Extraction of Texture Features from Shearlet Face using RLBP for Recognition

Nagaraja S.

Department of Computer Science, Karnatak Science College, Dharwad, Karnataka, India
Email: *nagaraja.s27[at]gmail.com*

Abstract: *In this paper, we introduced a method for representing faces using a combination of Shearlet Transform and Robust Local Binary Pattern (RLBP).* ***The shearlet transform exhibit improved multiscale directional capability, and a greater ability to localize distributed discontinuities such as edges along curves as compared to traditional multiscale transform such as wavelet transform and curvelet transform.*** *Thus, we convert the initial face images into the frequency domain by utilizing the shearlet transform. Noise-robust binary patterns are obtained from the approximate sub-band through the use of the RLBP technique in order to symbolize the face. These patterns create the feature vector. The effectiveness of the suggested approach for representing faces is assessed by performing face recognition on a benchmark database like ORL. The technique Support Vector Machines (SVM) with a polynomial kernel function is employed to perform classification. The experimental findings indicate that our method performs better when compared to approaches based on LBP.*

Keywords: Face Recognition, Shearlet Transform, Local Binary Pattern, Robust Local Binary Pattern

1. Introduction

In the last thirty years, there has been a lot of research activity in the areas of face recognition and texture analysis in fields like image processing, pattern recognition, and computer vision. This is primarily because these areas have a wide range of applications. There are numerous uses for facial recognition technology such as biometrics, controlling access to certain areas, monitoring and protecting, ensuring safety online and offline, and verifying credit card transactions. There are primarily two methods are used in face recognition: the geometry-focused approach and the appearance-oriented approach. In the geometry-based methods [1][2], changes in scale, location, in-plane rotation of the face, and rotation in depth is challenging to measure with any accuracy, especially from a single static image. However, this approach offers increased resilience against aging effects and disguises. While appearance-based methods[3][4][5], have been effective in accurately recognizing faces despite changes in facial expressions, they still face challenges in achieving optimal accuracy due to various factors such as personal appearance (such as glasses, make-up, facial hair, and hairstyle) that can impact the recognition process. Extracting discriminative features is a crucial preliminary stage before carrying out face recognition. The performance of a face recognition system can be significantly improved by extracting a discerning set of features. The Local Binary Pattern (LBP) is recognized as a highly effective tool for extracting discriminative features to represent faces[6]. The success of LBP face description due to its computation simplicity and discriminative power of the operator and its robustness to monotonic gray scale changes caused by illumination variations.

The researchers have investigated the use of LBP (Local Binary Patterns) for face recognition due to its ability to accurately extract facial features in difficult conditions where face recognition is challenging. In face recognition, it outperforms than Eigen face and Bayesian methods. Recently many authors have proposed algorithms for face recognition using LBP variants. Ahonen et al. [6] proposed a technique for face recognition using LBP. The face images are divided into several regions from which the LBP features are extracted and concatenated into an enhanced feature vector to be used as a face descriptor. Liao et al. [7] proposed Multi-scale Block Local Binary Patterns (MB-LBP) for face recognition uses sub-region average gray-values for comparison instead of single pixels. MB-LBP encodes both microstructures and macrostructures for better representation of image patterns and it can be computed very efficiently using integral images. Maturana et al. [26] proposed algorithm for face recognition. They extracted descriptors based on histograms of LBP, finally performed descriptor matching with spatial pyramid matching and Naive Bayes Nearest Neighbour. The drawback of Naive Bayes Nearest Neighbour is that it increases the computational cost relative to the original LBP based algorithm.

Pu et al. [8] proposed a method for face recognition based on multiresolution with multi-scale LBP features. The facial image pyramid is constructed and each facial image is divided into various regions from which partial and holistic LBP histograms are extracted. All LBP features of each image are concatenated to a single LBP eigenvector with different resolutions. Nguyen and Caplier [9] proposed Elliptical Local Binary Patterns (ELBP) for face recognition. In this approach, horizontal and vertical ellipse patterns are extracted to capture micro facial feature of face images in both horizontal and vertical directions. Ren et al. [10] proposed method Relaxed Local Ternary Patterns for face recognition. The ternary code is split into a positive LBP code and negative LBP code, it may result in a significant information loss. The positive and negative LBP histograms are strongly correlated, and hence a lot of redundant information may reside in those two histograms. The main drawback of LTP is that computationally it is more expensive than LBP. Gao et al. [11] presented a face description with single sample by Adaptively Weighted Extended Local Binary Pattern Pyramid (AWELBPP). AWELBPP feature are extracted from the fusion of the Sub-

Extended LBP pyramid and the Adaptively Weighting Map (AWM) according to the contribution of each sub-image to the final face feature description. Recently Anirudha B Shetty et.al [12] compared two face recognition techniques Haar Cascade and Local Binary Pattern edified for the classification. Haar Cascade method yield good recognition rate compare to Local Binary Pattern. Padmashree and Karunakar [13] proposed a method for recognition of face using Local Binary Pattern Histogram and achieved good recognition rate.

