

Fuzzy Face Recognition Based On Skin Texture **Fusion Model**



Yogish Naik G.R., Prabhakar C.J., Arun Kumar H.D., Thontadari C.

Abstract: Facerecognition is a research are in computer vision and pattern recognition because of its importance in real applications like human machine interaction, video surveillance, and security systems. Here we have proposed a fuzzy model for robust facerecognition using gradient and texture information. Initially, the local binary pattern (LBP) and histogram of oriented gradients (HOG) feature of face skin from the original images are extracted. These two features are used for the development of our fuzzy model. For the analysis of faces, a content-based similarity measure is developed and used for data analysis of trained face model and test face model. The proposed algorithm is experimented on LFW, AR, and ORL face databases. The proposed fuzzy face fusion model approach shows that our proposed method is having good recognition rate compared to facerecognition methods developed recently.

Index Terms: face recognitionl, histogram of oriented gradients, binary pattern, LBP.

I. INTRODUCTION

The facerecognition is a computer vision technique that uses the computer to analyses the face images to extract useful information for recognition from them, which is called as a feature vector, and it is used for distinguishing biological feature. With the development of computer vision, the facerecognition methods, have a larger application in our life, such as public security system, the bank and customs control system, and mobile phone application. The facerecognition methods help in securing the confidential information and have more secure financial transactions. Facerecognition is still very difficult for the computers, due to the facial expression changes by aging, the distance and angle of photograph, illumination of the face image. In summary, these difficulties make facerecognition a challenging task.

Facerecognition is associated with lot fields such as pattern recognition, neural networks, computer vision, image processing and computer cognition. In recent years, techniques based on biometrics have emerged as the most efficient methods for recognizing persons. In recent times, facerecognition has got clear advantage over different

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biometric methods, such as iris, fingerprints, hand geometry and retina for two main reasons. First, the face images can be acquired without any prior knowledge and the facial images can easily be captured from a distance. In the field of computer vision, facerecognition is challenging as it deals with the images of face having different expressions, illumination differences and different pose variation. Facerecognition algorithms with proper pre-processing of images may able to reduce the effect of illumination differences, pose variations and noise in the face images. A facerecognition system consists of two steps in general: (i) feature extraction and (ii) classifier design. outcome of classification stage mainly depends on the extraction process of facial features.

There have been many facerecognition techniques developed in recent years. The outcome of the different facerecognition techniques are impacted mainly by illumination, occlusion and changes in expression. [1]. The optimal feature extraction and efficient classification methods are the two stages of a facerecognition system. To increase the recognition rate of a facerecognition method, its necessary to find an effective feature extractor and a good classifier, [2]. To increase the robustness and efficiency of the algorithm during the classification stage, it is required to reduce the dimension of extracted feature.



Fig. 1. Pipeline of the proposed approach



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In recent years, there has been no approach being used for fuzzy fusion model like skin texture and gradient feature used for the facerecognition techniques. The proposed fuzzy facerecognition method based on skin texture fusion is illustrated in Fig. 1. The proposed method comprises of three stages: (i) extraction of texture and gradient features (ii) feature fusion (iii) testing face image matching with training set. In primary stage, texture feature is extracted by LBP and gradient feature from HOG method. In secondary stage, we combine these LBP texture feature and HOG gradient feature in to single vector. Then, in final stage, we match testing face fusion feature with training set.

