Performance Evaluation of Pose Invariant Face Recognition Systems using Different Feature Enhancement Technique

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Abstract:

Face recognition in the presence of different challenges is still a fascinating research field. This research, mainly focusing on the various enhancement feature extraction techniques like Local Binary Pattern, Local Directional Pattern and Symmetric Local Graph Structure, which are used to achieve enhanced recognition accuracy. Gabor Filters are initially applied to facial image and then this Gabor output image features are enhanced using feature enhancement technique. Minimized image features produced from enhanced images are used to train and test the recognition system. Extreme learning machine is used as recognitions system in proposed research. This research presents an evaluation of pose invariant face recognition systems using different feature reduction technique for different size of images. The proposed methods are implemented and compared based on ORL database. After comparing all the three methods of feature enhancement we can say that by using Local Directional Pattern we can gain more overall accuracy as compared to the Local Binary Pattern and Symmetric Local Graph Structure.

Keywords: Face Recognition; Image processing; Enhancement Feature Extraction; Extreme Learning Machine.

I. INTRODUCTION

In today's world, with the advancement of technology the privacy and security of information stored in various places is very important. Biometric based recognition [1] to achieve a more secure and accurate authentication in the wide range of commercial sectors and has become an active research area in computer vision and pattern recognition. Face recognition may be defined as a biometric approach that involves automated methods to verify or recognize the identity of a particular person based on his or her facial characteristics [2]. But changes in the face image like background, illumination, orientation, expression and pose are the key challenges to be deal cautiously to recognize a face. Pose invariant face recognition means recognizing face in the image even it is in different poses.

Many researches have worked on pose invariant face recognition system. Pentland et al. [3] proposed view based method for recognition under variable pose. In this method recognition is done on the basis of eigenvector of that view space and calculating distance from face image. Cootes et al. [4] presented view based active appearance model assuming that 2D statistical models can capture the facial features from any view point. Gross et al. [5] proposed an Eigen light fields (ELF) method to tackle the pose problem. Chai et al. [6] presented an affine transformation based on statistical analysis. Face is divided into three rectangular regions and affine transformation of rectangular regions with different poses is calculated and is used for recognition of face across pose. Prince et al. [7] proposed a generative model that generates poses from an identity space. Expectation maximization algorithm is used for estimating the linear transformation and noise data from training data. Sarfraz and Hellwich [8] developed a pose invariant method which does not require perfect alignment between the gallery and the probe image. It models approximated joint probability distribution of the gallery and the probe images at different poses. Choi et al. [9] proposed pose and illumination invariant face recognition where pose is estimated based on 2D image and uses a classification rule to classify a pose of a face image. The shadow compensation is obtained after determining the light direction and the feature is extracted by applying null space linear discriminant analysis. Then classification is done using nearest neighbor rule. Wang et al.[10] presented face recognition across pose by considering a probe image with a different pose from gallery images which is represented by a linear combination of the gallery images. They proved that orthogonal discriminant vector (ODV) is a pose invariant feature. Distance metric is used for classification. Moallem et al.[11] proposed a fuzzy rule based system for pose independent face detection. Person information such as skin, color, lip, face shape, ear texture etc. is fed to fuzzy rule based classifier for face candidate extraction. Threshold on face candidates is optimized by using genetic algorithm. Mohammed et al.[12] proposed a face recognition system which is based on multidimensional PCA and classification is done by using extreme learning machine. Singh et al. [13] proposed a hierarchical registration method by using affine transformation and mutual information based registration method. The mosaicing is done by mask generation, stitching and blending using Laplacian and Gaussian pyramids and SVM classifier is used for classification. Arashloo et al. [14] Proposed recognition of faces in arbitrary pose by using the energy of the established match between a pair of images as the matching criterion. The feature vector is obtained by using PCA and classification is done by using nearest neighbor classifier.This research has shown the performance of pose invariant face recognition systems which are using different enhancement feature extraction techniques like Local Binary Pattern(LBP), Local Directional Pattern(LDP) and Symmetric Local Graph Structure(SLGP). LBP is to be tolerant against the monotonic illumination changes and it is very simple in terms of computation [15, 16]. But it is sensitive to non-monotonic illumination variation and performance degrades in the presence of random noise. So Jabid et al. [17, 18] Presented a new method LDP. Many face recognition methods which are based on LBP utilized the descriptor for histogram feature extraction of the face image. Symmetric Local Graph Structure [19] is a latest and improvement version of LGS. Abdullan et al. [20] proposed this method to improve the performance of LGS operator.

