Recognition of Human Faces in the Presence of Incomplete Information

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Abstract—**Proposed face recognition in this paper is a block based approach. Gabor magnitude-phase centrally symmetric local binary pattern has been used to extract directional texture characteristics of face at different spatial frequencies. Centrally symmetric local binary pattern is applied on the sub-blocks of magnitude and phase responses of Gabor images, which is the important contribution of the proposed work. 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, Chi-Square weighted fusion of image sub blocks at decision level leads to significantly improved recognition accuracy. We also evaluate the performance of the proposed algorithm in the presence of incomplete information for low resolution and occluded images.**

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

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, access control, forensic images, surveillance cameras, and law enforcement [1]. The accuracy of face recognition is affected by challenging conditions due to partial occlusion, low resolution, poor illumination, head pose variation, facial expression and blur effect. In recent years, many identification techniques were proposed in order to increase the accuracy of face recognition versus degrading conditions [1]. 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 [2] 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 [3], where the local binary pattern (LBP) histograms of sub-blocks of Gabor magnitude images were combined. Different sub-blocks were differentiated in concatenation of features, by assigning a Kullback–Leibler divergence (KLD) weight to the corresponding sub-blocks. In [4] a block-based face recognition technique was proposed by extracting uniform LBP histograms. The results of local nearest neighbour classifiers were 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 [5]. Weighted fusion at score and decision level found the identity of unknown individuals. In [6] 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 [7]. 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 that 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 [1]. We need to find the most effective sub-image to identify an unknown individual. 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 or forensic images, we have incomplete information from low resolution or partial face images. In some cases only a partial image of the face with a small amount of discriminative information is available. The proposed approach in [8] addressed 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.

This paper is built upon our proposed work in [1]. However, in this work, we proposed a weighted fusion technique to differentiate the effect of image sub regions on the identification decision based on their discriminative effectiveness. 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 experiments on four different databases. We proposed Gabor magnitude-phase centrally

