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Pose and Illumination in Face Recognition Using Enhanced Gabor LBP & PCA

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Abstract: *This paper presents the face recognition based on Enhanced GABOR LBP and PCA. Some of the challenges in face recognition are occlusion, pose and illumination .In this paper, we are more focused on varying pose and illumination. We divided this algorithm into five stages. First stage finds the fiducial points on face using Gabor filter bank as this filter is well known for illumination compensation. Second stage applies the morphological techniques for reduce useless fiducial points. Third stage applies the LBP on reduced fiducial points with neighborhood pixel for improving the pose variation. Forth stage uses PCA to detect the best variance points which are necessary to characterize the training images. The last recognition stage includes finding the Euclidean norm of the feature weight vectors with the test weight vector. In this project, we used 20 images of 20 different persons from ORL database for training. For testing, we used images with varying illumination, pose and occluded images of the same training persons. Using this algorithm, testing results has shown significant improvement performance.*

Keyword: *Enhanced Gabor filter, Local binary pattern, Principal component analysis, Feature selection, Recognition*

I. INTRODUCTION

Face recognition is a very active research topic in the field of pattern recognition and computer vision[1]. Face recognition systems are important systems that can be used in various application areas such as entertainment, smartcards, information security, and law enforcement and surveillance. From a problems point of view, there are five major problems in face recognition which affect performance of a system: 1) Illumination variations 2) Pose changes 3) expression variations 4) time delay 5) Occlusions. Algorithms presented for pose variation are divided in two main categories based on their type of gallery images [2]. First of all, Multi-view face recognition system (FRS)[3] that requires several poses for every subject in gallery. Another category identifies probe faces that has different poses with gallery face. In general situations, a frontal face in gallery is available, but probe faces have unpredicted pose variations. So, the system must be robust for these types of situations. A key issue in face recognition is to find effective descriptors for face appearance. Hence it is difficult to develop a system which can recognize human faces under variable conditions and environment.

Face recognition has drawn a great deal of attention from the researchers and industrial communities over the past several decades. Since the early 70's, face recognition has drawn the attention of researchers in various fields, which include security, psychology, image processing and computer vision. Research in automatic face recognition started in the 1960s.Numerous approaches have been proposed, including eigenfaces [4], laplacianfaces [5], neural networks [6], elastic bunch graph matching [7], to overcome the challenges for recognition. To recognize face under illumination and pose variation of face image we introduced an image computationally the first method came into existence was template based matching. It required the administrator to locate the feature such as eyes, nose, and mouth on the photographs before it calculated distance and ratios between common reference points. This initial method had poor performance as the results were calculated manually.

Holistic methods tend to blur out small details owing to residual spatial registration errors. On the other hand, local descriptor methods have drawn increasing attention because they can capture small appearance details. Local descriptor methods include Gabor wavelets [8], Local Binary Patterns (LBP) [9], Local Ternate Patterns (LTP) [10]. Gabor wavelets were successfully used in face recognition. Moreover this method was not adaptable in any kind of variations. The approaches afterwards can be classified into two categories; including subspace based holistic feature and local appearance feature which brought a new revolution in the field of face recognition. In holistic matching method, the whole face image is represented as a high-dimensional vector. Due to the size of dimensionality, such vectors cannot be compared directly. Hence, holistic methods use dimensionality reduction techniques to resolve this problem and thus derive lower-dimensional vectors for subsequent classification. The most popular examples among such approaches are based on Principal Component Analysis (PCA) [11] and on Linear Discriminant Analysis (LDA) [12] Independent Component Analysis(ICA)[13].

The LBP is a powerful illumination invariant texture primitive. The histogram of the binary patterns computed over a region is used for texture description. LTP is a generalization of LBP. The Local Binary Pattern is originally proposed by Ojala for the aim of texture classification, and then extended for various fields, including face recognition, face detection[14], facial expression recognition. The Local Binary Pattern is a non parametric operator which is used for describing a local spatial structure of an image. Face image is divided into several regions and LBP is applied and features are extracted over the region. These Features are concatenated to form face descriptor. Although face recognition with local binary pattern has been Proven to be a robust algorithm, it suffers from heavy Computational load due to the very high dimensional feature vectors that are extracted by concatenating the LBP histograms from each local region[24].

