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Cross Local Gabor Binary Pattern Descriptor with Probabilistic Linear Discriminant Analysis for Pose-Invariant Face Recognition

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***Abstract*—Automatic face recognition is a well researched area, but still many of the current face recognition methods sensitive to lighting and pose changes. In this paper we introduce a novel facial feature representation to enhance the robustness of face recognition against pose and illumination changes. Here we combined Gabor wavelets and Cross Local Binary Patterns for facial feature representation. Gabor wavelets are known to extract shape information by detecting shape attributes like edges, corners and blobs. Cross Local Binary Patterns can be used for better feature representation in two levels. Probabilistic Linear Discriminant Analysis (PLDA) minimizes the intra-class distance and maximizes the inter-class distances and generates a model for classification purposes. During recognition, PLDA estimates the likelihood of the probe image in the gallery image set. Experimental results on YALE, FERET and our internal datasets show the significance of this method.**

Keywords*– *Gabor Wavelets, Cross Local Binary Patterns, Probabilistic Linear Discriminant Analysis, PLDA, Kernel-PCA

I. Introduction

Along with the advancements in technology, security issues are also increasing day by day. Therefore, it has became immensely important to use the security methods like passwords, pin and Biometric systems. Face recognition has been one of the most attractive research topics in computer vision for more than three decades as compared with other Biometrics like fingerprint, voice identification and iris recognition because of its non-intrusive nature, inexpensive and also have wide range of applications like surveillance, multimedia, human machine interaction, photo album management and digital entertainment. Significant performance has been achieved in face recognition recent years. However, recognition of unconstrained face images is still remained as a challenging task due to the quality degradation, wide range of variations in pose, expression, occlusion and expression changes [1]. An ideal face recognition system must overcome all of these limitations.

To overcome these challenges earlier we defined a new face descriptor called Cross Local Gabor Binary Patterns (XLGBP), which extracts both the shape and texture in both coarse and fine levels. XLGBP is a combination of Cross Local Binary Patterns (XLBP) [2], and Gabor filters [3]. Gabor filters are biologically motivated Gaussian kernels, which are optimal for measuring local spatial frequencies in multiple scales and orientations. XLBP is a modified version of traditional Local Binary Patterns (LBP) [4] which can extract the texture in both coarse and fine levels. As Gabor filters are robust against small translations and XLBP is robust against local intensity variations and rotations of the images, by combining these we can represent the local intensity distribution with spatial information. Hence, the descriptor became robust to lighting variations, pose changes and noise. In brief, XLGBP is a texture representation approach in multi-scale and multi-oriented spatial histogram. The feature histogram is computed by using filtering the image using Gabor Wavelets followed by Cross Local Binary Patterns (XLBP) operator.

For training and recognition Probabilistic Linear Discriminant Analysis (PLDA) [5] is used. PLDA is a probabilistic version of fisher-faces which models both intra-class and inter-class variance as multi dimensional Gaussian. As multidimensional Gaussian have maximum ability of discrimination, PLDA is suitable for class recognition tasks. Before modeling them with PLDA we used Kernel Principle Component Analysis (KPCA) [6] for dimensionality reduction of the feature vector.

The rest of the paper is organized as follows: section:II briefly explains the related work in state of the art, secction:III describes the background of the methods used in this work, section-IV explains the proposed method, section-V describes the experimental results and the conclusion is made in section-VI.

II. Related Work

Many of the conventional face representation methods use distance based approach in which the probe and gallery images are linearly projected to a lower dimensional plane to estimate the feature vectors and a match is carried out using distances between these feature vectors. Some of those feature based methods in the state of the art e.g., Local Binary Patterns (LBP) [4], Local Phase Quantization (LPQ) [8],[9],

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Dual-Cross Patterns (DCP) [10], Binarized Statistical Image Features (BSIF) [11], in which face image is represented using some patterns which can discriminate person to person efficiently. Many variants of LBP were proposed Direction Coded LBP (dLBP) [12], Transition LBP (tLBP) [12] which will extract the complementary information to enhance the robustness of LBP towards different facial variations, But the performance of these methods is decreases with changes in pose.

Pose invariant face recognition methods requires more than one image for each person (especially for each pose) or 3D models from the 2D image to estimate pose and lighting or estimation of statistical relation between faces under different conditions. In some of these methods complex pre-processing filters are used before the LBP operator to enhance the performance. In Local Radon Binary Patterns (LRBP) [13], Cross Local Radon Binary Patterns (XLRBP) [2], Radon transform is used as pre-filter to extract the shape which is robust to illumination but this will not consider pose variations.