The face recognition methods described above based on LBP and its variants have two important disadvantages. First disadvantage is that various structural patterns can result in identical binary patterns. For instance, the two vectors (55, 85, 80, 85, 45, 50, 35, 30) and (150, 230, 235, 240, 10, 100, 150, 150) have resulted in the identical binary vector (0, 1, 1, 1, 0, 0, 0, 0). However, it is difficult to determine whether they possess similar local structure. The second disadvantage is that, they are sensitive to noise. This is because, in LBP, the value of central pixel in 3 × 3 local area is subtracted by its neighbours and result yields LBP code. In order to overcome incorrect matches due to same binary code generated for different structural patterns, CLBP (Completed LBP) was introduced by Guo et al. [14], for texture classification. However, the CLBP method is sensitive to noise because in order to generate binary code, the value of central pixel value is still used as threshold directly. In order to make LBP robust against noise, Zhao et al. [15] have extended CLBP method called as CRLBP (Completed Robust LBP) for texture classification. Multiscale methods based on shearlets [16] not only have good localization and compactly support in the frequency domain, but also have directionality and anisotropy. With these properties, shearlets can accurately efficiently represent image geometrical information of edges and texture, which are very essential in face recognition.

We suggested a method for identifying faces by employing shearlet in combination with Robust Local Binary Pattern (RLBP). Instead of calculating three different elements like sign, magnitude, and central component, we only calculate the sign component by using the average local gray value of a 3 × 3 local area. Our method is not affected by noise and prevents the issue of generating identical binary codes for distinct patterns. We took into account the neighbours of every neighbouring pixel when calculating the binary code.

2. Shearlet Transform

2.1 Continuous Shearlet

The shearlet transform is a new multiscale geometric analysis tool which has been widely used in image approximation, edge analysis and other fields [17][18][19].

The continuous shearlet transform *f* is defined by

$$SH_f(a,s,t) = \langle f, \Psi_{ast} \rangle, \quad a \in R^+, s \in R, t \in R^2 \quad (1)$$

where $\Psi_{ast}(\mathrm{x}) = \mathrm{a}^{-3/4}\Psi\left(M_{as}^{-1}(x-t)\right)$ of three variables, the scale $a \in R^+$, the shear $s \in R$, the transform $t \in R^2$, is called a continuous shearlet system. $M_{as} = \left(a, s; 0, \sqrt{a}\right)$ is the composition of the shear matrices $B = (1, s; 0,1)$ and anisotropic matrices $A = \left(a, 0; 0, a^{1/2}\right)$. For any $\xi = (\xi_1, \xi_2) \in \hat{R}^2$, $\xi_1 \neq 0$, let

$$\hat{\Psi}(\xi) = \hat{\Psi}(\xi_1, \xi_2) = \hat{\Psi}_1(\xi_1)\hat{\Psi}_2\left(\frac{\xi_2}{\xi_1}\right) \quad (2)$$

where $\hat{\Psi}_1 \in C^\infty(R)$ with $supp\hat{\Psi}_1 \in [-2, -1/2] \cup [1/2, 2]$, $\hat{\Psi}_2 =\in C^\infty(R)$ with $supp\hat{\Psi}_2 \in [-1,1]$ and $\hat{\Psi}_2 > 0$ on $(-1,1)$. Thus, each function $\hat{\Psi}_{ast}$ has frequency support

$$supp\hat{\Psi}_{ast} \subset \left\{(\xi_1, \xi_2): \xi_1 \in \left[-\frac{2}{a}, -\frac{1}{2a}\right] \cup \left[\frac{1}{2a}, -\frac{2}{a}\right], \left|\frac{\xi_2}{\xi_1} - s\right| \leq a \quad (3)$$

Each element Ψ_{ast} is supported on a pair of trapezoids, oriented along lines of slope *s*. The support becomes increasingly thin as $a \to 0$. That is say the scale of the shearlets controlled by the anisotropic scaling matrices A, while the shear matrices B only control the orientation of the shearlets. Those matrices lead to windows which can be elongated along arbitrary directions and the geometric structures fo singularities in images can be efficiently represented and analyzed by using them.

