Partial GMP-CS-LBP Face Recognition using Image Subblocks

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***Abstract*—Proposed face recognition in this paper is a block based approach. Gabor magnitude-phase centrally symmetric local binary pattern (GMP-CS-LBP) has been used to extract directional texture characteristics of face at different spatial frequencies. CS-LBP is applied on the sub-blocks of magnitude and phase responses of Gabor images. Sparse classifier is employed as local classifier to find the sub-blocks class labels. We have evaluated the performance of the proposed algorithm on AR and ORL databases. In real world scenarios, partial face images are available to recognize the identity of an unknown individual. By comparing the recognition accuracy on the recognition results of image sub-blocks, we find the location and size of the most effective face sub-region for identification. Moreover, fusion of image sub-blocks at decision level leads to significantly improved recognition accuracy.**

Keywords-face recognition; block based; effective subregion; partial image.

I. INTRODUCTION

Face recognition is widely used as a biological identification technique which is applied to recognize an unknown individual by analyzing and comparing their facial image to the available database of known identities. It has a wide range of applications such as social networking, border monitoring, access control and law enforcement. The accuracy of face recognition is affected by variation in the appearance of face due to poor illumination, head pose, facial expression, partial occlusion or degradation. In recent years, many identification techniques were proposed in order to increase the accuracy of recognition versus appearance changes. In holistic based approaches, the whole face area is employed to extract features and deciding on the identity label. A robust image representation against occlusion and illumination variation was proposed in [1] using the combination of subspace learning and cosine-based correlation approach which was applied on the orientation of gradient. However, local based techniques by dividing image into sub-regions and fusion of the extracted features or classification results, leads to robustness against variations in the appearance. Local Gabor binary pattern histogram (LGBPH) technique was proposed in [2] where, the local binary pattern (LBP) histograms of sub-blocks of Gabor magnitude images are combined. Different sub-blocks were differentiated in concatenation of features, by assigning a Kullback–Leibler divergence (KLD) weight to the corresponding sub-blocks. In [3], a block-based face recognition technique was proposed by extracting uniform LBP histograms. The results of local nearest neighbour classifiers are combined using an entropy weighted decision fusion to reduce the effect of sub-blocks with less information content. Local phase quantization (LPQ) and multi-scale LBP were applied on the proposed gradient based illumination insensitive representation of image sub-blocks in [4]. Weighted fusion at score and decision level finds the identity of unknown individuals. In [5] the gray values of pixels in image sub-regions were concatenated and class specific multi sub-region based correlation filter bank technique (MS-CFB) was calculated for the training samples and test images. Local polynomial approximation (LPA) filter and directional scale optimization was proposed in [6]. LBP directional images were divided into sub-blocks at four levels. Finally, linear discriminant analysis (LDA) was applied on the concatenation of local histograms at four levels. Nevertheless, some facial areas which contain non-discriminative information can be excluded in the recognition process and computational complexity is reduced by analyzing fewer image sub-blocks instead of the whole face area. This technique is very effective when some parts of the face are occluded by an external object. In some application such as images acquired by surveillance cameras, only a small amount of discriminative information in a partial image of the face is available. We need to find the most effective sub-image to identify an unknown individual whose face is partially covered. The proposed approach in [7] addresses partial face recognition using an alignment-free combination of multi-keypoint descriptors (MKD) and sparse representation-based classification (SRC). A set of MKDs were applied on images in the gallery set and a partial probe image was represented as a sparse linear combination of gallery dictionary.

In this paper, the image is divided into sub-blocks and the proposed face recognition technique which is shown in Fig 1, is applied on local areas. The size and location of the most effective area of the face in identification process has been investigated through the experimental results. We proposed Gabor magnitude-phase centrally symmetric local binary pattern (GMP-CS-LBP) technique as feature extractor based on the symmetry in a local area around image pixels [8]. In order to include the magnitude and phase information of local characteristics of face which are insensitive against appearance changes, we have applied texture descriptor on the magnitude and phase responses of Gabor images. The extracted features are concatenated for each image sub-block.