Rest of the paper is organized in four sections. Section 2 discusses about proposed pose invariant face recognition system which uses the different feature descriptors to compare their performance. Section 3 presents basic concepts of Gabor filters. It explains three different local feature descriptors. It finally discusses about the basics of extreme learning machine. Section 4 explains how to evaluate the performance of proposed system. Itshows the results of proposed pose invariant face recognition system for different datasets. Section 5 presents the conclusions of research done and some suggestions for future work.

II. BACKGROUND METHODOLOGIES

This section presents basic concepts of background methodologies which are used in proposed algorithm. It starts the discussion with basics of Gabor filters. It explains three different local feature descriptors. It finally discusses about the basics of extreme learning machine.

A. Gabor Filters

The Gabor wavelet transform provides an effective way to analyze images [21, 22]. The Gabor Filters are mainly applied to facial image analysis. They are spatial filters that apply the kernels to make the sin/cos function localization by the Gaussian function, and extract the local feature in an image, so there are advantages that much robust to image variation caused by the occlusion of facial feature and illumination environment. The Gabor filters we applied are defined in equation 1.

$$\psi_{\mu,v}(x) = \frac{\| k_{\mu,v} \|^2}{\sigma^2} e^{\left(-\frac{\|k_{\mu,v}\|^2 \|x\|^2}{2\sigma^2}\right)} \left[e^{ik_{\mu,v}x} - e^{-\sigma^2/2}\right] \qquad ..(1)$$

Where x= (x, y), μ and ν are the orientation and scale of the Gabor filters respectively. The frequency vector $k_{\mu,v}$ is given as follows:

$$k_{\mu,v} = k_v e^{i\emptyset_\mu}$$

Where $k_v = \frac{k_{max}}{f_v}$ and $\emptyset_\mu = \prod \frac{\mu}{8\emptyset_v} = \pi\mu$. k_{max} is the maximum frequency and f is the spacing factor between filters in the frequency domain and σ is variance of the Gabor filter image.

B. Local Binary Pattern

The LBP extraction algorithm[16, 17] contains two main steps, that is, the thresholding step and the encoding step. In the thresholding step, all the neighboring pixel values in each pattern are compared with the value of their central pixel of the pattern to convert their values to binary values (0 or 1). This step helps to get the information about the local binary differences. Then in the encoding step, the binary numbers obtained from the thresholding step are encoded and converted into a decimal number to characterize a structural pattern. Example of LBP calculation for middle value 50 has shown in figure 1.

43	18	5		0	0	0				
60	50	52	→	1		1	→		25	
37	42	78		0	0	1				

Figure 1: Example of LBP Operator

C. Local Directional Pattern

A LDP[17, 18] operator computes the edge response values in all eight directions at each pixel position and generates a code from the relative strength magnitude. In LDP given a central pixel in the image, the eight directional edge response values m_i (i=0 to 7) are obtained by applying kirsch masks in eight directions M_i (i=0 to 7) centered on its position. The eight kirsch marks[23] are shown in Figure 2.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}$$

East M_0 North East M_1 North M_2 North West M_3

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

West M_4 South West M_5 South M_6 South East M_7

Figure 2: Kirsch edge response masks in eight directions

These eight edge responses magnitude are used to generate an eight bit binary number which can describe the local edge pattern of a particular pixel. Here the top k directional bit responses are set to 1, the remaining (8-k) bits of 8-bit LDP pattern are set to 0. Finally we convert the binary code into a decimal number to get LDP value as shown in Figure 3.4 where k=4 is taken.

