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Fourier Spectrum Features for Face Recognition

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***Abstract:** The objective is to introduce a novel approach which deals with the challenges: uneven illumination and partial occlusion. This method performs face recognition by extracting the magnitude spectra features. At each point on the face, largest matching areas were found. Thus robustness is achieved using Fourier magnitude spectra feature extraction and largest matching area comparison. This method performs competitively with corrupted images and other unsupervised methods. The proposed approach is experimented on Yale B and AR datasets.*

***Keywords**-Face Recognition, LMA, Fourier transform*

I. INTRODUCTION

Face recognition is the technique used for identifying a person from the image[5]. Facial recognition is achieved by extracting features from the input face image. The extracted features are compared with the features of the database. The facial expression is used in security purposes such as Biometric Artificial Intelligence based applications [14]. Matching methods are used for the verification of persons. Facial texture and shape patterns are used for the verifications. This system is used in most of the security applications. The performance of the face recognition system is similar to performance of the other biometric systems such as iris recognition and fingerprint recognition. Due to its non-invasive and contactless process it can be widely adopted, although the accuracy of facial recognition system is lower than iris recognition and fingerprint recognition [13]. Facial recognition faces the problem of uneven illumination and partial occlusion [1]. Because of these problems changes were caused in its feature representation which may result in variation between the images of the same person.

II. RELATED WORK

Face recognition performs various processes. Some of the important steps are feature extraction and classification [3]. The distance between center pixel and neighboring pixels are determined, Locally Adaptive Regression Kernel (LARK) [12] descriptor measures the self-similarity between the testing and training images. A new technique developed for the improvement of LARK concept [2].

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This concept is constructed based on the binary like representation of the face image. It is obtained using Principal Component Analysis and logistic functions to the kernel. Geodesic distance was measured for the determination of LARK. If noise is available in the image, it identifies the unconstrained geometric structure of the face image. Blocked based weighted local binary pattern was used for the recognition of un-occluded area of the image [4].

For non-occluded images, the face recognition carried out by Blocked -based weighted local binary patterns (LBP) method [20]. The detection of occlusion in the images is carried out using PCA and Support Vector Machines (SVM) model. Markov Random Field model to find the discontinuity in spatial domain [6]. It can be identified in different occlusions. It is also used for the determination of sparse illustration of the image. The distribution error of the pixel identity can be identified for the improvement of sparse illustration based algorithm [7]. Adaptive sparse representation-based classification (ASRC) which is a framework used for the sparse representation [8]. In this procedure, it is considered that sparsity and correlation are the representations. The low correlation samples are identified by ASRC. These samples which are different from low correlation samples are selected. ASRC does not select the samples randomly; it selects the most discriminative and correlated samples. The correlation structure is adaptive that are benefited in the representation model. Band reweighed Gabor kernel for the recognitions of human faces in different illumination conditions [9,21,24]. The Gabor filter is used to process the input image. It transforms the input image. The transformed image provides the Gabor features. Gabor features are determined in different scales and orientations [10,22,23]. Fisher scoring function was used for the measure of features in different bands. The feature having highest score is selected for memory requirements. The different band which stores the features is represented as vector. The features in the vector representation can be identified using weighted kernel discriminant criterion. Constrained quadratic programming method is used to solve these vectors. The similarities between two images are the weighted sum of nonlinear bands [11]. The Mahalanobis distance is measured for feature matching. The minimum Mahalanobis distance is used for matching. The sparse inverse covariance matrix was determined using graphical Lasso function [15]. The face recognition with different illumination conditions and different occlusions are considered for the recognition. The accuracy of the system is considered as the correct recognition of the testing images. It is also applicable for the real time face recognition system. It is applicable in major security systems like password checking, defense and banking systems. Most of the developed countries using these features in day to day life [16].

III. PROPOSED WORK

A. Band pass filtering

A band pass filter is used for the preprocessing. The low frequency illumination error is reduced using band pass filtering. It is used to preserve the discriminative reflectance information. The illumination factors in the high frequency range are normalized and noises in the high frequency components are removed.

