Improving the Recognition of Faces Occluded by Facial Accessories

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***Abstract*—Facial occlusions, due for example to sunglasses, hats, scarf, beards etc., can significantly affect the performance of any face recognition system. Unfortunately, the presence of facial occlusions is quite common in real-world applications especially when the individuals are not cooperative with the system such as in video surveillance scenarios. While there has been an enormous amount of research on face recognition under pose/illumination changes and image degradations, problems caused by occlusions are mostly overlooked. The focus of this paper is thus on facial occlusions, and particularly on how to improve the recognition of faces occluded by sunglasses and scarf. We propose an efficient approach which consists of first detecting the presence of scarf/sunglasses and then processing the non-occluded facial regions only. The occlusion detection problem is approached using Gabor wavelets, PCA and support vector machines (SVM), while the recognition of the non-occluded facial part is performed using block-based local binary patterns. Experiments on AR face database showed that the proposed method yields significant performance improvements compared to existing works for recognizing partially occluded and also non-occluded faces. Furthermore, the performance of the proposed approach is also assessed under illumination and extreme facial expression changes, demonstrating interesting results.**

Keywords-component; face recognition; occlusion detection; local binary patterns

I. INTRODUCTION

Although a significant progress has been made in face recognition technology during the last decade, current systems still tend to suffer when facing uncontrolled environments in which image degradations, occlusions, drastic illumination changes, facial pose variations and other constraints usually occur. While there has been an enormous amount of research on face recognition under pose/illumination changes and image degradations, problems caused by occlusions are mostly overlooked, although facial occlusion is quite common in real-world applications especially when the individuals are not cooperative with the system such as in video surveillance scenarios.

Facial occlusions may occur for several intentional or undeliberate reasons (See Fig. 1). For example, football hooligans and ATM criminals tend to wear scarf and/or sunglasses to prevent their faces from being recognized. Some other people do wear veils for religious convictions or cultural habits. Other sources of occlusions include medical masks, hats, beards, moustaches, hairs covering the face, make up, etc. Undoubtedly, occlusions can significantly affect the performance of even most sophisticated face recognition systems, if occlusion analysis is not specifically taken into account. Robustness to partial occlusions is thus crucial in nowadays face recognition systems. The focus of this paper is on how to improve face recognition performance under occlusions, particularly caused by sunglasses and scarf.

Figure 1. Examples of occluded face images from different sources

It is well-known that conventional holistic approaches, such as PCA [1], LDA [2] and ICA [3], are not robust to partial occlusions, while local feature based methods are less sensitive to such problems. Therefore, a number of local feature-based and component-based methods were proposed for dealing with the occlusion problem. For instance, Penev and Atick [4] proposed the local feature analysis (LFA) to extract local features by second order statistics. Martinez [5] proposed a probabilistic approach (AMM) which can compensate for partially occluded faces. Tan et al. [6] extended Martinez's work by using the self-organizing map (SOM) to learn the subspace instead of using the mixture of Gaussians. In [7], Jim et al. proposed a method named locally salient ICA (LS-ICA) which only employs locally salient information to create part-based local basis images by imposing additional localization constraint in the process of computing ICA architecture I basis images. In [8], Fidler et al. presented a method which combines the reconstructive and discriminative models by constructing a basis containing the complete discriminative information. In [9], Park et al. proposed to use a line feature based face attributed relational graph (ARG) model which encodes the whole geometric structure information and local features of a face. Zhang et al. [10] proposed to use Kullback-Leibler

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divergence (KLD) to estimate the probability of occlusion in the feature space, so as to improve the standard local Gabor binary patterns (LGBP) [11] for partially occluded face. More recently, Wright et al. [12] applied sparse signal representation for faces to deal with the corruption and occlusion problem. In [13], Jia and Martinez proposed the use of Partial Support Vector Machines (PSVM) in scenarios where occlusions may occur in both the training and testing sets.