In other literature, Gabor filters [7] are used as pre-filters to extract the shape information from the face images, e.g. Local Gabor Binary Pattern (LGBP) [14], Histogram of Gabor Phase Pattern (HGPP) [15] and Local Gabor Phase Difference Patterns (LGPDP) [16] in which the face image is initially convolved with multi-scale and multi-oriented Gabor filters to extract shape in different orientations and scales and later applied to pattern extraction methods to represent the face image. This representation is robust to translations, small pose variations and illumination changes. In these methods if the feature vector is large then we have to use dimensionality reduction algorithms for further processing.

Dimensionality reduction algorithms like Component Analysis (PCA) [17], Linear Discriminant Analysis (LDA) [18] and Independent Component Analysis (ICA) [19] reduce the dimension of the feature vector by considering statistical properties (like mean, standard deviation etc) of the gallery image feature vectors. These methods projects the feature vectors into lower dimensional space while preserving the characteristics of the feature vector.

III. BACKGROUND

A. Gabor Wavelets

Gabor filters are biologically motivated convolution kernels in the shape of plane waves restricted by Gaussian envelop function, which are optimal for measuring local spatial frequencies in multiple scales and orientations [3]. The Gabor filters we used are defined as follows

$$\psi\left(z\right)=\frac{\left\|k_{\mu,\nu}\right\|^2}{\sigma^2}e^{\left(-\|k_{\mu,\nu}\|^2\|z\|^2/2\sigma^2\right)}\left[e^{ik_{\mu,\nu}z}-e^{\sigma^2/2}\right] \quad (1)$$

where μ and ν are the orientation and scaling factors. The Gabor representation of the face image is derived by convolving the face image with the Gabor filters.

B. Cross Local Binary Patterns

LBP patterns are found to be more efficient for face recognition, when we take larger radius. But when we consider larger radius, the number of neighborhood pixels increase which results in large number of bins in the feature histogram. Apart from this close neighborhood pixel variations are missed in this case. XLBP [2] is an enhanced model of LBP operator which considers only radial pixels in all four diagonal directions. An XLBP operator with radius 2 and neighborhood 8 can be shown as in figure 1.

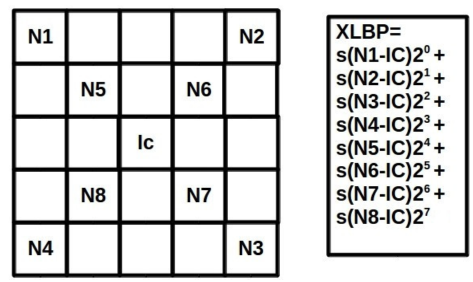

Figure 1. XLBP Operator With Radius 2 and Diagonal Pixels 8

In traditional LBP, if we consider radius as two, number of neighborhood pixels will be 16, while those in XLBP have eight only. The XLBP patterns can be computed by using following equation:

$$XLBP_R^P\left(I_c\right)=\sum_{n=0}^{P-1}s\left(I_n-I_c-T\right)2^n,\quad T\geq 0 \quad (2)$$

where I_c and I_n are center and diagonal pixels and $s(.)$ is thresholding function.

$$s(x)=\begin{cases}1 & \text{for} \quad x\geq 0\\ 0 & \text{for} \quad x<0\end{cases} \quad (3)$$

This is especially useful where we use video based face recognition. Number computation required for LBP are more compared with XLBP, as LBP need extra computations in interpolation in certain cases, while XLBP does not require an interpolation.

C. Kernel-PCA

In basic principle component analysis (PCA), to reduce the dimensionality of the feature vector we compute the projections of data on the Eigen vectors V^k of the feature vectors $F(k=p,.......M)$. Let x be a test point, with an image $\Phi(\mathbf{x})$ in F then,

$$(V^k.\Phi(\mathbf{x}))=\sum_{i=1}^{M}\alpha_i^k(\Phi(\mathbf{x}_i).(\Phi(\mathbf{x})) \quad (4)$$

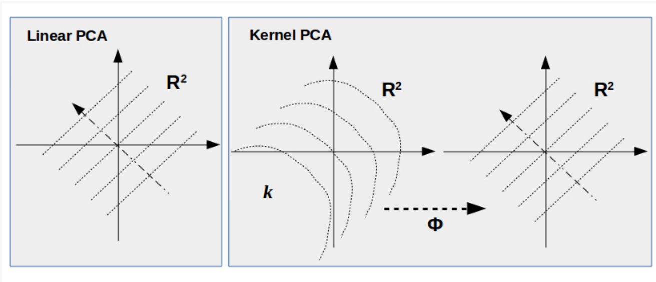

Figure 2. Basic idea of kernel PCA: by using a non-linear kernel function k instead of the standard dot product, we implicitly perform PCA in a possibly high dimensional space F which is non-linearly related to input space. The dotted lines are contour lines of constant feature value[6].