The filter used is the difference of Gaussians (DoGs) kernel. DoGs perform effectively for illumination–invariant face recognition.

$$\mathrm{DoG}(x,y) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-(x-y)^2/2\sigma_1^2} - \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-(x-y)^2/2\sigma_2^2} \quad (1)$$

The filter is applied to the entire testing and training images in advance to the other processes were conceded out. The variance of the Gaussian functions is fixed.

B. Patch Selection

Facial recognition is performed by partitioning the face image into blocks in a piecewise manner. Then based on the new lighting model the illumination within each block is normalized. Face image is separated into a quantity of limited patches. Gaussian function is used to model numerical changeability of the training data inside each patch zone. The occluded and partially illuminated face image is first splitted in to sub patches. The features are extracted from these sub patches. Images patches are used to find a largest matching area over with even illumination

C. Fourier magnitude feature extraction

Any deviations in the perception of person's appearance and body gesture, it smoothen the aligned face image and it may not correspond to the same physical location. Two dimensional Fourier magnitude spectrums are used as the piece to characterize each limited image area to reduce these errors. Due to the shift invariance characteristics of the Fourier series representation, stoutness to minor misalignment mistakes and facial countenance changes is improved. Here the phase information is omitted. Two dimensional Fourier transforms is applied to an area in the testing image. Testing image is a band pass filtered image. Assume that piecewise interminable brightness model poppers for the region, the important stimulating image magnitude spectrum is given by,

$$\left|\tilde{\mathcal{I}}^m_{\delta(x,y)}(u,v)\right| \simeq \beta^m \left|\tilde{\mathcal{R}}^m_{\delta(x,y)}(u,v)\right| + \delta(u,v)\tilde{\alpha}^m$$

(2)

The feature vector set is formed by taking the magnitude spectral coefficients, discarding the zeroth coefficient and then concatenating the outstanding coefficient into a vector. The vectors containing features from the preparation and challenging images is compared using Cosine similarity.

$$\mathrm{CS}\left(s_{\delta(x,y)} \middle| s^m_{\delta(x,y)}\right) = \frac{s_{\delta(x,y)} \cdot s^m_{\delta(x,y)}}{\left\|s_{\delta(x,y)}\right\| \left\|s^m_{\delta(x,y)}\right\|} \quad (3)$$

To calculate the matching response of testing image vector is matches with a training image vector likelihood function is used. The largest matching areas are determined using this matching concept. It is done with different illumination conditions. The cosine similarity based likelihood function. This prospect utility is centered on the cosine connection. The cosine connection precedes tenets in the series [0, 1] for feature vectors of magnitude spectrum based concept. Likelihood function is represented in exponential form.

$$P\left(s_{\delta(x,y)} \middle| s^m_{\delta(x,y)}\right) = M^{CS(s_{\delta(x,y)}, s^m_{\delta(x,y)})} \quad (4)$$

D. Image Matching using LMA

The partial occlusion problem can be rectified using Largest Matching Area approach. If partial occlusion present in the image, then the matching scores are determined. These matching scores are used to emphasize to solve the issue. The altered chunks of the face image are considered for the recognition. The highest matching scores are determined to avoid the individual areas to be not considered for matching. It is difficult to find the exclusion areas of the face image. Because, there is a possibility of removing important data used for the recognition. The Largest Matching Areas including the occluded part of the image will be determined for training and testing. Here, some parts are not identified because of occlusion. The occluded parts of the image are removed from the list. During facial recognition, when relating a challenging image against each of the training images the feature vectors of testing and training images from image locations are compared, where within the compared locations, the testing image is supposed to have a continual illumination [17]. The largest matching area is determined to progress the accurateness of the structure. The accuracy can be improved by the assumption of matching scores for the constant illumination areas. Based on the possibility task, the problem of guessing the biggest area as an MAP problem is framed. Feature vector contains the parameters which are included for testing and an identical aforementioned probability is expected for all likely matching image areas. The successive probability of similarity is defined as,

$$P\left(s^m_{\delta(x,y)} \middle| s_{\delta(x,y)}\right) = \frac{P\left(s_{\delta(x,y)} \middle| s^m_{\delta(x,y)}\right) P}{\sum_{All\, s'} P\left(s_{\delta(x,y)} \middle| s'\right) P} \quad (5)$$