In [20] shows that shearlets are localized well and are compactly supported in the frequency domain. Shearlets show highly directional sensitivity and anisotropy. In fact, for two-dimension signal, the band limited shearlets can detect all singular points and track the direction of singular curve adaptively. Furthermore, along with the parameter changes, shearlets can completely analyse the singular structures of 2-D piecewise smooth functions. Those properties of shearlets are useful especially in image edge and detail information processing.

2.2 Discrete Shearlet Transform

The elements of the traditional shearlet can't be separated in the spatial domain, and this property often leads to the difficulty in practically relevant discrete implementation. Based on the above discussion, Lim (W.Q. Lim) [17] constructed compactly supported shearlets generated by separable functions which are constructed using multiresolution analysis, this led to a fast discrete shearlet transform implementation. The fast discrete shearlet transform of the image *f*. Specifically, the shear matrix B_0^s and B_1^s corresponded to the horizontal cone C_0 and vertical cone C_1dimensions respectively, while the anisotropic scaling matrix A_0 and A_1 were offered to construct the anisotropic discrete wavelet basis along the shear direction and complete the multiscale decomposition. The fast discrete shearlet transform is also computationally very efficient and it requires $O\left((2^{M+2}+2)N\right)$ operations where N is the size of the input image and $2^{M+2}+2$ is the number of directions, while the 2D-FRFT costs $O\left(N(\log N)\right)$, the curvelet transform costs $O\left(N\left(\log\sqrt{N}\right)^2\right)$, the ridgelets transform costs $O\left(N\left(\log\sqrt{N}\right)\right)$ [25].

Using the shearlets, a given image can be analysed at various resolutions for each direction. The low frequency components are the upper left corner of the shearlet coefficients matrix, which concentrate most important information and discard the influence of noises and irrelevant parts, will be adopted for further analysis in our approach. Thus, the dimensionality of the data is reduced effectively for computation at the next stage.

3. Robust Local Binary Pattern (RLBP)

The RLBP produces code, which is invariant to monotonic gray scale transformation and insensitive to noise. The gray value of centre pixel in 3x3 local area is replaced by its average local gray value of the neighbourhood pixel values instead of the gray value of centre pixel value, in which the RLBP is calculated. The Average Local Gray value (ALG) is defined as

$$\mathrm{ALG} = \frac{\sum_{i=1}^{8} g_i + g}{9}, \quad (4)$$

where g is the gray value of the centre pixel and g_i (i=0,1,…8) represents the gray value of the neighbor pixels. ALG is the average gray level of local area, which is obviously more robust to noise than the gray value of the centre pixel. The LBP process is applied by using ALG as the threshold instead of the gray value of central pixel, named as Robust Local Binary pattern (RLBP). This can be defined as

$$\mathrm{RLBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - \mathrm{ALG}_c)2^p$$
$$= \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + g_c}{9}\right)2^p \quad (5)$$

where g_c is the gray value of central pixel and g_p(p=0,1,…P-1) represents the gray value of the neighbor pixel on 3x3 local area of radius R, P is the number of neighbors and g_{ci}(i=0,1,…8) is the gray values of the neighbor pixel of g_c. Average local gray level of pixel is used as threshold, therefore RLBP is insensitive to noise and also two different patterns with same LBP code may have different RLBP code, because that neighbors of each neighbor pixel are considered. The RLBP can overcome mentioned demerits of LBP.

Sometimes specific information of the central pixel is needed, but ALG ignores the specific information of individual pixel. In order to define Weighted Local Gray Value (WLG) to balance between anti-noise and information of individual pixel. The WLG is defined as follows

$$\mathrm{WLG} = \frac{\sum_{i=1}^{8} g_i + \alpha g}{8 + \alpha}, \quad (6)$$

where g and g_i are defined in Eq. (4), α is a parameter set by user. If α is set to 1, WLG is equivalent to ALG. The RLBP is calculated as follows

$$\mathrm{RLBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - \mathrm{WLG}_c)2^p$$
$$= \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + \alpha g_c}{8 + \alpha}\right)2^p \quad (7)$$

where g_p, g_c and g_{ci} are defined Eq. (5), α is a parameter of WLG.