85	32	26		313	97	503		1	0	1
53	50	10	$\xrightarrow{Mi}$	537	X	393	$\xrightarrow{m_k}$	1	x	1
60	38	45		161	97	161		0	0	0

Figure 3: Calculation of LDP Decimal code

D. Symmetric Local Graph Structure

LGS[20] is totally based on graph theory to represent the relationship between a pixel and its neighboring pixel. The graph structure which is shown in figure 4 was applied on each pixel of an image. All neighbor's pixels of each pixel are thresholded based on the direction of the graph. A decimal value is calculated for each pixel of an image based on binary number as shown in figure 4. SLGS[19] has an important property i.e. it uses Symmetric graph structure. The symmetric structure consists of same number of neighbor pixels in left side as well as right side as shown in figure 5.

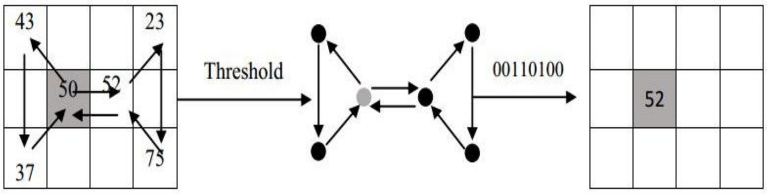

Figure 4: The LGS Operator

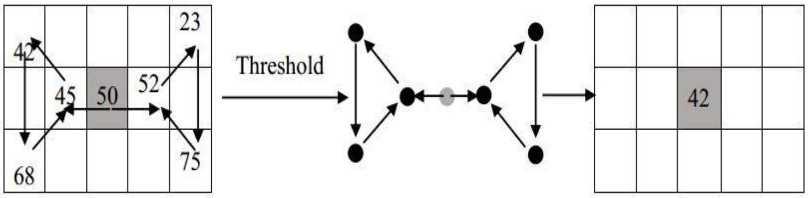

Figure 5: The SLGS operator

E. Extreme Learning Machine

Extreme Learning Machine is basically a learning algorithm of single layer feed forward neural network which is proposed by Huang et al. [24] in 2006. For N distinct samples (x_i, t_i) where $x_i = [x_{i1}, x_{i2}, x_{i3}, \ldots\ldots, x_{in}] \in R^n$ and $t_i = [t_{i1}, t_{i2}, t_{i3}, \ldots\ldots, t_{in}] \in R^m$.

The standard single layer feed forward neural network with $\tilde{N}$ hidden neurons and activation function g (x) are mathematically modeled as equation 2.

$$\sum_{i=1}^{\tilde{N}} \beta_i g_i(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i\, g(w_i x_j + b_i) = o_j \qquad \ldots\ldots\ldots(2)$$

$$j = 1,2, \ldots\ldots\ldots\ldots\ldots, N$$

where $w_i = [w_{i1}, w_{i2}, w_{i3}, \ldots\ldots, w_{in}]$ is the weight matrix which is connected to the i^{th} hidden neurons to input neurons, b_i is the threshold (bias) of i^{th} hidden neuron, β_i is the weight matrix which is connected to to the i^{th} hidden neurons to output neurons $\beta_i = [\beta_{i1}, \beta_{i2}, \beta_{i3}, \ldots\ldots, \beta_{in}]$ and $O_j$is a $1 \times m$ output vector for values of all the output neurons. $w_i x_j$ denotes the inner product of wi and x_j. The basic intension of a learning machine is to minimize the difference between the output o and the actual output t . To solve this problem Extreme learning machine is used by randomly assigning the input weights w_i and the thresholds of the hidden neurons b_i and analytically calculate the output weights β_i so that the final output o of the neural network becomes much closer to the actual output t That standard SLFNs with $\tilde{N}$ hidden nodes with activation function g (x) can approximate these N samples with zero error means that $\sum_{i=1}^{\tilde{N}} \| o_j - t_j \| = 0$, i.e., there exist β_i, w_i and b_i such that

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i x_j + b_i) = t_j \qquad where \quad j = 1,2, \ldots\ldots.. N \qquad \ldots\ldots(3)$$

The above N equations can be written as:

$H\beta$=T

Where

$$H = \begin{bmatrix} g(w_1 x_1 + b_1) & \ldots & g(w_{\tilde{N}} x_1 + b_{\tilde{N}}) \\ \vdots & \ldots & \vdots \\ g(w_1 x_N + b_1) & \ldots & g(w_{\tilde{N}} x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}} \quad \text{and } \beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m} \quad \text{and} T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N \times m}$$

H is the hidden layer output matrix of the neural network, the i^{th} column of H is the i^{th} hidden node output with respect to the input $x_1, x_2, \cdots, x_N$. β is the output weight matrix and T is the actual output.