II. RELATED WORK

In recent years, many algorithms are being proposed for reducing the dimension of features and many techniques are developed for increasing the accuracy in recognition and speed of facerecognition algorithms [3]. The facerecognition techniques are classified into component based (local feature based) or holistic methods. The holistic appearance based recognition techniques use a vector to represent the face feature entirely in high dimension feature space. The local feature based facerecognition techniques before performing the facerecognition depend on the components of the face like mouth, nose and eyes. In holistic as well as local feature based facerecognition techniques, representing the facial features to a lower dimension is challenging work. The traditional method used for reducing the dimension of the face features is Principal Component Analysis(PCA). PCA based techniques include changing over unique face feature into a high-dimensional covariance matrix and is hard for assessing covariance matrix precisely because of its large size. Henceforth PCA techniques require high calculation time and experience the ill effects of poor decision making for huge feature set. So as to overcome these issues, different strategies, like, a 2 dimensional Principal Component Analysis(2DPCA), Independent Component Analysis(ICA), Linear Discriminant Analysis(LDA), Kernel Linear Discriminant Analysis(KLDA), Kernel PrincipalComponent Analysis(KPCA), [4], Etc. are proposed by numerous researchers. The 2DPCA technique depends on the matrix and it processes the covariance matrix for face feature without changing matrix to vector. The LDA is a reduction method for dimensionality that records a higher facerecognition performance compared to the other techniques. It gives a small feature set that carry the maximum information relevant for classification of face features. Be that as it may, the performance efficiency of these techniques depend on the statistical distribution of the information and the complex embedding of the neighborhoods and these techniques require re calculation of base vectors every time a new feature of face is added in to the database. In order to conquer these limitations, appearance based strategies have been presented by Hiremath P. S. et al., 2005 [5].Recently, numerous facerecognition techniques based on appearance techniques have been developed for reducing the calculation time required for face image classification. The facerecognition systems based on appearance use the intensity value of the pixel of face image for the recognition. These are represented as single valued

variable, which are unable to extract the variation in the feature value of the different images from the same face and likewise have a high dimensional feature data. One of the methods adapted by researchers to develop more efficient recognition system with lesser number of features is the methodology of feature learning. To improve the performance of the process of classification, feature learning is used for extracting the features from the face image datasets to construct the training face image data [2]. Thus, various active learning strategies have been developed, which combine informativeness and representativeness of training feature sets to achieve better accuracy in classification. Chong Peng et al., 2017, have developed methods for classification of high dimensional and low dimensional data, a supervised feature learning model [6]. The recognition technique estimates the regression vector with the help of discriminative regression method, that is used for estimating the similarity between training data and test data. The presence of distortions like pose variation, illumination, geometrical variations and occlusion affects the high dimensional and low dimensional data, the task of classification becomes more challenging. To deal with these kinds of distortions, a mathematical multiclass classification for the high dimensional face image data has been developed. The min-max framework estimates a representation model, that is optimal and limits the fitting error for the distortions to the feature data in an application of interest. The categorical information is inferred depending upon the regression model and estimated models used for classification [7].

III. FUZZY DATA MODELING APPROACH TO FACE RECOGNITION

Feature extraction is the major step in facerecognition. The recognition can be made easier and accurate by extracting face feature from the face images. Both the texture (global) and gradient (local) features are important for the representation as well recognition of the faces. Both the texture feature and gradient feature play different roles in facerecognition. Therefore, it is required to combine both the features together. In the proposed technique, both texture feature as Local Binary Pattern and local features as Histogram of Gradient Orientation (HOG) are extracted.

A. LBP Features

The LBP (Local Binary Pattern) descriptor was first presented by Ojala et al., in 2002. The LBP descriptor defines each pixel by comparing its value with that of the neighboring pixel. In the case where the neighboring pixel value is than or equivalent, at that point the value is set to 1, otherwise it is set to 0. At that point the concatenation of binary patterns over the neighborhood as a decimal number is a single interpreter for each pixel [8]. The LBP(Local Binary Pattern) is described as:

$$LBP_{R,P} = \sum_{p=0}^{p-1} S(g_p - g_c) 2^p \qquad (1)$$

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Where, g_c is the central pixel gray value and g_p is neighboring pixel gray value, the spacing **R** is equal to the radius, and **P** is the neighborhood size. The S (X) is the threshold function defined as

$$S_{x} = \begin{cases} 1 & x \ge 0\\ 0 & Otherwise \end{cases}$$
(2)

B. Gradient Features

The histogram of oriented gradients descriptor was proposed for detection of human by Dalal et al in 2005 [9]. The application of HOG descriptor has been in many research areas like word spotting in documents, Body part detection, characterrecognition, facerecognition, detection of vehicle in traffic videos, classification problem of text and non-text.