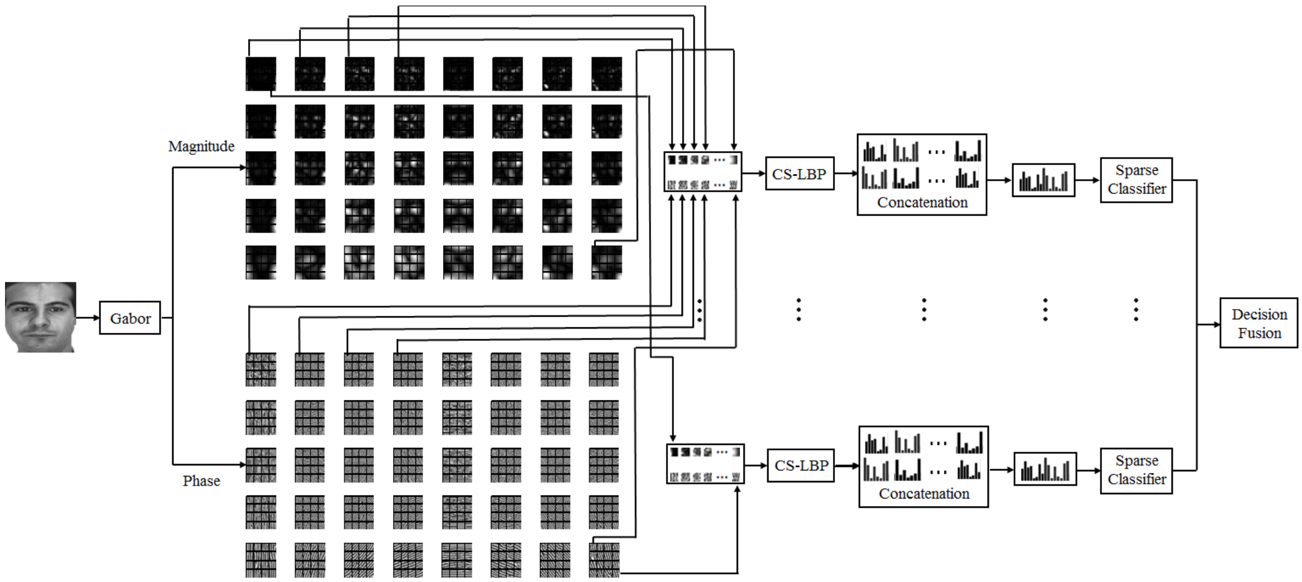


Figure 1. Block diagram of the proposed face recognition technique [1].

symmetric local binary pattern (GMP-CS-LBP) technique as feature extractor based on the symmetry in a local area around image pixels [1, 9]. In order to include the magnitude and phase information of the 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. Sparse classifier is employed on image sub-regions to find the local class labels [1]. In this paper, we propose a weighted majority voting (MV) scheme, which combines local decisions. The Chi-Square (CSQ) distance measurement [10] of the histograms of image sub blocks is applied as the local weights. We also evaluate the performance of the proposed technique in the presence of incomplete information due to low resolution and partial occlusion.

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 [1].

A. Gabor Filter

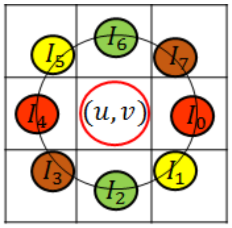
Gabor filter extracts the characteristics of signal at different scales and orientations, which resembles the mammalia response of vision cells. In order to acquire directionally selective local properties of a face image at various spatial frequencies, which are invariant against appearance changes due to expression and illumination variations, 2-D Gabor filters at S_{max} scales and O_{max} orientaions are convolved by image [1]. 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} [11, 12],

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

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 $\sigma = 2\pi$ [11, 12]. The magnitude and phase responses of Gabor filtered image are shown in Fig. 1 [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 a very fast technique and easy to execute [9, 12]. In a circular neighbourhood with radius R and P neighbours around each image pixel, we compared 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 [9], 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



$$CS_{pattern}(u,v) = \begin{array}{l}\{F(I_0 - I_4).2^0 + F(I_1 - I_5).2^1 + \\ F(I_2 - I_6).2^2 + F(I_3 - I_7).2^3\}\end{array}$$

Figure 2. Calculation of CS-LBP for a pixel at (u, v) [1].

against flat texture is increased. The calculation of decimal value associated with the binary patterns is as follows [1, 9],

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

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

(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 [9]. The value that is assigned as threshold is defined in the following section [1].

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 [1].

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 [1].

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 [13]. Image samples, which are belonging to the same individual, lie on a linear subspace [1].

$$g = [g_1, g_2, g_3, \dots, g_M]. \tag{3}$$

$$g_i = \left[f_1^g, f_2^g, f_3^g, \dots, f_N^g\right]. \tag{4}$$

Where g is gallery dictionary, which is including all gallery samples in the database. g_k is 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 [1, 13],

$$f_i^p = g.B. \tag{5}$$

Where $B = [0,0, \dots ,0, \beta_1^k, \beta_2^k, \dots , \beta_N^k, 0,0, \dots ,0]$ and $\beta_j^k$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 [1, 13].

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

IV. Decision Fusion

In order to combine the local result on the image sub blocks and come up with a final decision on the identity of the unknown probe sample, majority voting scheme is applied as the decision fusion strategy. The votes of the image sub blocks are combined by adding up the local votes for each class of subject. Finally, the class of identity with maximum total votes is selected as the final decision [1].