A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or 1 to 0, when the binary string is considered circular. For example, 00000001, 00011111 and 11000111 are uniform patterns. We extend the RLBP to uniform RLBP, the notation used for the RLBP operator: $RLBP_{P,R}^{u2}$ or $U(RLBP_{P,R})$ as defined below:

$$U(RLBP_{P,R}) = |s(g_{P-1} - WLG_c) - s(g_0 - WLG_c)| + \sum_{P=1}^{P-1} |s(g_P - WLG_c) - s(g_{P-1} - WLG_c)| \quad (8)$$

The subscript represents using the operator in a *(P, R)* neighbourhood. Superscript *u2* stands for using only uniform patterns and labelling all remaining patterns with a single label.

The $LBP_{P,R}$ operator produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the *P* pixels in the neighbour set. When the image is rotated, the gray values g_P will correspondingly move along the perimeter of the circle around g_0. Since g_0 is always assigned to be the gray value of element (0, *R)* to the right of g_c rotating a particular binary pattern naturally results in a different $LBP_{P,R}$ value. This does not apply to patterns comprising on only 0s (or 1s) which remain constant at all rotation, i.e., to assign a unique identifier to each rotation invariant local binary patterns. We extend the rotation invariant local binary pattern to RLBP as defined below:

$$RLBP_{P,R}^{ri} = min\{ROR(RLBP_{P,R}, i) \mid i = 0,1, \dots P-1\} \quad (9)$$

Where $ROR(x, i)$ performs a circular bit-wise right shift on the *P*-bit number *x*, *i* times. In terms of pixels, simply corresponds to rotating the neighbour set clockwise so many times that a maximal number of the most significant bits, starting from g_{P-1}, is 0. $RLBP_{P,R}^{ri}$ quantifies the occurrence statistics of individual rotation invariant patterns corresponding to certain micro features in the image:

$$RLBP_{P,R}^{riu2} = \begin{cases} \sum_{P=0}^{P-1} s(g_P - WLG_c) & if\ U(RLBP_{P,R}) \le 2 \\ P+1 & otherwise \end{cases} \quad (10)$$

superscript $riu2$ reflects the use of rotation invariant uniform patterns. A histogram of the labelled image $f_l(x, y)$ can be defined as

$$H_i = \sum_{x,y} I\{f_l(x, y) = i\},\ i = 0, \dots, n-1 \quad (11)$$

in which n is the number of different labels produced by the LBP operator and

$$I\{A\} = \begin{cases} 1, & A \text{ is true} \\ 0, & A \text{ is false} \end{cases} \quad (12)$$

This histogram contains information about the distribution of the local micropatterns, such as edges, spots and flat areas, over the whole image.

4. Experimental Results

In order to assess the effectiveness of the suggested combination, which involves using the multiresolution tool shearlet along with RLBP, experiments were carried out using widely recognized face databases such as the ORL face database. We assessed the effectiveness of the suggested method by comparing it to the performance of the original LBP, Eigenface, Curvelets combined with PCA, and Curvelets integrated with LBP variants.Initially, we break down the image into an approximation sub-band and detailed sub-bands by employing the shearlet transform. The approximate sub-band is found to contain a greater amount of energy compared to the detailed sub-bands. As a result, we utilize RLBP on the approximate sub-band by adjusting the weighing parameter α within the range of 1 to 8. We have performed a number of experiments on the ORL face database to find the best possible value for parameters such as α, R and P for RLBP. Once the best values of parameters α, R, and P for RLBP are determined, the SVM classifier with a polynomial kernel function (degree 3) is used. The RLBP histogram, which represents the facial feature vector of face images, is computed in all the experiments. The experiments are conducted for RLBP and its extensions such as uniform RLBP (($RLBP^{u2}$) and rotation invariant uniform ($RLBP^{u2}$).

The ORL database contains ten different images of forty distinct subjects, were taken between April 1992 and April 1994 at the AT & T lab [21], Cambridge. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses), All the images were taken against a dark homogeneous background with the subjects in an upright frontal position. The size of each image is 92 x 112 pixels, with 256 grey levels per pixel. We randomly selected five images for training and the rest of the images are used for testing. The sharelet RLBP features are extracted from the face images and SVM classifier with polynomial kernel function of degree 3 is used for face recognition. A ten-fold cross-validation has been performed and average recognition rate is considered. Table 1 shows the recognition rate obtained using various combinations of shearlet and neighbourhood, radius for RLBP. The experimental results show that highest recognition rate is achieved for shearlet and $RLBP_{8.1}^{u2}$ (uniform RLBP with P=8, R=1).