In 1988, Kirby and Sirovich applied principal component analysis , a standard linear algebra technique, used to transform one set of variables into another smaller set, and the newly created variables are not usually easy to interpret. ICA is a generalization of PCA, which is sensitive to high order relationship among the image pixels. The primary advantages of these techniques are that it provides more robust to the effect of noise. The local approaches, such as Gabor filter extract information from local facial features to distinguish faces, and have the advantage of robustness to environmental changes like illumination and expressional variability, so are used extensively in face recognition. The local binary pattern (LBP) features are originally designed for texture description. The operator has been successfully applied to pose change and facial expression analysis and face recognition.

The idea behind using the LBP features is that a face can be seen as a composition of micro patterns. LBP in nature represents the first-order circular derivative pattern of images, a micro pattern generated by the concatenation of the binary gradient directions. However, the first-order pattern fails to extract more detailed information contained in the input object. To the best of our knowledge, no high-order local pattern operator has been investigated for face representation. In fact, the high-order operator can capture more detailed discriminative information. Some high-order non local pattern methods have been successfully used to solve the face recognition problem.

We work on face recognition with combining the holistic, local approach and LBP. Gabor wavelets capture the local structure corresponding to specific spatial frequency, spatial locality, and selective orientation which are demonstrated to be discriminative and robust to illumination and expression changes. LBP operator which describes the neighboring changes around the central point is a simple yet effective way to represent faces. In this paper, these combinations of LBP and Gabor features have improved the face recognition performance significantly compared to the individual representation. The feature points extracted using Gabor Filter and LBP on feature point that shows better response irrespective of the illumination, rotation and occlusion. The performances of three statistical face recognition techniques namely Principal Component Analysis (PCA) Combined LBP Gabor and PCA for selecting fiducial points gives better recognition result.

Facial feature point extraction is explained overview of Gabor Filter, LBP and PCA for better recognition. Last sections will give the comparison of experimental results and compare all the results with conclusion that how it improves illumination and pose variation recognition.

II. Enhanced Gabor Feature Extraction

Gabor filters are used in representation of face due to their biological relevance and computational properties. Gabor filters are principally band pass filters which exhibit desirable characteristics of spatial localization and orientation selectivity, spatial frequency selectivity and quadrature phase relationship. Gabor filter representations of face image are robust for illumination and expressional variability, so are used extensively in face recognition. Therefore, when the goal is the derivation of local and discriminating feature, adopting Gabor transformation has become a popular method of feature extraction. In our work, 2D Gabor wavelet is applied to create are presentation of facial features. The Gabor kernels can be defined as following:

$$\Psi_{\mu,v}(z) = \frac{\|k_{\mu,v}\|^2}{\sigma^2} e^{-\left(\|k_{\mu,v}\|^2 \|z\|^2 \middle| 2\sigma^2\right)} \left[e^{ik_{\mu,v} z} - e^{-\left(\frac{\sigma^2}{2}\right)}\right] \qquad (1)$$

Where μ and v define the orientation and scale of the Gabor kernels, z=(x, y),$\|.\|$ denotes the norm operator, and thewave vector $k_{\mu,v}$is defined as follows:

$$k_{\mu,v} = k_v e^{i\Phi_\mu} \qquad (2)$$

Where $k_v = \frac{k_{max}}{f^v}$and $\Phi_\mu = \frac{\Pi\mu}{8}$.f is the spacing factor between kernels in the frequency domain. The Gabor Kernel is a product of Gaussian envelope which is shown outside the square brackets in and a complex plane wave which is the first term inside the square brackets determines the oscillatory part of the kernel and the second term compensates for the dc value. The remaining kernels can be generated from the mother wavelet by scaling and rotating the mother wavelet.

The Gabor wavelet representation of an image has been designed image features at different locations having different frequency can be extracted by convolving the image I(x, y)with the filters. Let I(x, y) be a gray scale image, the convolution of image I and a Gabor kernel QPM is defined as follows

$$O_{\mu,v} = I(z) * \varphi_{\mu,v}(z) \tag{3}$$

Where z=(x, y)* denotes the convolution operator, and $O\mu, v$is the convolution result corresponding to the Gabor kernel at orientationμ and scale v.

Enhanced Gabor filter is enhancement in Gabor filter with the use of morphological techniques that adjust the contrast and clearing the border in an image and label only the useful feature points. These are used for feature extraction, texture analysis and texture segmentation, target detection, fractal dimension management, Document analysis, edge detection, retina identification, image coding and image representation. The main advantage of this approach is that if prominent facial features are occluded, for instance due to facial hair, glasses or expressions even then the algorithm should still recognize the face optimally basing on the features extracted from other regions of the face. However, they perform poorly when classifying face images having even a slight side rotation.

