A Theoretical Approach on Face Recognition with Single Sample Per Class using CS-LBP and Gabor Magnitude and Phase

A. Usha Ruby^{1*} and J. George Chellin Chandran²

¹Department of CSE, Bharath University, Chennai - 600073, Tamil Nadu, India; ausharuby@gmail.com ²CSI College of Engineering, Ketti, Nilgiris - 643215, Tamil Nadu, India; chellin1968@gmail.com

Abstract

Objectives: To develop a theoretical model in order to understand how to recognize acquainted faces and the relationship between face processing acknowledgement with other aspects in face. Greater Performance is achieved in face recognition by local appearance based methods. **Methods:** The Centre Symmetric local binary pattern with gabor magnitude phase have been proposed in this paper to provide an expression, illumination and pose invariant in a single sample problem for face recognition approach with local spatial, scale and directional discriminate and low dimensional face representation based on features. The proposed methodology was compared with PCA and LBP. **Findings:** Gabor magnitude and Gabor phase tracks the texture boundaries of textured regions accurately. The evaluated Face features from CS-LBP and gabor magnitude phase has better performance. The Photometric descriptors are used in recent years, proven successful for computing regions which are in interest. In this approach the strength of SIFT descriptors are used in combination with LBP texture operator collectively called CS-LBP descriptor. This nullified illumination changes, strengthening flat image areas, and proficiency in computation. **Improvements:** For images with severe illumination variations SIFT descriptor is outperformed by CSLBP descriptor this was proved experimentally. The face recognition rate is increased by selective local texture feature Gabor Magnitude and Phase CS-LBP when compared with LBP method and Gabor filter.

Keywords: Center Symmetric Local Binary Pattern (CS-LBP), Independent Component Analysis (ICA), Invariant Feature Transform (SIFT), Local Binary Pattern (LBP), Linear Discriminate Analysis (LDA), Scale Principle Component analysis (PCA)

1. Introduction

A Person is identified during face recognition by his or her biometric parameters. Today Face recognition plays a vital role in many areas of security, law enforcement, Bank, National and International identification etc. Most of the face recognition techniques used are Eigen faces¹, Fisher faces, Laplacian faces, Neural Networks². Due to illumination, pose, facial expressions, ageing in practice it is difficult to recognize a person accurately. Single sample problem³ also faces difficulties because here we are using only one sample per class for training. Many of the National and International authentication example, Passport, Voters ID, Aadhar card etc, we are matching method and local matching methods are used for recognition, entire face image is considered for the Holistic matching method this is done based on the application of Principle Component Analysis (PCA)⁴, Linear Discriminate Analysis (LDA)⁵, and Independent Component Analysis (ICA) on training data. Here for each image a eigen value is calculated based on eigen vector, the highest value represent a particular image. LDA minimizes the intra class scatter like ICA. Local matching method is superior to Holistic method for single sample per class. In local matching rather than considering the whole image a single feature in the face

using only one image for training. The single sample per class can be solved by using some algorithms. Holistic

is considered. Here the original feature is represented by a low dimensional local vector feature. The classifiers diversity is improved by different facial features, example, length, breadth, contrast etc of local features. Face recognition application uses Local Binary Pattern (LBP)⁶ method which was earlier used for image texture descriptor. Better result in speed and performance is achieved by LBP method⁷. LBP is less sensitive to illumination and scale variation. For image processing, pattern recognition etc, mainly feature based⁸ recognition is used. The spatial frequency characteristics, localization and orientation are exploited by Gabor filter. The essential features of face are extracted by Gabor filter for the creation of binary face template.

2. An Outlook LBP and Gabor Filter

This section provide an outlook of LBP and Gabor filter

2.1 Local Binary Patterns

The operation of Local Binary Pattern⁹ was introduced by Ojale et al in 1996. Here the local neighbourhood values around the pixel is taken by the operator. Figure 1 represent the basic operation of LBP, here the operator takes the neighbourhood of central pixel and form a 3X3 neighbourhood, based on central pixel, the operator works on the eight neighbours of center pixel. The neighbours are represented by binary forming an eight bit code, where central pixel is represented by 2.2 as threshold. One is assigned to a pixel only if the neighbour pixel has higher or same grey value than the central pixel, otherwise it is zero. The binary code ones and zeros produce center pixel LBP code. The features of LBP is computed using equation 1.

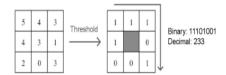


Figure 1. Basic LBP operator.

LBP
$$(x_c, y_c) = \sum^7 n = 0 2^n s (i_n - i_c)$$
 (1)

Here i_n has eight neighbours over central pixel c, where i_n and i_c are gray scale values of c and n, S(x) = 1 $x \ge 0$,

otherwise

0

Here in LBP method we divide the face image into a regular grid of cell. And histogram is applied for equalization. At last cell-level histogram concatenation produces uniform results.

LBP Calculations	Binary Bit Values Summed
[0,0] 6>[-1,-1] 7=0	LBP=0
[0,0] 6>[-1,0] 9=0	LBP=00
[0,0] 6>[-1,1] 9=0	LBP=000
[0,0] 6>[0,-1] 5=1	LBP=0001
[0,0] 6>[0,+1] 7=0	LBP=00010
[0,0] 6>[+1,-1] 5=1	LBP=000101
[0,0] 6>[+1,-1] 4=1	LBP=0001011
[0,0] 6>[+1,-1] 7=0	LBP=00010110

LBP Descriptor=00010110 is the Hex Representation of the Binary Value

A kernel is formed by comparing each pixels to its neigbours. This is shown in Figure: 2 and Figure: 3, the binary pattern will be one if it is greater than the center pixel, the binary pattern is 0 otherwise. The histogram records all LBP descriptor on face and form a cumulative texture feature.