III. PROPOSED ALGORITHM

Step 1: Initially, the face image is resized and normalized.

Step 2: Apply the Gabor wavelet transform on each normalized face image to get Gabor Magnitude Pattern. In this thesis, we are using 40 Gabor filter of 5 frequencies $\nu \in 0,1,\cdots,4$ and 8 orientations $\mu \in 0,1,2,\cdots,8$, we will describe about Gabor filter in details in section 3.3.

Step 3: To enhance the local information of GMPs (Gabor Magnitude Pattern), we encode the magnitude values with three different local feature descriptors i.e. LBP (Local Binary Pattern), LDP (Local Directional Pattern), SLGS (Symmetric Local Graph Structure) and get different maps.

Step 4: Now, each map is divided into 9 regions i.e. R0, R1,…., R8. The feature vector can be defined in the form of histograms which is given below in equation 3.1

$$Ƒ = (R0, R1, \ldots, R8) \qquad \ldots\ldots\ldots (4)$$

Where R0 is defined as:

$$R0 = \{H_{\mu,\nu}\}\ \forall \mu, \nu \qquad \ldots\ldots\ldots (5)$$

Where $H_{\mu,\nu}$ is also defined as:

$$H_{\mu,\nu} = \{h_i\}\ \forall\ i = 0,1,\ldots,L\text{-}1 \qquad \ldots\ldots\ldots (6)$$

The histogram H for a particular image f(x, y), at a frequency μ and orientation ν of Gabor Magnitude Pattern, which is having the gray levels from 0 to L-1, is obtained by performing concatenation of all histograms as follows:

$$H_{\mu,\nu} = \{h_i\}\ \forall\ i = 0,1,\ldots,L\text{-}1$$

Here, L represents the no. of grayscale levels in the face image and h_i is the number of pixels in image which is having i grayscale value.

h_i is defined as: $h_i = \begin{cases} \sum xy\, 1 & if(f(x,y) = i) \\ 0 & if(f(x,y) \neq i) \end{cases}$

Step 5: After that, we will take two elements per region i.e. mean and variance for each image. It means for each image 18 elements are calculated because we are having 9 regions per image. Finally, the outputs for each image are [1×720] elements of 40 Gabor's form a row vector.

Step 6: Voting based extreme learning machine is used for classification. Feature vector obtained in step 5 is used for classification.

Step 7: Repeat steps 2 to 6 for all training images.

Step 8: For the images not included in training set repeat steps 1 to 6 and tested using the trained neural network.

IV. RESULT AND ANALYSIS

A. Experimental Setup

The performance evaluation of different feature descriptors is carried out by using ORL [25] database. ORL database is a collection of 400 face images i.e. 10 different images each for 40 distinct subjects. All 400 images are divided into two sets, one set of images is used to train the neural network and another set of images is used for training. We can select randomly 5 images from first subject to train the VELM and remaining 5 images from first subject are used for testing the VELM. Same numbered images which are selected from first subject are also selected from other subjects for training of VELM and remaining is used for testing.

Initially, after applying resizing and normalization on database images, normalized images are applied to 40 Gabor wavelet filter and performed convolution to get 40 Gabor Magnitude Pattern (GMP). After that we encode the magnitude values with three different local feature descriptors i.e. LBP (Local Binary pattern), LDP (Local Directional Pattern), SLGS (Symmetric Local Graph Structure). Then, the output maps after performing LBP, LDP and SLGS are divided into 9 sub regions and then we take two values i.e. mean and variance for each sub region of the face image which gives a row vector of 18 elements. Finally, performing the above procedure, we get a row vector of 720 elements for each image. This row vector for each image is used by VELM for classification.