V. Local Weighting

In order to differentiate between the effects of image sub blocks on the final decision on the identity of the probe sample, local weights are calculated on image sub regions. In this paper, we calculate the Chi-Square (CSQ) distance [10] between the histograms of probe image sub blocks and the local histograms in the class-prototype of corresponding class of probe sub-block. The class-prototype (CP) image in the proposed approach in this paper is the average image of all gallery samples belonging to each class of subject as follows.

$$W_{CS}(PI^m, CP^m) = \sum_{j=1}^{N_b} \frac{(PI_{b_j}^m - CP_{b_j}^m)^2}{PI_{b_j}^m + CP_{b_j}^m}. \tag{7}$$

$$CP_k = \frac{1}{N_k} \sum_{l=1}^{N_k} g_{k,l} \,, \qquad k = 1, 2, \dots, N_c. \tag{8}$$

Where $PI_{b_j}^m$ and $CP_{b_j}^m$ are the j^{th} histogram bin in the m^{th} sub-block of the probe image (PI) and class-prototype images, respectively. CP_k is the class-prototype of k^{th} class of subject. N_c is the number of classes and N_k is the number of gallery samples belonging to k^{th} class ($g_{k,l}$) [5].

VI. Experimental Results

In order to evaluate the performance of proposed face recognition technique and effectiveness of image sub blocks on the recognition accuracy, we adopt four popular AR, ORL, LFW and FERET databases. We conduct four experiments and apply the identification algorithm on the 128×128 pixel images in the databases [1].

A. Face databases

- AR Database: AR face database includes 2600 images of 100 individuals (50 men and 50 women) [14]. 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. 3a [1].
- 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 [15]. 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. Figure 3b shows gallery and probe image samples of one individual in ORL database [1].
- LFW Database: Labeled faces in the wild (LFW) database includes 13,233 web-downloaded images of 5749 individuals [16]. LFW-a is the aligned version of LFW. Images are affected by pose and illumination changes, occlusion, blur, low resolution, race and aging effect in real-world scenarios. Some samples of LFW-a images are shown in Fig. 3c. In this paper, we randomly select 20 subjects with 12 images and less than 30 degree pose variation. Gallery set consists of the first half of 12 samples per individual ad probe set includes the rest.
- FERET Database: The Face Recognition Technology (FERET) program database [17] is a huge database consists of 14,051 grayscale images in different subsets based on various illumination, facial expression and pose conditions. In this experiment, we use subset ba, bj and bk of 200 individuals and one images per subject in each subset. Subset ba includes regular frontal images. Subset bj consists of alternative frontal images corresponding to ba set. Subset bk also contains frontal images corresponding to ba but with different lighting conditions. 400 images in subsets bj and bk are used as the gallery set and subset ba is the probe set. Fig. 3d shows some samples of the probe images [5].