III. Local Binary Pattern (LBP)

The LBP operator is one of the best performing texture Descriptors The standard version of the LBP of a pixel is formed by thresholding the 3X3 neighborhood of each pixel value with the center pixel's value and concatenating the results binomially to form a number. Let Z_o be the center pixel gray level and Z_i (i=0, 1, 7) be the gray level of each surrounding pixel. Fig.1 illustrates the basic LBP operation. If $Z_i$is smaller than Z_o, the binary result of the pixel is set to 0 otherwise set to 1 is in equation. The eight binary associated with eight neighbors are the read sequentially in clockwise direction to form binary equivalent. This binary equivalent in decimal system may be assigned to the central pixel and may be used to characterize to local texture is shown in fig 2.

$$f\left(I(Z_0), I(Z_i)\right) = \begin{cases} 0, & if\ I(Z_i) - I(Z_0) \leq \text{threshold} \\ 1, & if\ I(Z_i) - I(Z_0) > \text{threshold} \end{cases}, \ i = 1, 2, \cdots, 8$$

This method makes use of the most frequently occurred patterns to capture descriptive textural information. LBP is a grayscale invariant texture measure and is a useful tool to model texture images.

Z_1	Z_2	Z_3
Z_8	Z_0	Z_4
Z_7	Z_6	Z_5

Figure 1.Eight neighborhood around central pixel Zo

An LBP can also be considered as the concatenation of the binary gradient directions, and is called micro pattern. When the threshold is set to zero. The histograms of these micropatterns contain information of the distribution of the edges, spots, and other local features in an image. LBP has been successfully used for face recognition.

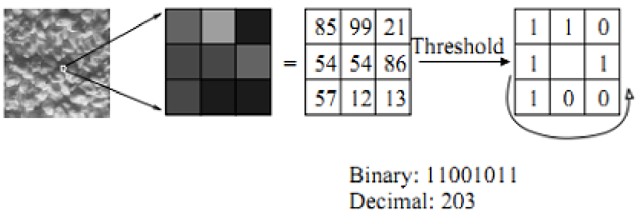

Figure 2. Calculating LBP from 3x3 window

IV. Principal Component Analysis

The Principal component analysis (PCA) is often referred to as a technique for reducing the number of variables in a data set without loss of information, and as a possible process for identifying new variables with greater meaning. Unfortunately, while PCA can be used to transform one set of variables into another smaller set, the newly created variables are not usually easy to interpret.PCA has been most successful in applications such as image compression. In many applications, PCA is used to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. The most of the variation PCA identify directions in which there is very little variation. The eigenvectors correspond to the directions of principal components of the original data and their statistical significance is given by their corresponding eigenvalues. The eigenvectors constitute the transformation matrix. Eigen-vectors are unit vectors that identify the basic characteristics of the input data in a nonparametric format so eigenvectors are also called basis vectors. The eigenvectors form the basis of the feature space and the eigenvalues show the weightings of the individual contributions of the eigenvectors. Since the eigenvectors are unit vectors, their contribution incompletely normalized. However, the relative importance of the eigenvectors is indicated by the corresponding eigenvalues. The larger the eigenvalue the more the associated eigenvector contributes to explaining the variance of the input data. The significant eigenvalues and their associated eigenvector called principal components.

4.1. PCA Algorithm

As the standard PCA algorithm is well known, we briefly define in the algorithm. In Standard PCA consists of two stages, Training stage and Recognition stage. Training stage is used to convert the original space to subspace using basis vectors correspond to maximum variance direction in the original space is in fig 3. Let p-dimensional space data is transformed to q-dimensional data using the linear transformation. Where q<<p which is of key importance in case of large database. Let us see how the transformation function is derived and face space is formed. Suppose the given database consists of K number of M×N size images. We adjust these images column wise vectors of ((M×N)×K) size so that we can calculate the covariance matrix for one dimension signal which is of less complexity. We then calculate the mean vector of all images and mean adjusted them to ensure that the Eigen vector corresponding to Eigen value represents the dimension in Eigen space in which variance of vectors is maximized in correlation sense.

$$B = x_i - \overline{x_i} \qquad (4)$$

$$\bar{x} = \frac{1}{K}\sum_{i=0}^{K} x_i \qquad (5)$$

x_i is column vector of i^{th} image. The covariance matrix is found from the mean subtracted vectors.

$$C = B \times B^T \qquad (6)$$

The linear transform function can be found using Eigen vectors corresponding to Eigen values (i.e., selected by thresholding process) found from the covariance matrix.

$$\lambda_i e_i = C e_i \qquad (7)$$

By solving the equation 4 we get Eigen values (λ_i) and corresponding Eigen vectors (e_i). The Eigen values are arranged in decreasing order because the largest Eigen values one of more importance as they represent maximum variance in the space. We select the Eigen values by thresholding because not all Eigen values are necessary to represent the original space and this helps in dimension reduction. The corresponding Eigen vectors of selected Eigen values are used to linearly transform the original space to feature space or face space.