As shown in figure 2, the main difference between PCA and Kernel-PCA is F is non-linearly related to the input space, the contour lines of the constant projections onto principle Eigenvector become non-linear in input space. To extract the principal components (corresponding to the kernel K) of a test point $\mathbf{x}$, we have to compute projections onto the Eigenvectors by

$$(kPC)_n(\mathbf{x}) = (\mathbf{V}^n \cdot \Phi(\mathbf{x})) = \sum_{i=1}^{M} \alpha_i^n k(\mathbf{x}_i, \mathbf{x}) \qquad (5)$$

D. PLDA

Linear discriminant analysis (LDA), models both the inter-class and intra-class variance using multidimensional Gaussian. It searches for the directions in the space in which feature vectors have maximum ability of discrimination, hence it is most suitable for recognition tasks. We assume that the training data consists of J images each of I individuals. Let $\mathbf{X}_{ij}$ is j^{th} image of the i^{th} individual, then the model data is generated by the process:

$$\mathbf{x}_{ij} = \mu + \mathbf{F}\mathbf{h}_i + \mathbf{G}\mathbf{w}_{ij} + \epsilon_{ij} \qquad (6)$$

where $\mu, \mathbf{F}\mathbf{h}_i, \mathbf{G}\mathbf{w}_{i,j}$ and ϵ_{ij} are model parameters to be estimated. This model comprises two parts: (i) the signal component $\mu + \mathbf{F}\mathbf{h}_i$, which depends on the identity of the person but not the specific image (depends on i but not on j), that describes the inter-class variation. (ii) the noise component $\mathbf{G}\mathbf{w}_{ij} + \epsilon_{ij}$, represents the intra-class noise, which is different from image to image even those belongs to same individual. The term μ represents the overall mean of the training dataset. The columns of the matrix $\mathbf{F}$ contain a basis for the inter-class subspace and the term $\mathbf{h}_i$ represents the position in that subspace. The matrix $\mathbf{G}$ contains a basis for the intra-class subspace and $\mathbf{w}_{ij}$ represents the position in this subspace. Remaining unexplained data variation is explained by the residual noise term ϵ_{ij} which is defined to be Gaussian with diagonal covariance Σ.

1) Training: In training process we need to estimate the model parameters $\theta = \{\mu, \mathbf{F}\mathbf{h}_i, \mathbf{G}\mathbf{w}_{ij}, \Sigma\}$ such that the true positives are most likely. This would be easy if the values of the latent variables $\mathbf{h}_i$ and $\mathbf{w}_{ij}$ are known. Similarly it would be easy to estimate $\mathbf{h}_i$ and $\mathbf{w}_{ij}$ for given μ. But, none of these parameters known. For solving this equation(6) Expectation Maximization algorithm is used which alternately estimates the two sets of parameters in such a way that the likelihood is guaranteed to increase at each iteration. This algorithm has two steps: in Expectation- or E-Step, a full posterior distribution over the latent variables $\mathbf{h}_i$ and $\mathbf{w}_{ij}$ for fixed parameter values is estimated, while in the Maximization- or M-Step, point estimates of the parameters $\theta = \{\mu, \mathbf{F}\mathbf{h}_i, \mathbf{G}\mathbf{w}_{ij}, \epsilon_{ij}\}$ are optimized.

