of scales. For dimensionality reduction they applied PCA for both feature sets. After extracting the feature vector, the Kernel Discriminative Common Vector method is then applied to the combined feature vector to extract discriminant nonlinear features for recognition. Aroussi et al., (2008) analyzed a face recognition system with LBP and DCT. For representing facial image they combined LBP (which provides micro texture in spatial domain) and DCT (which acquires macro information in frequency domain). The support vector machines (SVMs) is used to perform the classification of these feature sets. Chi Ho Chan et al., (2007) studied a face recognition system using Multi-scale Local Binary Pattern Histogram (MLBPH) descriptor. They also studied on other descriptor namely Multispectral Local Binary Pattern Histogram (MSLBP).

Gritti et al., (2008) studied a system for facial expression recognition with LBP. They used histogram of oriented gradients (HOG) descriptors for facial representation. They applied LBP and local ternary patterns (LTP). Timo Ahonen et al., (2009) studied a face verification system based on kernel density estimation of local LBP distributions. The developed system is a spatially precise model. They used the weighted information fusion for each individual pixels by using the linear support vector machine. Hazim et al., (2010), evaluated four local descriptors, namely, A V1-like feature, the LBP and two patch-based variants, the three patch local binary pattern (TPLBP) and the four patch local binary pattern (FPLBP). An image pair is extracted as a feature from each image using one of the local descriptors. They used four different comparison methods: concatenating, similarity measure, block wise similarity measure and LDA one shot similarity score. Among the four local descriptors, V1-like features do not perform well. Pei-zhi Chen et al., (2010) studied a face recognition system based on DCT and LBP. They applied DCT for the input face image. For dimensionality reduction they used only few DCT coefficients. A few DCT coefficients on the left top corner are chosen as the global feature. The face image is divided into several blocks. For each block they applied LBP and then LBP histogram sequences (Uniform LBP used) are accepted as the local feature. For classification they used Support Vector Machine (SVM). Juefei Xu et al., (2010) investigated the feature extraction methods for biometric identification. They considered LBP, DCT and DWT. They used simple distance measures for the verification rate (VR). Rui et al., (2011) studied a face recognition algorithm by combining LBP with SRC. Divide-and-conquer technique is used in order to solve the problem of dimensionality and the discriminative power is strengthen via its pyramid architecture. Huang et al., (2011) analyzed a comprehensive survey of LBP methodology, including several more recent variations. The standard LBP approach was discussed and also facial image analysis using this LBP approach is reviewed. In addition to this, its successful extensions, which deal with various tasks of facial image analysis, are also highlighted. Several variations to the LBP technique are also mentioned. In the local or component-oriented LBP representations are effective representations for facial image analysis, as they encode the information of facial configuration while providing local structure patterns. Md Jan Nordin et al., (2011) analyzed combination techniques of appearance-based and feature-based feature extraction on the T-Zone face area to improve the recognition performance for the face recognition system. They studied the influence of T-Zone area and the combined technique on the face recognition rate. A T-Zone face image is first divided into small regions where LBP histograms are extracted and then concatenated into a single feature vector. The T-Zone area consists of only eyes and nose region. Further dimensionality reduction of feature vector, PCA technique is applied.

3. PROPOSED ALGORITHM

Block diagram for the proposed method is shown below detailed algorithm is presented below:



1. Each image is decomposed as sub band.
2. Sub band is resized to the original image size.
3. Each resized image is partitioned into sub images.

4. Convert the each sub image into column data matrix. Each of them can be expressed in the order of a D-by-N. $C_i = \{c_{i1}+c_{i2}+c_{i3}+\ldots c_{iN}\}$ with i = 1, 2,…….. K. here N is the total number of images
5. Calculate mean value for each sub image.
6. Subtract the mean value from column data matrix of each sub image then obtain vertically centered column data matrix $C_{vi} = \{\hat{c}_{i1}+\hat{c}_{i2}+\hat{c}_{i3}+\ldots\hat{c}_{iN}\}$,i = 1, 2,……...K.
7. Rearrange the elements to get square matrix.
8. Collect Eigen values, Eigen vectors, and diagonal values of the square matrix
9. Repeat the same procedure for row data matrix.
10. Reduce the feature size as per the requirement as feature 1.
11. Above steps are repeated for the whole image without DWT to generate the feature 2.
12. Feature 1 and 2 are combined to get the global feature.
13. Minkowski distance is used to retrieve the relevant images.
14. Minkowski distance is concentrated on Euclidean [19] space, which can be considered as a generalization of both Euclidean and Manhattan distance for getting more recognition efficiency.