Table 1: Face Recognition rate of our approach for Shearlet and different combination of Neighborhood (P), Radius (R) for $RLBP_{P.R}$ on ORL database

Methods	Recognition Rate (%)	
	$\alpha = 1$	$\alpha = 8$
Shearlet + $RLBP_{8.1}$	97.00	98.25
Shearlet + $RLBP_{8.1}^{u2}$	**97.50**	**99.25**
Shearlet + $RLBP_{8.1}^{riu2}$	96.75	97.50
Shearlet + $RLBP_{8.2}$	96.00	97.50
Shearlet + $RLBP_{8.2}^{u2}$	97.25	98.00
Shearlet + $RLBP_{8.2}^{riu2}$	95.00	96.00

As like normal images of ORL database, we conduct the experiments with proposed method under various noise levels. Gaussian noise with mean 0 and variance 0.01 to 0.04 (Figure 1) has been added to the input images. The two sets with 3 and 5 images per subject of ORL database are used for training and the rest of the images are considered as a test sets. A ten-fold cross-validation has been performed and average recognition rate is considered. The shearlet based RLBP features are extracted from the face images and SVM classifier with polynomial kernel function of degree 3 is used for face recognition. Table 2 shows the recognition rate obtained with various noise levels.

Table 2: Face Recognition rate in noisy condition with Shearlet + RLBP and RLBP on ORL database.(For training set 5 images/subject)

Methods	Recognition Rate of noisy images with mean= 0			
	variance=0.01	variance=0.02	Variance=0.03	Variance=0.04
Shearlet + $RLBP_{8.1}^{u2}(\alpha = 8)$	99.25	99.24	99.20	99.10
$RLBP_{8.1}^{u2}(\alpha = 8)$	98.00	97.95	97.80	97.65

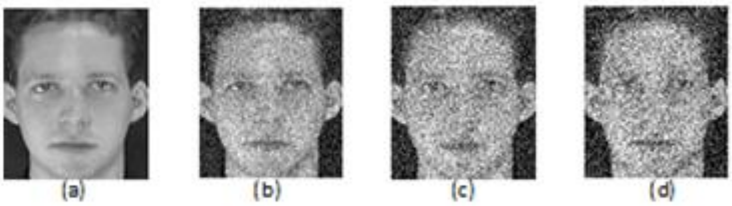

Figure 1: (a) Original Image of ORL database, Gaussian noise added images: (b)m=0,v=0.01 (c) m=0, v=0.02 and (d) m=0, v=0.03

We illustrated different results of proposed face recognition method on ORL database. In order to establish reliability of the proposed method, we have compared results of our approach with standard techniques like Eigenface [5], Original LBP [17], Curvelet with PCA [15] and Curvelets with CLBP [27]. Recognition rates reported in Table 3 are achieved after ten-fold cross-validation. The proposed method yields highest recognition rate compared to other methods.

Table 3: Comparison of proposed method with other methods for normal images

Methods	Recognition Accuracy (%)
Eigenface [3]	92.20
LBP [6]	95.45
Curvelet + PCA [22]	96.60
Curvelet + LBP [23]	94.00
Curvelet + CLBP [24]	98.50
Our Approach	99.25

The results achieved on corrupted images by various Gaussian noise levels were very interesting. Almost equal results achieved by Shearlet + RLBP combination and RLBP alone with noisy images compared to original face images of the both the datasets. We compared results of our approach with RLBP, LBP and Curvelet+PCA. The recognition rates for our approach is shown in the Table 4 are achieved using SVM classifier with polynomial degree 3. The proposed method outperforms compared to other methods, this shows that Shearlet + RLBP and RLBP method is robust against noise.

Table 4: Comparison of proposed method with other methods for noisy images (m=0, V=0.02)

Methods	**Recognition Accuracy (%)**
LBP	75.45
Curvelet + PCA [22]	94.20
$RLBP_{8,1}^{u2}$[25]	97.25
Our Approach	**99.24**

5. Conclusion

We introduce a novel method for identifying faces by using both shearlet transform and Robust Local Binary Pattern (RLBP). Our method delivers encouraging outcomes on the ORL face database when compared to other conventional and curvelet-based techniques for face recognition. This is because the shearlet transform maintains the edges and other changes that occur in the face. Further, the approximate sub-band of shearlet represents these variations accurately compared to other detailed sub-bands. We extracted robust local binary patterns from shearlet approximate sub-band and constructed a global histogram that represents the statistics of the facial micro-patterns. These features are insensitive to noise and robust against illumination variants. Extensive experiments conducted on ORL face databases, it clearly shows the superiority of the method against different facial expression, various noise levels, lighting variation and postures of the subjects.

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