2) Recognition: In recognition, if we have **R** different models $\mathbf{M}_1 \ldots \mathbf{M}_R$, then we compare the likelihood of the data with these models. A model **M** can be represented as the relationship between the underlying identity variables, $\mathbf{h}_i$ and the data. If two or more faces belong to the same person, then they must have the same identity variable $\mathbf{h}_i$. If two faces belong to different people they will have different identity variables. For the q^{th} model calculate a likelihood term $P(\mathbf{x}/\mathrm{M}_q)$ where $\mathbf{x}$ is all of the observed data. Posterior probability of the image for which model is correct using Bayes rule:

$$P(\mathrm{M}_q|\mathbf{x}) = \frac{P(\mathbf{x}|\mathrm{M}_q)P(\mathrm{M}_q)}{\sum_{r=0}^{R} P(\mathbf{x}|\mathrm{M}_r)P(\mathrm{M}_r)} \qquad (7)$$

IV. Proposed Approach

The overall framework of proposed method is based on Cross Local Binary Pattern histogram sequence which is computed using following procedure. (i) An input face image is normalized and convolved with 40 Gabor wavelets (5 scales and 8 orientations) to obtain multiple Gabor Magnitude images in frequency domain. (ii) each Gabor Magnitude Image is transformed into binary patterns using Cross Local Binary Patterns (XLBP). (iii) each XLGBP map pattern image is divided into non-overlapping rectangle regions with specific size and histograms are computed on each block; (iv) The XLGBP histograms of all LGBP images are concatenated to form the final histogram sequence as feature descriptor of the face image. (v) as the feature vector size to large dimensionality is decreased by using Kernel-PCA to make feature vector suitable for training and recognition process and also for storing. (vi) PLDA is used for training and recognition. The following subsections will describe the procedure in detail.

A. Face Representation Using XLGBPH

The Gabor representation of the face image is derived by convolving the face image with the Gabor filters. Let $I(x, y)$

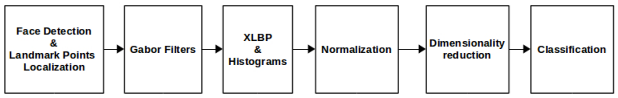

Figure 3. Functional Diagram of Proposed Approach

be the face image, the Gabor representation can be obtained by using following equation:

$$G_{\Psi I}(x, y, \mu, \nu) = I(x, y) * \Psi_{\mu,\nu}(z) \tag{8}$$

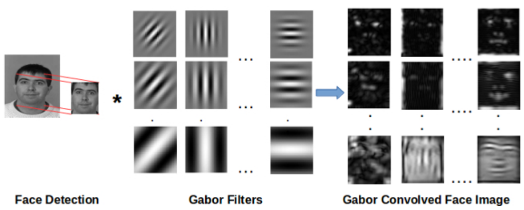

Figure 4. Convolution of Face Image with 40 Gabor filters (5-scales * 8 - orientations)

where $\mu = 0, 1, \ldots, 7$ id orientation and $\nu = 0, \ldots, 4$ is scale factors of the Gabor filter. Here we are consider only magnitude of the Gabor images. The Magnitude values of the Gabor images change very slowly with displacement, so that they can be further encoded. The performance of LBP increases enormously when it used with preprocessing filters. So in order to represent the information in the Gabor images we encode magnitude values with Cross Local Binary Patterns operator. The convolution of face image with 40 Gabor filters is carried out as shown in figure 4. Consider g is one of the 40 Gabor images then XLGBP pattern images can be computed to obtain XLGBP maps using

$$XLGBP_R^P\left(I_c^g\right) = \sum_{n=0}^{P-1} s\left(I_n^g - I_c^g - T\right)2^n, T \geq 0 \tag{9}$$

where g is Gabor transform and $s(.)$ is thresholding function.

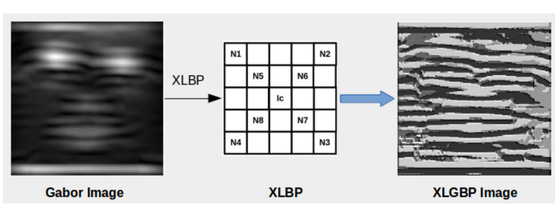

Figure 5. Texture extraction on Gabor Convoluted Face Image. (XLBP with radius 2 and neighborhood 8)

Some facial expression and illumination changes are specific to some regions in the face. So to summarize the region property we can use the local feature histograms of the XLGBP maps as shown in figure 5. This process is carried out by spatially dividing the XLGBP image into multiple non-overlapping regions as shown in figure 6. The histograms estimated on all these regions are concatenated to form a single vector sequence to represent the facial features of a single person. Histogram of each spatially divided region $(sg_{\mu,\nu,m} : 1 \leq m \leq \textit{no of regions})$ of an XLGBP image f is computed by

$$h_{XLGBP(sg_{\mu,\nu,m}),j} = \sum_{x,y} I\left(XLGBP(sg_{\mu,\nu,m})(x,y) = j\right) \tag{10}$$

where i is the i^{th} region of the XLGBP image f, j is the j^{th} gray level and

$$s(x) = \begin{cases} 1, & \text{A is True} \\ 0, & \text{A is False} \end{cases} \tag{11}$$