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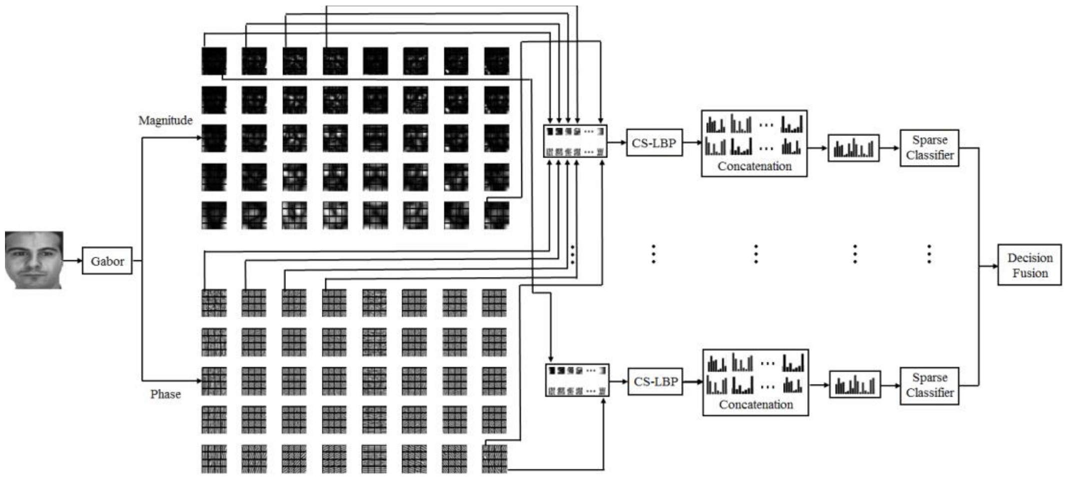

Figure 1. Block diagram of the proposed face recognition technique.

Sparse classifier is employed on image sub-regions to find the local class labels. Majority voting (MV) combines local decisions.

The rest of paper is organized as follows. In Section II, the configuration of feature extraction technique is explained in detail. Section III describes the classification approach. Section IV provides the experimental results. The paper is concluded in Section V.

II. FEATURE EXTRACTION

The proposed GMP-CS-LBP feature extraction in this paper is the fusion of magnitude and phase information of Gabor coefficients. Configuration of the proposed feature extraction technique is shown in Fig 1.

A. Gabor Filter

Gabor filter extracts the characteristics of signal at different scales and orientations which resembles the mammalia response of vision cells. In order to acquire directionally selective local properties of a face image at various spatial frequencies which are invariant against appearance changes due to expression and illumination variations, 2-D Gabor filters at S_{max} scales and O_{max} orientaions are convolved by image. Gabor filters are obtained as follows by ranging the spatial scale s from 1 to S_{max} and orientation o from 1 to O_{max} [9, 10],

$$\psi_{s,o}(x,y) = \frac{q_{o,s}^2}{\sigma^2} . e^{-\left(\frac{z^2 q_{s,o}^2}{2\sigma^2}\right)} . \left[e^{(jzq_{s,o})} - e^{\left(-\frac{\sigma^2}{2}\right)}\right], \quad (1)$$

where, $q_{s,o} = q_s \exp(j\theta_o) = [\pi/2(\sqrt{2})^s] \exp(j\pi\, o/8)$ (in this paper we defined 5 scales and 8 orientations). $z = (x,y)$, and $\sigma = 2\pi$ [9, 10]. The magnitude and phase responses of Gabor filtered image are shown in Fig. 1.

B. Centrally Symmetric Local Binary Pattern (CS-LBP)

One of the most powerful local descriptors where the texture information are analysed by comparing the intensity value of local texture in a small neighbourhood and supress the monotonic offset of neighbour pixels is local binary pattern (LBP) analysis. LBP is very fast technique and easy to execute [8, 10]. In a circular neighbourhood with radius R and P neighbours around each image pixel, we compare the neighbours with the centre pixel and depending on the sign of their difference a 1 or 0 value (for positive difference or negative difference, respectively) is assigned to the corresponding neighbours. Therefore, a P-bit binary pattern is associated with the centre pixel. Thus, for image pixels we have decimal values ranging from 0 to 2^P which are used to construct a histogram of 2^P-bin as the texture features. We can reduce the number of histogram bins which decreases the size of extracted features by employing the symmetry in the local area around each pixel. In centrally symmetric LBP (CS-LBP) technique [8], the centre symmetric pairs of neighbours are compared instead of comparing each of them with the centre, as shown in Fig 2. Therefore, the range of decimal values is reduced to $0 - 2^{(P/2)}$ and the stability of the extracted features against flat texture is increased. The calculation of decimal value associated with the binary patterns is as follows [8],