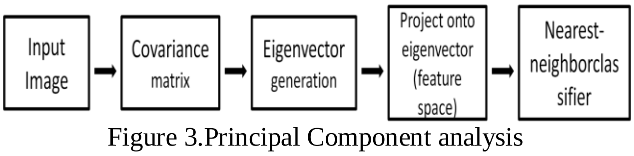

Figure 3.Principal Component analysis

The eigenvectors correspond to the directions of principal components of the original data and their statistical significance is given by their corresponding Eigenvalues. The database images are then projected onto this feature space (the feature space is the collection of parameters) or face space.

The recognition stage consists of mean adjusted test image projected onto face space. Then Euclidean distance is calculated between projected test image and all projected images in the face space. The image satisfying the minimum Euclidean distance will be the matched face. Thus the projected test image (noisy image) is gradually replaced by the stored image or restoring the image.

V. Combined Recognition With Enhanced Gabor LBP And PCA

In paper, Gabor filter bank is proposed and combined with the local binary pattern. Both the theoretical analysis and the experiment results show that the combined LBP Gabor filter is effective for illumination and pose variation. In our experiments, we choose 6 orientations and 5 frequencies and 30 Gabor filters are combined to form a Gabor filter bank. We are taking the 10 database images for training the recognition system. The noise is removed by applying the median filter and Gabor bank is used for extracting the feature points. The morphological enhancement is used to correct uneven illumination and reduce the useless feature points. This filtering can be used together to enhance contrast and clearing the border in an image and label only the useful feature points. Then take centroid of each labeled region of the image.

The LBP is applied on that features points. It automatically identify the feature points the neighborhood pixel of 3x3 windows threshold to the binary equivalent that improves the head rotated face image. In order to reduce the dimension further, Principal Component Analysis (PCA) is applied in which each image is represented by a t-dimensional feature vector. The PCA can be used to transform the t-dimensional vector into a f-dimensional vector, where normally $f << t$ then we can project the test vector to the lower space and calculate the minimal Euclidean distances between these vectors. Closest vector is the exact recognized face image.

The recognition process is occur in two stages testing stage having one test face image and training stage. In which the training the database of all the training face images and check the Euclidian distance between the test and trained image.

VI. Experiments And Results

6.1 Experimental Data

In the experiment we are taking the 10 training set database images as shown in Fig 4. We are testing the training database face images at different conditions light, crop, pose and expressions changes. We trained the database images with Gabor LBP and PCA algorithm and then test all the face images having different conditions is shown in fig 5.The degree of recognition is tested on expression and light gives better results in fig:6.

Figure 4. Sample Images for training set database

Figure 5. Experimental results of combined Gabor LBP and PCA

Figure 6.Face expression and light image with Gabor LBP & PCA

The comparison results of combined Local binary pattern (LBP) Enhanced Gabor filter and principal component analysis (PCA) shows the pose variation improves 79.48% and light effect improves 95.98% so recognition rate increases and recognition improves.

Table1: Test Results For LBP Enhanced Gabor+PCA and PCA

Database	LBP+Enhanced Gabor+PCA	Gabor+PCA	PCA	No. of Images
Light	95.98	90	50	20
Crop	70.25	65	50	20
Pose variation	79.48	55	46	10
Light + Crop	59	55	22.5	40
Expression	85.51	84.21	78.95	19
Expression+Light	53	45	40	20
Expression+Light+Crop Pose change	56	50	50	10

VII. Conclusion And Future Work

The Combined performance of Gabor LBP and traditional PCA algorithm gives better result on illumination and pose variation. The Gabor filter bank with different frequencies and orientations outputs finds the large number of important fiducial facial feature points all over the face. If some portion of the face is occluded then the remaining feature points are enough to represent the face. The LBP is applied on Gabor feature points and with neighborhood window improves the pose variation recognition result. In this way the proposed algorithm outperforms the traditional PCA algorithm in case of occlusion and non uniform pose and illumination changes. We also modified the selection criteria for the fiducial points by using morphological techniques. This gave good results compare to simple Gabor and PCA in case of combination attacks like illumination and occlusion, illumination and expression change. The combined performance improves efficient of face recognition but poor performance for large pose variation or orientation change.

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