The HOG of the image is calculated as the gradient-orientation histogram in the local area of that image I. The major difference between HOG and SIFT is that HOG normalize the histogram in the overlapping local blocks and makes the redundant expression. And another difference is that SIFT describes the magnitude and orientation of the generalized image patch around the detected key point, while the HOG is calculated in a grid of regular window without scaling or normalizing. The gradient orientation of pixel is calculated as follows for extracting the HOG feature:

$$\theta = \arctan\left(\frac{I_x}{I_y}\right) \tag{3}$$

where, $\arctan(I_y/I_x)$ is the inverse tangent of element in degree. The vertical and horizontal gradient calculated by the Gaussian filter are I_y and I_x . Then, histogram of each orientation in the rectangular region is calculated. The histogram of each orientation is then computed of the rectangular area. The orientation of the pixel is quantified in Nbin and the orientation histogram is calculated for each bin as follows

$$H(i) = \sum_{x,y \in I, G_{m(x,y)}} G_x(x, y) \quad i = 1, 2, 3, \dots n \quad (4)$$

where, **Gm** and **Gg** are the magnitude and gradient orientation at (x, y) respectively. In the end, the descriptor for HOG is calculated by linking the histogram H(i) to all regions.

C. Image Fusion

Combining two or more image with the corresponding information in one image is called image fusion. The result of the fusion will be informative of any input image. Methods for the combination of images in the spatial domain create spatial distortion in the acquired image, and the error of the misregistration is more obvious. Therfore, the region-based method are used. The region-based methods are more advantageous, as they are less affected by misregistration, less sensitive to noise, and have better contrast.

D. Similarity Measure

The similarity between the testing skin texture face image feature and training skin texture image feature present in the

Retrieval Number E7315068519/2019©BEIESP DOI: 10.35940/ijeat.E7315.088619 Journal Website: <u>www.ijeat.org</u> dataset is computed, to extract the face image identical to the testing face image. Lowe [10] has proposed a nearest neighbor search (NNS) method, considering an appropriate threshold T between training image and testing image with Euclidiandistance, to obtain the matches.

$$NNS = \sqrt{\sum_{i=1}^{n} (d_i(i) - q(i))^2} < T$$
 (5)

Where, d_j and q are fusion skin texture feature of **jth** training and testing face image respectively and **n** is the training set dimension

IV. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

To evaluate the implementation of the proposed method, experiments were conducted with individual databases, such as the LFW, AR, and ORL databases. Various images of the ORL database and the FRGC database are used for testing. The ORL database contains 400 images of 40 persons, 10 faces of the person with differences in pose and expression. FRGC database consists of 12,776 images with expression under different lighting condition. Sample images of the ORL and FRGC database are shown in Figure 2. Variation in lighting conditions, facial expression changes, such as open eyes (or) closed eyes, smiling (or) not smiling and occlusion details, are displayed on the face images. The implementation of the method proposed is assessed by considering the LFW database. The LFW database contains over 13,000 face images of 5,749 persons.



Fig. 2. Images from ORL and FRGC database





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V. CONCLUSION

For facerecognition global and local face feature are important. The global face feature is derived from the entire face image, and the local face feature are extracted from the spatially isolated face patches. For facerecognition, local feature is better than global feature. In methodology proposed above, we have extracted both the global and local features and the classification errors are reduced. The fuzzy fusion of the face image is done by region-based face image fusion. For the test image matching with the image in the database, Correlation Coefficient is used. For testing, face image from FRGC and ORL database are utilized. The comparison of the face features is made first by examining the local feature, then the global feature and then combining local feature with global feature. The recognition rate for the global feature is 64%, for local feature is 80% and for the combined global and local feature is 92%.

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