When the size of coordinated image areas with uniform brightness upsurges the subsequent probability upsurges. Thus the approximation of the largest matching area of the test image is found. If the images are not identified and it has stagnant lighting conditions, then the best approximation of the largest area in terms of the maximum succeeding possibility will be found on the training image and it is given by,

$$\hat{\delta}^m(x,y) = \arg\left\{ P\left(s^m_{\hat{\delta}^m(x,y)} \middle| s_{\hat{\delta}^m(x,y)}\right) = \max_{\delta(x,y)} P\left(s^m_{\delta(x,y)} \middle| s_{\delta(x,y)}\right) \right\}.$$

(6)

By using the conforming subsequent of the evaluation, similarity grade for all training image is mounded [18]. Then, the complete score for exercise image is calculated.

$$\Gamma\left(I^{m}, I\right) = \sum_{(x,y)} \ln P\left(s^{m}_{\hat{\delta}^{m}(x,y)} | s_{\hat{\delta}^{m}(x,y)}\right) \quad (7)$$

IV. EXPERIMENTAL ANALYSIS

The trained input images are of various pixel sizes. They are cropped to required pixel size. Here the input images are imperiled to pre-processing, patch selection, feature extraction and then compared with test image for recognition. Figure 1 shows the trained input images.

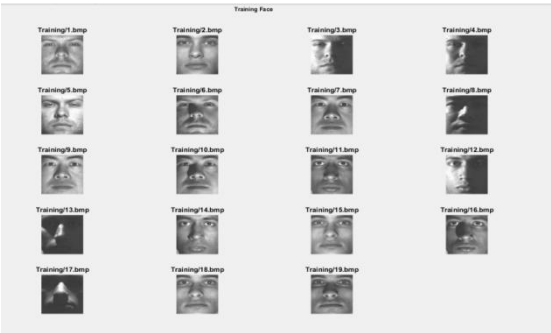

Fig.1 Trained images

The input image taken from Yale B database named test image. The system will extract image features for this face. The face images have different pixel size. Here the face image taken for face recognition is converted to required pixel size. Figure 2 shows the input test image

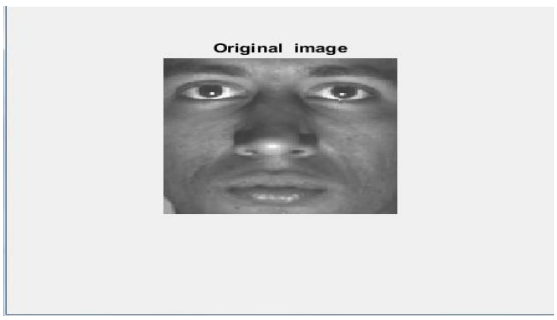

Fig.2 Input test Image

The task of preprocessing is to progress the feature of images. The input image is given to the bandpass filter. Figure 3 shows the test image subjected to preprocessing

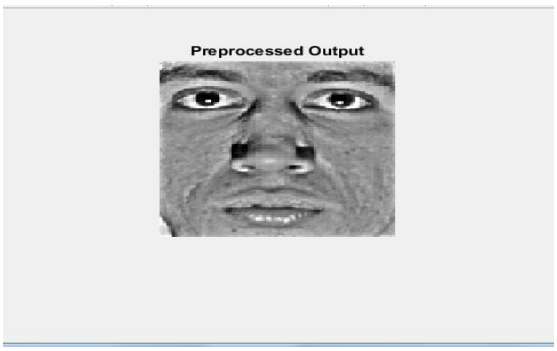

Fig.3 Preprocessed test image

The patch extraction in which face image is separated into a number of indigenous patches [19]. Gaussian function is used to model the algebraic erraticism of the training data within each patch. The occluded and partially illuminated face image is first splitted in to sub patches wherein the features are extracted.