While the local feature-based and component-based methods are shown to be less sensitive to occlusions than the holistic methods, information from the occluded parts can still hinder the recognition performance for both categories of methods. Recently, Rama et al. [14] demonstrated that prior knowledge about occlusion can be used to improve face recognition. In their experiment, three PCA based methods were tested with and without occlusion information. The results showed significant performance enhancement when explicitly considering occlusion information. Nevertheless, in their experiment, the component locations and occlusions were manually annotated, thus making their system not very practical for real-world applications. In [15], Oh et al. have proposed an algorithm based on local non-negative matrix factorization (LNMF) [16], named Selective LNMF (S-LNMF) that automatically detects the presence of occlusion in pre-defined local patches. Face recognition is then performed by selecting LNMF bases in the non-occluded patches. The method showed good results for occluded faces, but poor performance under facial expression changes, illumination variations and time elapse. Obviously, like in the example of video surveillance scenario, all kinds of variations can occur. Hence, a face recognition system should be robust not only to occlusions but also against illumination variations, facial expression changes and other factors. Inspired by the progress in soft biometrics research [17], we believe that prior knowledge on the face can be exploited to enhance the recognition performance.

In this paper, we address then the problem of face recognition under occlusions caused by facial accessories, particularly sunglasses and scarf. The proposed approach consists of first detecting the presence of scarf/sunglasses and then processing the non-occluded facial regions only. The occlusion detection problem is approached using Gabor wavelets, PCA and support vector machines (SVM), while the recognition of the non-occluded facial part is performed using block-based local binary patterns [18]. The choice of adopting LBP is motivated by its recent success in representing facial images under various constraints. The rest of this paper is structured as follows. First, our proposed approach is outlined in Section 2. Then, descriptions on occlusion detection and block-based LBP face recognition are detailed in Sections 3 and 4, respectively. Section 5 presents the experimental results and analysis. Finally, we draw a conclusion and discuss future directions in Section 6.

II. PROPOSED APPROACH

Our proposed approach to the problem of robust face recognition under occlusions is illustrated in Fig. 2. During the training phase, local binary patterns (LBP) [18] are used to efficiently represent the gallery images (face templates), thus obtaining an LBP feature space. The adopted LBP-based facial representation and the motivations behind it are described in more details in Section IV. Then, given a target (i.e. probe) face image (which can be occluded or not) to be recognized, its LBP representation is first computed. The probe image is then divided into a number of facial components for occlusion detection. Each component is individually analyzed by an occlusion detection module, which is described below in Section III. As a result, potential occluded facial components are identified. Then, the LBP features from only the non-occluded parts are selected and used for recognition. The recognition is performed by comparing the selected LBP features from the probe image against selected LBP features from the corresponding non-occluded components of the templates images. The nearest neighbor (NN) classifier and Chi-square distance are adopted for the recognition.

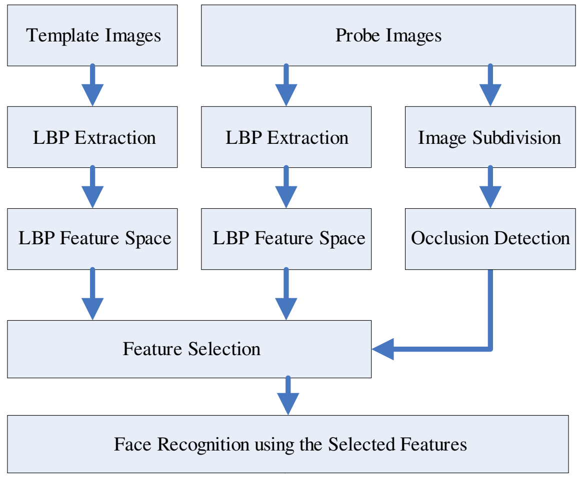

Figure 2. Flowchart of our proposed approach to robust face recognition under occlusions

III. OCCLUSION DETECTION

As depicted in Fig. 3, our occlusion detection method starts by dividing the face image into different facial components. The number and the shape of the components are determined by the nature of the occlusions that are searched for. Since our focus in this work is on scarf and sunglass detection, we divide then the face images into two equally components as shown in Fig. 3. The upper part is used for analyzing the presence of sunglasses while the lower part is used for detecting scarf. A more elaborated approach for dividing the face images into facial components for more general occlusion detection is discussed in Section VI.