B. Performance measures

1) Confusion matrix: To visualize the performance of the proposed algorithm, confusion matrix is used. The number of the columns in the confusion matrix is number of images in the predicted class and the number of rows in the confusion matrix is number of images in the actual class. Here we are taking a confusion matrixof two classes i.e. A and B as shown in table 1.

Table 1: A Typical Confusion Matrix

	A	B
A	Samples actually belonging to class A that are predicted to be in class A (True Positives)	Samples actually belonging to class A that are predicted to be in class B (False Negatives)
B	Samples actually belonging to class B that are predicted to be in class A (False Positives)	Samples actually belonging to class B that are predicted to be in class B (True Negatives)

2) Overall accuracy: Overall accuracy is the percentage of a system correctly recognize genuine user (legal users) and correctly rejects illegal users. Overall accuracy is most simple performance measurement parameter and is used to measure that how many images are correctly classified by the proposed algorithm. It simply describes how good the proposed algorithm works. For a two class problem, it is defined mathematically as shown below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP= True positives, TN= True negatives, FP= False positives and FN= False negatives. To see the clear performance of LBP, LDP and SLGS we can refer table 2, 3, 4, 5, which represents the overall accuracy of all the local feature descriptors at different size i.e. 16x16, 32x32, 64x64 and 128x128.

Table 2: Comparison of LBP And Ldp At Size 16x16 For ORL Database

Local Feature Descriptor at size 16x16	**Number of Hidden Neurons**				
	10	**20**	**30**	**40**	**50**
LBP(16X16)	97.40	97.80	97.90	97.80	97.60
LDP(16X16)	98.00	97.80	97.60	97.60	97.75

Table 3: Comparison of LBP And Ldp At Size 32x32 For ORL Database

Local Feature Descriptor at size 32x32	**Number of Hidden Neurons**				
	10	**20**	**30**	**40**	**50**
LBP(32X32)	97.40	97.50	97.40	97.65	97.45
LDP(32X32)	97.60	97.50	97.60	97.60	97.60

Table 4: Comparison of Lbp and Ldp At Size 64x64 For ORL Database

Local Feature Descriptor at size 64x64	**Number of Hidden Neurons**				
	10	**20**	**30**	**40**	**50**
LBP(64X64)	97	97.70	97.20	97.80	97.10
LDP(64X64)	97.90	97.55	97.50	97.85	97.40

Table 5: Comparison of LBP and SLGS at Size 128x128 for ORL Database

Local Feature Descriptor at size 128x128	**Number of Hidden Neurons**				
	10	**20**	**30**	**40**	**50**
LBP(128X128)	97.50	97.70	97.50	97.20	97.60
LDP(128X128)	97.40	97.20	97.60	97.65	97.40

By using Table 2, 3, 4 and 5 we can easily conclude that sizing factor is not that much important because if we increase size of image then sometimes overall accuracy increases and sometimes it decreases. But if we compare all the three local feature descriptors then we can say that by using LDP we can gain more overall accuracy as compared to the LBP and SLGS.

Now, table6 shows the comparison between the proposed work and other existing method by using ORL database:

Table 6: Comparison of Overall Accuracy of LBP, LDP and SLGS with Other Existing Methods

Methods	**Overall accuracy by using ORL database**
LSPBP[3]	96%
NeNMF[23]	92.36%
Block based Steerable pyramid[5]	99%
Gabor filter + LBP + GMN Network[2]	96.25%
Proposed LBP with size factor 16x16	97.90%
Proposed LDP with size factor 16x16	98%
Proposed SLGS with size factor 128x128	97.65%

V. CONCLUSION

The experimental results clearly show that the result of proposed pose invariant face recognition system by using three different local feature descriptors is good. If we compare LBP and SLGS then we can easily see that SLGS is better. SLGS is very easy to implement and produce better result as compare to LBP. If we compare the performance of LBP and LDP then we can easily Say that LDP is better than LBP. Over all we found that LDP is giving best results in all the three techniques.

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