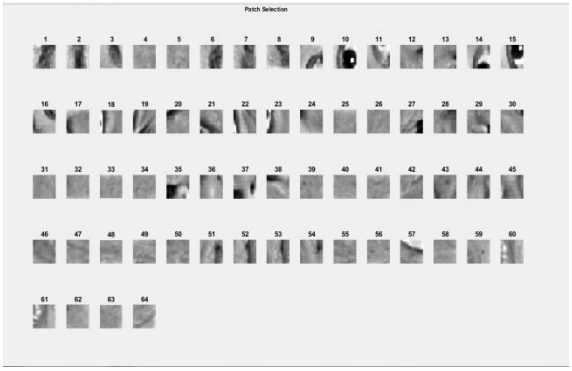

Fig.4 Patch selection

By applying two dimensional Fourier transform to an area in the testing image the respective feature vectors are acquired for every patch. The feature vectors for each patch are formed by taking the magnitude spectral coefficients and neglecting the zeroth coefficient. Then the remaining coefficients are concatenated into a vector.

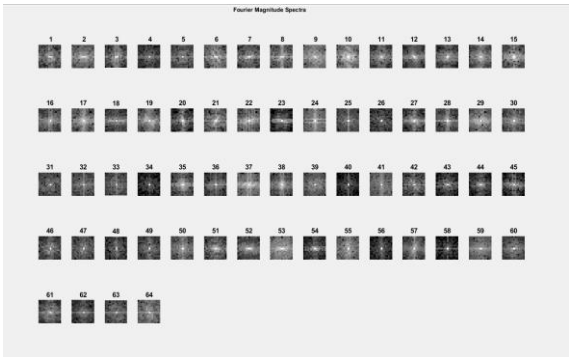

Fig.5 Fourier Magnitude Feature Extraction

By the obtained feature vectors, the testing image is compared with each of the training images. The most-likely matched trained and tested images areas were identified using posterior probability. The overall matching score for exercise image is calculated. Figure 6 shows the matched images for the given input from the database.

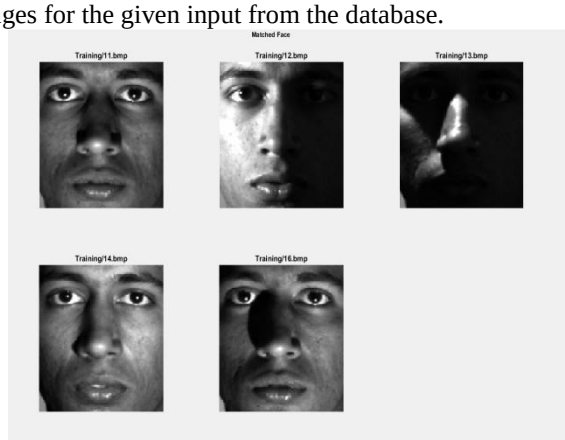

Fig.6 Image matching

V. PERFORMANCE ANALYSIS

For retrieving the enactment of LMA, several set of experimentation were conducted. A solitary un-occluded regularly floodlit face of every person is trained.

The images with computer-generated fractional occlusion are generated throughout testing by substituting the adjoining square of testing image by the unconnected image. It covers the testing image area with an value of 20%, 40%, 60% or 80%. The performance of system falls when the amount of occlusion rises.

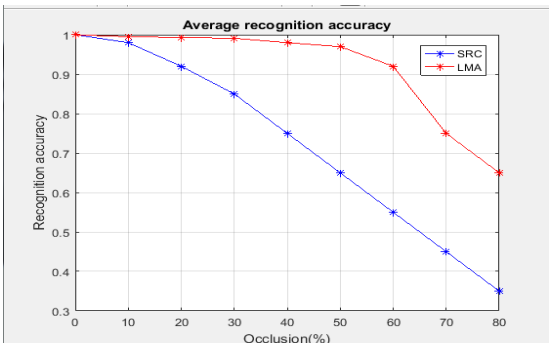

Fig.7 Average recognition accuracy

VI. CONCLUSION

Robustness is achieved by ruling the biggest matching area at each point. It deals effectively with the problem of uneven illumination and partial occlusion. This method performs better when the training image is non-occluded and also performs well when then the training image is corrupted. The success of this method shows the importance of two factors: inclusion of unseen data model and finding largest matching area.

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