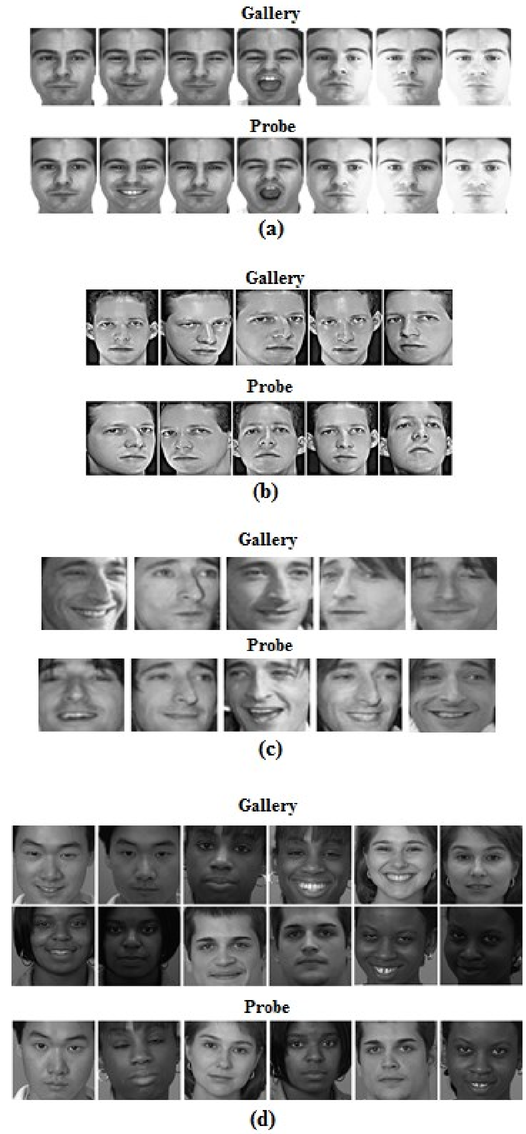


Figure 3. Sample images of one subject in (a) AR database, (b) ORL database, (c) LFW database, (d) FERET database.

B. 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. 4. It is shown that for all four databases, block size 32×16 pixels leads to the highest recognition accuracy. The location of the sub-block is near to the eye area. Fig. 5 shows the selected subregion for AR, ORL, LFW and FERET databases [1].

C. 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 four face databases. In this experiment, we employed the most effective block size and apply CSQ-weighted majority voting scheme by adding up the votes of

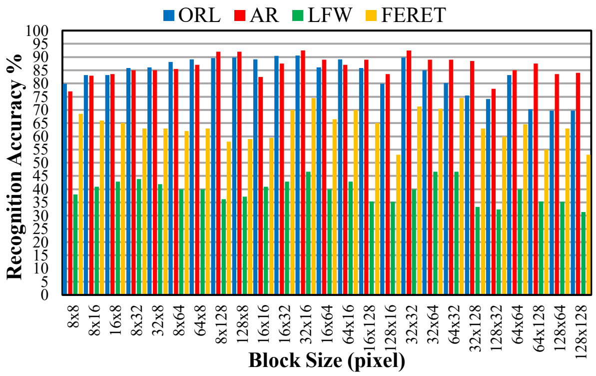


Figure 4. Recognition accuracy (%) of image subblocks for different block sizes.

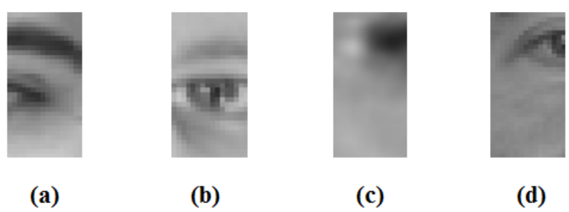


Figure 5. Location of the most effective image subregion: (a) AR database, (b) ORL database, (c) LFW database, (d) FERET database.

Figure 6. Sample images of four databases at different resolutions (128x128, 64x64, 32x32, 16x16 and 8x8 pixels, respectively from left to right): (a) AR database, (b) ORL database, (c) LFW database, (d) FERET database.

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 I and compared to the accuracy of other existing 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 cost is reduced up to $\frac{1}{40}$ [1].

D. Effect of Low Resolution

In this experiment, based on the results of previous sections, we use the block size of 32x16 pixels for images of size 128x128 pixels and apply the proposed face recognition technique on image sub blocks and find the final decision using majority voting scheme. We aimed to evaluate the effect of low resolution images on the recognition accuracies of four databases. In order to verify the effect of resolution, we reduced the size of images from 128x128 to 64x64, 32x32, 16x16 and 8x8 pixels, respectively, and reduced the block sizes, relatively. Figure 6 shows images of four adopted databases at different resolutions. The recognition accuracy versus the image size is illustrated in Fig. 7. Reducing the resolution of images, degraded the accuracy of face recognition. However, the proposed technique shows relative stability against decreasing the resolution up to size of 32x32 pixels.

E. Effect of Partial Occlusion

In this experiment, we evaluated the effect of partial occlusions on the face, which included non-facial information, on the recognition accuracy. We conduct two experiments in this section as follows.