4. Experimental Results

Recognition performance in terms of average recognition rate and recognition time of the proposed face recognition system is tested by conducting experiments on Yale data base [7]. A face database set was constructed by selecting 40 images of 4 individuals, ten images per person. These images of a person used for training and testing. With these initial estimates the refined estimates of the model parameters are obtained by using the updated equations of the EM algorithm. The parameters of the generic model are stored under the parametric set . The individual face image model parameters are stored with the parametric set , i= 1, 2, ... N. N is the number of face images in the database. The recognition rate of each database is computed for different threshold values of t in (0, 1). The False rejection rate, False acceptance rate and half total error rate for each threshold are computed using the formula's given by Conrad Sanderson et al., (2003).Feature selection

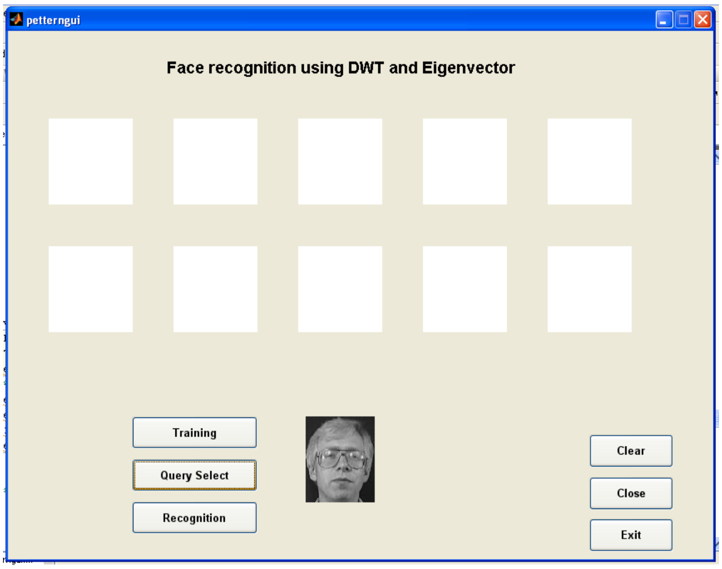


Fig2. *Sample image from face database*

From the query image feature is taken based on the proposed method. In this paper 64×1 vector is generated for all images of the particular image(S=16). For each sub-pattern [14] four positive eigenvectors (largest eigenvector) [21][22][24] of the sub-part is considered. By considering query image results are shown in figure.

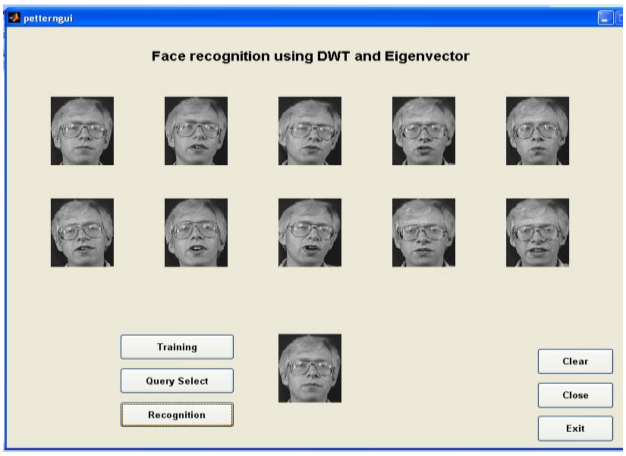


Fig3. *Sample image from face database*

Table1. *Recognized rate on face database (1, 3, 5,7,10 are Top 'N' recognized images)*

	Number of top matches				
	1	3	5	7	10
Mean value	100	77.5	71	65	58
Variance	100	58.5	50.5	44.2	36.25
Diagonal (SVD)	100	60	54.5	48.2	42.25
Hybrid Approach (improved PCA + transforms)	100	99.16	95.5	87.4	78.75

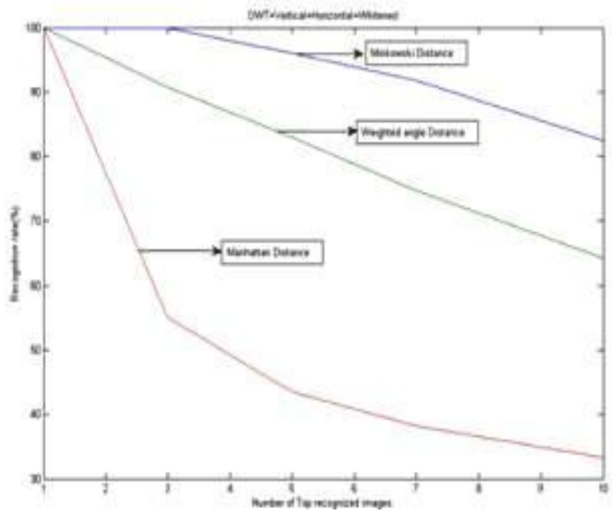


Fig4. *Comparative recognition rates*

4.1. Average recognition time

Face recognition using DWT and Eigen vector is presented. Time taken for generating the features for the entire database is 53.98 seconds. Recognition time for Minkowski, Weighted angle and Manhattan are 0.44, 0.46, 0.44seconds respectively for weighted angle based approach. Similarly database time for DWT and Eigen vector is 52.84 seconds. Recognized time for Minkowski, Weighted angle and Manhattan are 0.45, 0.45, 0.39 seconds respectively.

5. CONCLUSION

Face recognition using discrete wavelet transform (DWT) and eigenvector is presented in this paper. Global feature vector is generated and used for face recognition. Horizontal and vertical variations are considered in feature vector. Face recognition using discrete wavelet transform gives better performance in terms of average recognized rate 3.25% improvement is observed at top ten matches and retrieval time compared to the existing methods.

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