If each XLGBP map image divided into m regions overall concatenated histogram sequence can be shown by:

$$\mathbf{H} = \{h_{0,0,1}, \ldots, h_{0,0,m}, \ldots, h_{7,4,1}, \ldots, h_{7,4,m}\} \tag{12}$$

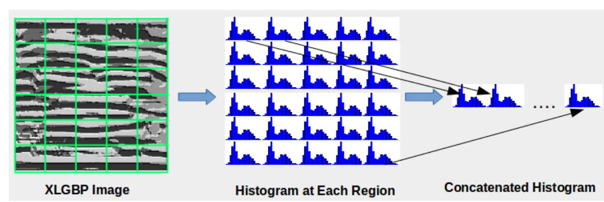

Figure 6. XLGBP histogram patterns concatenation (Figure shows for one XLGBP image. This process should be followed for all 40 XLGBP images for complete histogram feature vector)

B. Training and Classification

Consider a face image of size 192×160, is spatially divided non-overlapped regions of size 32×32 and the number of bins in each histogram are 8, then the length of the feature vector would be 9600 (40*(192*160)/(32*32)*8) which is relatively large for both processing and storing. As we know that number of training samples for any classifier should be more than dimension of the feature vector. Hence, we used k-PCA for dimensionality reduction. In PLDA based training using these low dimensional feature vector we computed a generative model with model parameters $\theta = \{\mu, \mathbf{F}, \mathbf{G}, \Sigma\}$ which can maximize the inter-class difference and minimize the intra-class difference. Recognition process carried out in following manner. Consider two gallery faces $\mathbf{x}_1$ and $\mathbf{x}_2$ which belongs two different persons and a probe face $\mathbf{x}_p$. In training there would be two models generated $\mathbf{M}_1$ and $\mathbf{M}_2$. If the probe image $\mathbf{x}_p$ matches with model $\mathbf{M}_1$, then it will share the latent variable $\mathbf{h}_1$ and gallery image $\mathbf{x}_2$ has its own identity variable, similarly if the probe image matches with model $\mathbf{M}_2$, then it will share the identity variable $\mathbf{h}_2$. As $\mathbf{x}_1$ and $\mathbf{x}_2$ are independent the likelihood model of the data under $\mathbf{M}_1$ can be written as:

$$P\left(\mathbf{x}_{1,2,p}|\mathrm{M}_1\right) = P\left(\mathbf{x}_{1,p}|\mathrm{M}_1\right) P\left(\mathbf{x}_2|\mathrm{M}_1\right) \tag{13}$$

In case of verification if the probe image $\mathbf{x}_p$ matches with the model $\mathbf{M}_1$ then $\mathbf{x}_1$ and $\mathbf{x}_p$ will share same identity variables otherwise they will share different identity variables. The process of recognition and verification can be illustrated clearly in following figure 7:

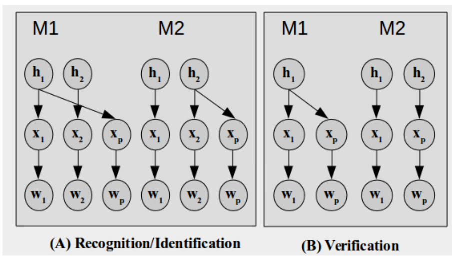

Figure 7. Recognition and Verification Process Using PLDA

If a probe image is given, in PLDA based approach the gallery Model with maximum probability would be considered as matched model. Even though we are getting good recognition rate with this approach the false positive rate is high.

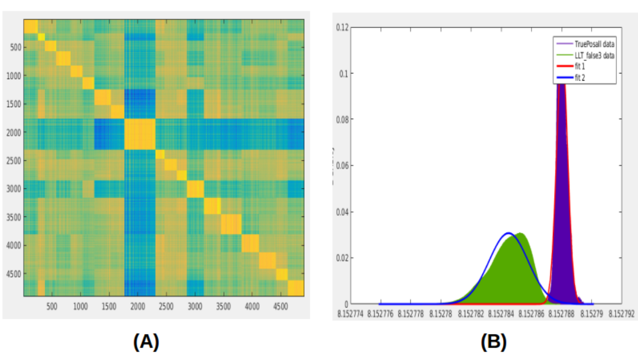

Figure 8. (A) PLDA training model: bright regions are matchings with maximum probabilities remaining are matchings with minimum probabilities. (B) Taking bright regions and remaining regions separately and fitting two different Gaussian distributions. Generally the intersection point of these Gaussians will the threshold value.