$$CSLBP_{dec}(u,v) = \sum_{l=0}^{(P/2)-1} F\left(I_l - I_{l+(P/2)}\right) 2^l,$$

$$where \quad F(x) = \begin{cases} 1 & x \geq Th. \\ 0 & otherwise. \end{cases} \quad (2)$$

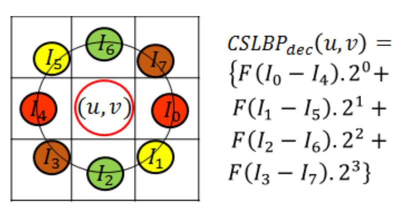

Figure 2. Calculation of CS-LBP for a pixel at (u,v).

(u, v) is the position of centre pixel and I_l is the intensity value of l^{th} neighbor of the centre. R and P are 1 and 8 in this paper. In order to increase the stability against flat areas, the intensity differences between centre symmetric pairs are compared to a threshold value (Th) greater than 0, which is used as threshold in LBP technique [8]. The value which is assigned as threshold is defined in the following section.

C. Local GMP-CS-LBP Histograms

In order to employ magnitude and phase information simultaneously, CS-LBP technique is applied on the magnitude and phase responses of Gabor images at different scales and orientations. However, the threshold value in (2) is different for comparing magnitude or phase information. Through the exhaustive search, in this paper we employ 0.1 as the magnitude threshold and 90° as phase threshold. Following by calculation of the binary patterns and the corresponding decimal values of image pixels and constructing histograms, the $2^{(P/2)}$-bin magnitude and phase histograms are concatenated.

Furthermore, to find the most effective sub region of face image on the identification accuracy, we divide Gabor images into rectangular non overlapping sub blocks of $m \times n$ pixels. By concatenating the histograms of magnitude and phase responses of all scales and orientations of Gabor responses, we obtain a histogram of $2^{(P/2)+1} \times S_{max} \times O_{max}$ bins for each image sub region.

III. SPARSE CLASSIFICATION

Local classifiers are based on the sparsest representation of the probe sample using the combination of corresponding gallery samples of the same class label [11]. Image samples which are belonging to the same individual lie on a linear subspace.

$$g = [g_1, g_2, g_3, \dots, g_M]. \quad (3)$$

$$g_i = [f_1^g, f_2^g, f_3^g, \dots, f_N^g]. \quad (4)$$

Where, g is gallery dictionary which is including all gallery samples in the database. g_k is the matrix of k^{th} class of subject which consists of gallery feature vectors as its columns (f_k^g is the feature vector of the k^{th} sample in g_k), where M and N are the number of classes and gallery samples per class, respectively. Therefore, using the matrix of gallery dictionary and a coefficient vector we can define the feature vector of a probe sample as a linear combination as follows [11],

$$f_i^p = g.B. \quad (5)$$

Where, $B = [0,0, \dots, 0, \beta_1^k, \beta_2^k, \dots, \beta_N^k, 0,0, \dots, 0]$ and β_j^k is the j^{th} coefficient corresponding to the k^{th} class. The sparsest representation of probe sample can be achieved, if only the coefficients associated with class label of the probe sample are non-zero. Those coefficients are calculated using the l_1-norm solution of equation (5) and the identity label of the probe sample as follows [11].

Figure 3. Sample images of one subject in AR database.

$$(l_1): \quad \hat{B}_1 = argmin\|B\|_1 \quad while\ f^p = g.B. \quad (6)$$

IV. EXPERIMENTAL RESULTS

In order to evaluate the performance of proposed face recognition technique and effectiveness of face image sub blocks on the recognition accuracy, we employ two popular databases and apply the identification algorithm on the 128×128 pixel images in the databases.