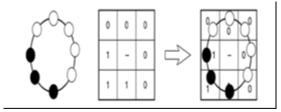


Figure 2. Concept of LBP Directionality.

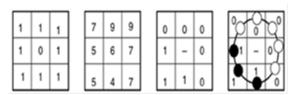


Figure 3. Steps involved in calculating 3X3 LBP.

2.2 Gabor Filter

Binary face template is obtained by extracting and converting the textual features using Gabor filter, hence noises in the extracted images are reduced and improves recognition rate. Gabor filter frequency and orientation are similar to Human visual system. Equation 2 represent the 2D $\psi_{f,\theta}(x,y)$ since the signal is a complex sinusoidal signal using Gaussian kernel function it is modulated.

$$\psi_{f\theta}(x,y) =$$

$$\operatorname{"exp}[-\mathsf{"} 1/2 \{ (x^{\dagger} 2 \theta n) / (\sigma^{\dagger} 2 x) + (y^{\dagger} 2 \theta n) / (\sigma^{\dagger} 2 y) \}] \exp(2\pi f \theta n)$$
(2)

In equation (2) f represent sinusoidal plane central frequency and θ represent the xy plane orientation

$$\begin{bmatrix} x\theta_n \\ y\theta_n \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} (n-1)$$
(3)

where θ_n is the rotation of xy plane by θ_n angle gabor filter at the orientation θ_n in the equation (3).

$$\theta_n = \frac{\pi}{p}$$

where p is the orientation and n = 1, 2, ... p.

3. Proposed Approach

Two techniques are proposed in this paper. Gabor Magnitude Phase and CS LBP proved better performance in Local texture based face recognition.

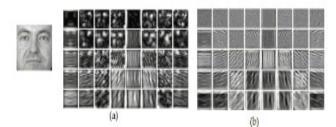


Figure 4. Visualization of (a) Gabor Magnitude (b) Gabor Phase response.

3.1 Gabor Magnitude Phase

Gabor Magnitude Phase is used for tracking the texture boundaries. The textured regions boundaries are precisely tracked by phase gradient of Gabor phase. On absorbtion Gabor phase equals the performance of Human visual system in distinguishing the areas of same magnitude of patterns with dissimilar frequencies. So for texture perception Gabor magnitude phase will provide good result.

$$({}_{(","(","("))(z))} = I(z) * ({}_{(","(","("))(z))} (z)$$
(4)

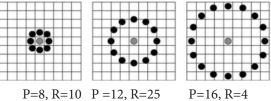


Figure 5. Circularly Symmetric neighbour sets for three different values of P & R.

((°(°, °(°)) (z) shows the spectrum result similar to gabor kernel corresponding to orientation μ and scale ν .

The magnitude spectrum is obtained by

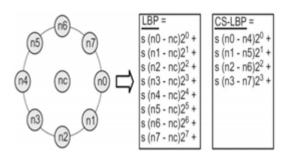
M ((("(","("))(z) =

 $\sqrt{(\mathbb{R}_{Re}(((("(","("))))))^{1} + \mathbb{L}_{lm}(((("(","(")))))^{1}))$ (5) The phase spectrum is calculated by

$[(]]_{("(", "("))(z)} =$

arctan[(lm(((("(","(")(z)))/(Re(((("(","(")(z))))) (6)

Thus the texture boundaries are obtained from equation 5 and 6. The figure 4 shows the visualization of Gabor magnitude and Gabor phase response.



Neighbourhood Binary Pattern **Figure 6.** LBP and CSLBP features for a neighbourhood of eight pixels.

3.2 Center Symmetric Local Binary Pattern

In CS-LBP, pairs of pixels are compared, instead of comparing neighbourhood as in LBP, this is shown in Figure: 5. The flat image where the the gray level difference areas are strengthening by thresholding with a parameter T. T is the user given value, which consider the grey level differences.

$$CS-LBP_{P,R}(C) = \sum_{i=0}^{l} S(g_i + g_{i+p})^{2^i}$$

$$S(x) = 1 \qquad x \ge T,$$

$$0 \qquad \text{otherwise} \qquad (7)$$

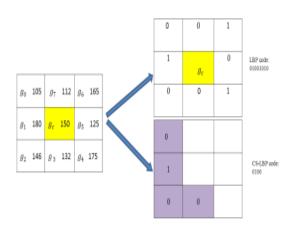


Figure 7. LBP and CS-LBP operators.



Figure 8. Pre-processed Image.

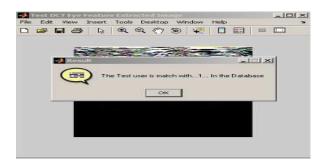


Figure 9. The test user match with the data base using Gabor Magnitude Phase and CS-LBP.

In equation 7, g_i and $g_i + g_i$ are the gray level of center-symmetric pairs of pixels of a 3x3 descriptor. CS-LBP perform operation of gradient operator by considering only the neighbour opposite pixels gray-level differences.

CS-LBP incorporate the advantages of LBP and the gradient-based features. Figure: 6 and Figure: 7 represent the encoding procedures of LBP and CS-LBP operators.

4. Conclusion

The features evaluated by CS-LBP shows the better performance and result in terms of illumination and computation because of less parameters. Using Gabor Magnitude and Phase the required face features are extracted and converted into a binary template using. Center Symmetric Local binary pattern is used to extract the local texture features. The results shows that CSLBP increases the rate of face recognition when compare to LBP method and Gabor filter.

5. References

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