To overcome this issue, we defined a threshold based on these two regions. To find the correct threshold we used the complete gallery set for validation and computed the matching probabilities of the images of same individual and different individuals and fitted two separate Gaussian distributions as shown in figure 8. By conducting experiments on different datasets, we observed that the Gaussian of the same individual is narrower than the Gaussian of the the different individuals. Hence the threshold is fixed around the mean of the pdf of same individuals. From observations, we set the threshold probability for the better classification is given by:

$$\mathbf{T} = \mu_{true} - 2 * \sigma_{true} \tag{14}$$

where μ_{true} and σ_{true} are mean and standard deviation of the probability distribution of the true positives.

V. Experimental Results

Our method is carried out in two steps. i) computing XLGBP feature vectors: in which a face image of size 192×160 is convolved with 40 different Gabor wavelets (5 scales and 8 orientations). These convolved images are applied with XLBP(2,8) operator for texture extraction. Later each XLGBP map image is divided into 32×32 sizes non-overlapping regions. The histograms of all the regions are concatenated sequentially to compute a XLGBP histogram feature vector. ii) The feature vectors are normalized and dimensionality reduced. We conducted a few experiments and by statistical analysis we estimated a threshold value for correct classification with reduced false positives. We conducted two types of experiments on this method. First experiment considers frontal faces with different illumination conditions and the second one involved images with pose changes.

The first experiment is carried on color FERET [20] and Extended YaleB [21] datasets. We considered 900 images of FERET dataset from each Fa and Fb categories with single image per subject while from YaleB dataset we considered 1520 images of 38 subjects with 45 different illumination variations with frontal pose. Experimental results on frontal pose are given in tables I and II.

TABLE I
Performance Comparison on FERET Dataset (frontal only)

Method	Fa	Fb	Recognition Rate
LBP [4]	900	900	88.96
LRBP [13]	900	900	95.31
XLRBP [2]	900	900	98.89
LGBP [14]	900	900	97.33
XLGBP	900	900	99
XLGBP+PLDA	900	900	100

TABLE II
Performance Comparison on YaleB Dataset (frontal images with different illumination conditions)

Method	Train	Test	Recognition Rate
LBP [4]	38	1520	83.86
LRBP [13]	38	1520	88.57
XLRBP [2]	38	1520	90.20
LGBP [14]	38	1520	91.40
XLGBP	38	1520	93.03
XLGBP+PLDA	38	1520	96.7

In the second experiment we used GrayFERET dataset, and also an internally collected dataset for testing pose invariance. GrayFERET contains 2200 images of 200 persons with 11 pose variations. Our Internal dataset contains 4910 images of 19 subjects with several poses. The experimental results on pose invariant face recognition are as given in tables III and IV.

TABLE III
PERFORMANCE COMPARISON ON GREYFERET DATASET (11 POSES PER EACH OF 200 PERSONS)

Method	Recognition Rate
LBP [4]	83.86
DCP [10]	95.57
LRBP [13]	94.41
XLRBP [2]	94.54
LGBP [14]	93.69
XLGBP	95.32
XLGBP+PLDA	98.09

TABLE IV
PERFORMANCE COMPARISON ON OUR INTERNAL DATASET (4910 IMAGES OF 19 PERSONS)

Method	Recognition Rate
LBP [4]	92.87
DCP [10]	95.72
LRBP [13]	94.42
XLRBP [2]	94.70
LGBP [14]	97.35
XLGBP	97.75
XLGBP+PLDA	98.07

VI. CONCLUSION

The degree of image processing and feature computation is a key factor for the performance of any feature based face recognition methods. In this paper, we presented a new approach based on the Gabor magnitude and Cross Local Binary Patterns for face recognition in illumination and pose variations. This method intends to encode the local Gabor magnitude differences between neighborhood pixels which resembles the patternizing the shape attributes of the face image. The spatial histograms at each scale and orientation are concatenated to represent the feature vector of the image, which contains both the structure information and texture information. We used PLDA because the probabilistic approach allows the non-linearity which helps in determining the non-linear relationship among the different poses of the same person. We conducted experiments on both frontal faces and images with pose variations. The experimental results shows that this method performs better than other LBP based methods with Bhattacharya distance and even better when PLDA is used for classification.

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