A. AR Database

AR face database includes 2600 images of 100 individuals (50 men and 50 women) [12]. Each subject has 26 images taken at two different sessions in two weeks (13 images per session). The images in the database are affected by illumination variation, facial expression and partial occlusion. We have employed non-occluded images in session 1 as gallery set and non-occluded images in session 2 with appearance changes in different time as probe set. Sample images of one subject in AR database are shown in Fig. 3.

B. ORL Database

Olivetti research lab (ORL) database consists of 40 individuals with 10 images per subject and appearance variation due to illumination changes, different time of acquiring image, facial expressions (open/close eyes and smiling/not smiling), up to 20 degree tilting and scales [13]. We randomly used 5 samples per individual in the gallery set and the remaining 5 images per subject in the probe set. Thus, we have 200 images per set. Fig. 4 shows of gallery and probe image samples of one individual in ORL database.

C. Partial Recognition Based on the Image Subblocks

In this experiment, we employ the proposed face recognition algorithm using an image sub-block at different locations and sizes. In order to find the effective size of selected sub-block, we find the accuracy of face recognition versus block size which is shown in Fig. 5. It is shown that for both databases, block size 32×16 pixels leads the highest recognition accuracy. The location of the sub-block is near the eye area. Fig. 6 shows the selected subregion for AR and ORL databases.

Figure 4. Sample images of one subject in AR database.

D. Decision Fusion for Selected Size of Subblock

Based on the results of previous section, the highest recognition accuracy is obtained at the block size of 32x16 pixels for both face databases. In this experiment, we employ the most effective block size and apply majority voting scheme by adding up the votes of local classification results of image sub-blocks and finding the class label with maximum vote as the final decision. The result of sub-blocks fusion is shown in Table 1 and compared to the accuracy of the state of the art techniques which shows the effectiveness of the proposed face recognition technique.

However, by employing the recognition process using only one sub-block of 32×16 pixels rather than the whole image or fusion of local recognition results, the computational complexity is reduced up to $\frac{1}{40}$.

V. CONCLUSION

A block based face recognition technology has been proposed in this paper by dividing the magnitude and phase responses of Gabor filtered images. CS-LBP is applied on image sub-blocks and concatenation of local histograms at different scales and orientations gives the features of image sub-regions. Fusion of local decisions made by applying sparse classifiers, leads to the final decision on the identification of unknown individuals which outperforms the state of the art algorithms. However, evaluating the recognition accuracy of different sub-regions of the face images in AR and ORL databases, gives the size and location of the most effective local area which reduces computational complexity up to 2.5%.

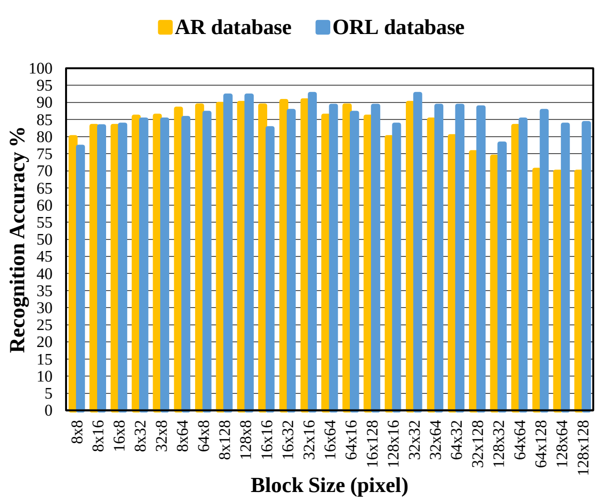

Figure 5. Recognition accuracy (%) of image subblocks for different block sizes.

(a) (b)

Figure 6. Location of the most effective image subregion: (a) AR database, (b) ORL database.

TABLE I. RECOGNITION ACCURACY (%) OF DIFFERENT ALGORITHMS.

Block Size	Recognition Accuracy (%)	
	AR	***ORL***
LBP+MV [3]	93.42	95.50
CS-LBP+MV	80.42	91.50
LGBFR [4]	99	98
MS-CFB [5]	95	-
SADTF [6]	-	98.50
LCCR [13]	95.86	98
Proposed Method (Decision Fusion using MV)	99.42	98.50

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