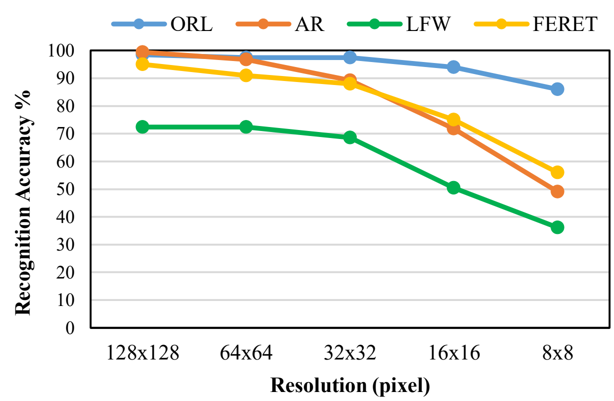


Figure 7. Recognition accuracy (%) of image subblocks for different block sizes.

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

Block Size	Recognition Accuracy (%)			
	AR	*ORL*	*LFW*	*FERET*
LBP+MV [4]	93.42	95.50	63.81	95
CS-LBP+MV	80.42	91.50	53.33	56
LGBFR [5]	99	98	63.81	96.5
MS-CFB [6]	95	-	-	-
SADTF [7]	-	98.50	-	-
LCCR [18]	95.86	98	-	-
Proposed Method (Decision Fusion using weighted MV)	99.42	98.50	72.38	95

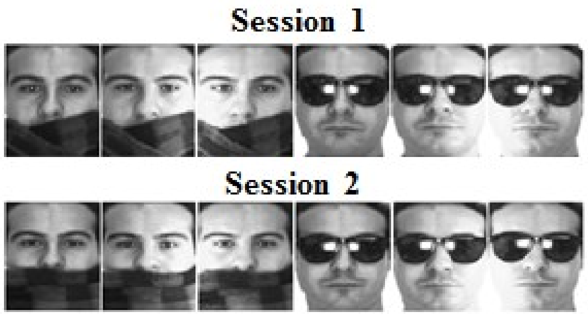


Figure 8. Occluded images of one subject in AR database at two sessions.

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

Method	Sunglasses	Scarf
E-GV-LBP-M[19]	47.22	82.78
E-GV-LBP-P[19]	44.07	86.67
SADT[20]	95.5	75
Proposed Method (Decision Fusion using weighted MV)	88.83	97.17

- Real occlusion: AR database contains occluded images with sunglasses and scarf on the face, which are real occlusions. Figure 8 shows some occluded samples in AR database. We used gallery set of 200 images, by employing just two non-occluded images per subject with neutral expression in sessions 1 and 2. Two probe sets of 600 images consist of 6 occluded images per individual with scarf and 6 with sun glasses from both sessions, respectively. Table II shows the recognition accuracy of the proposed approach compared to the previous works.
- Unreal occlusion: In order to evaluate the performance of the proposed approach in the presence of incomplete information, we put a mandrill image and a black box at random positions on the images of the probe set of LFW database and varied the size of occlusion box form 0% to 90% of the complete image size (128x128 pixels). The accuracy percentage of identification versus the percentage of the occlusion box coverage is shown in Fig. 9. Figure 10 shows occluded images of one subject in the LFW database with different size of occlusion box. The recognition breakdown point of the mandrill occlusion occurs at 50% of the occlusion coverage while for the black box it occurs at 70% coverage, from where the identification accuracy decreases drastically. This is due to the fact that mandrill image contains facial components similar to the human's which leads to the misclassification.

VII. CONCLUSION

A block based face recognition algorithm 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. Weighted majority voting is applied to combine the local decisions, made by sparse classifiers, which leads to the final decision on the identification of unknown individuals. Chi-square distance measurements are adopted as the local weights. The proposed approach outperforms the previous works for AR, ORL, LFW and FERET databases. Evaluating the recognition accuracy of different sub-regions of the face images gives the size and location of the most effective local area, which reduces computational complexity up to 2.5% and is very close the eyes area [1]. Moreover, the performance of proposed technique is verified versus the presence of incomplete information by resolution reduction and partial real and unreal occlusion. Reducing the resolution of images, degrades the accuracy of face recognition. However, the proposed technique shows relative stability against decreasing the resolution up to size of 32x32 pixels and the reduction in the identification accuracy is not noticeable. The proposed technique outperforms the previous works for real occlusion by scarf and sunglasses on images in the AR database. Based on the results partial recognition experiment, eyes area is the most effective sub region. Covering the eyes area by sunglasses leads to more reduction in the recognition accuracy. In addition, for artificial occlusion, occluding the image by more than 70% of the face area with black box and more than 50% with mandrill image, reduces the identification accuracy drastically.

Although the recognition results in the presence of incomplete information are impressive, further research to improve the applicability of the proposed technique to more challenging scenarios is required. Moreover, adopting other weighting techniques in the decision fusion to reduce the effect of undesirable regions is a possible direction to extend this work.

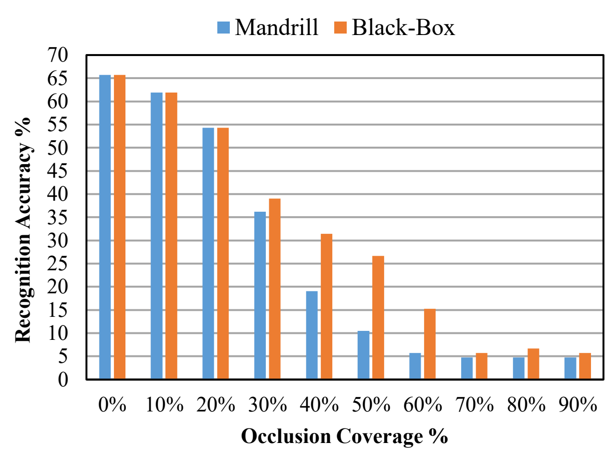


Figure 9. Recognition accuracy (%) of image subblocks for different block sizes.

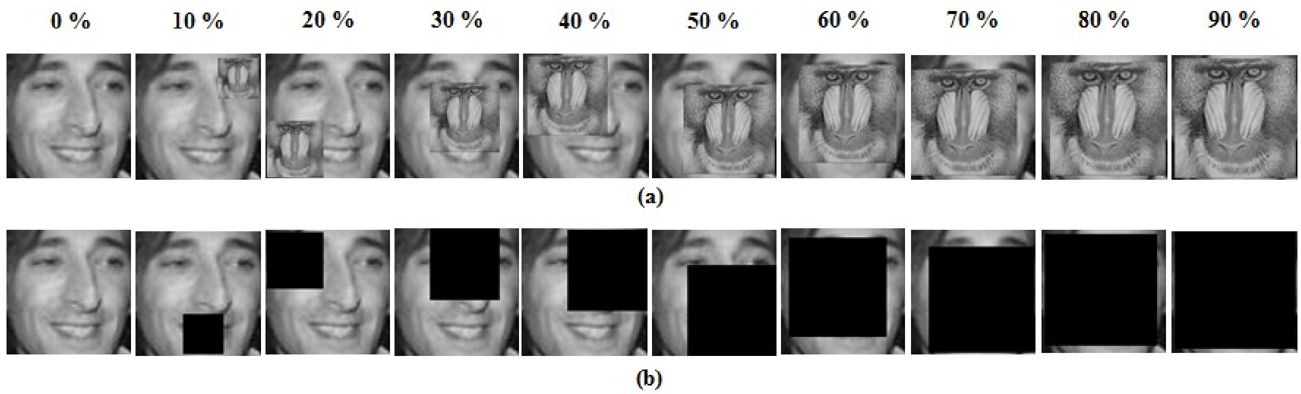


Figure 10. Recognition accuracy (%) of image subblocks for different block sizes.

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