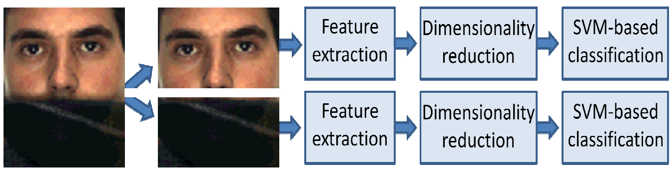

Figure 3. Our occlusion detection scheme

Once the face is divided into facial components, Gabor wavelet features are extracted from each component. The feature vector is then subject to dimensionality reduction. The result is fed to an SVM classifier for determining whether an occlusion is present or not in each facial component. In comparison to other methods that exploit information on facial features (e.g. skin color, mouth etc.), our occlusion detection method is more robust against texture variations and it also tolerates better image degradation as demonstrated in [19].

A. *Gabor Wavelet based Feature Extraction*

Gabor wavelets are used for extracting features from the potentially occluded regions. The choice of using Gabor wavelets is motivated by their biological relevance, discriminative power and computational properties. A Gabor wavelet consists of a complex sinusoidal carrier and a Gaussian envelope which can be written as:

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

where μ and γ are the orientation and scale of the Gabor kernels. $z = (P, Q)$ is the size of the kernel window. $\|\bullet\|$ denotes the norm operator. $k_{\mu,\gamma}$ is a wave vector written as following:

$$k_{\mu,\gamma} = k_\gamma e^{i\Phi_\mu} \quad (2)$$

where

$$k_\gamma = k_{max}/f^\gamma \quad (3)$$

$$\Phi_\mu = \pi\mu/8 \quad (4)$$

k_{max} is the maximum frequency, and f is the spacing factor between kernels in the frequency domain.

In our experiments, we set z = (20, 20), δ = 2π, k_{max}= π/2 and $f = \sqrt{2}$ as also suggested in [20]. Five scales γ ∈ [0, ..., 4], and eight orientations μ ∈ [0, ..., 7] are selected in order to extract the features in different scales and orientations. In total, 40 Gabor wavelets are generated. We denote these Gabor wavelets as GW_i, where i ∈ [0, ..., 39]).

Once the Gabor wavelets are generated, feature extraction is performed by 2-D convolution on the original image I. Alternatively, this could also be done through a multiplication in the Fourier domain. Because the Gabor wavelets are described in complex domain containing a real part GW_i^{Real} and an imaginary part GW_i^{Imag}, the two parts are separately convoluted with the image I. The process of 2-D convolution with the real and the imaginary parts of Gabor kernels is described as follows:

$$C_i^{Real}(x,y) = \sum_{p=0}^{P-1}\sum_{q=0}^{Q-1} GW_i^{Real}(p,q)I(x-p,y-q) \quad (5)$$

$$C_i^{Imag}(x,y) = \sum_{p=0}^{P-1}\sum_{q=0}^{Q-1} GW_i^{Imag}(p,q)I(x-p,y-q) \quad (6)$$

Then, the two filtered images C_i^{Real} and C_i^{Imag} are combined using a linear method as follows:

$$C_i(x,y) = \sqrt{C_i^{Real}(x,y)^2 + C_i^{Imag}(x,y)^2} \quad (7)$$

The filtered images thus form a set $\Omega = \{C_i, i \in [0,\dots,39]\}$, in which an augmented feature vector is constructed by concatenating all the filtered images. The obtained feature vector is down-sampled by a factor λ (here λ=5) for further processing.

B. *Dimensionality reduction using PCA*

In order to reduce the dimension of the feature vectors while preserving the discriminative power, the principal component analysis (PCA) is applied to the extracted feature vectors. To compute the PCA subspace, we considered a training dataset consisting of feature vectors from both occluded and non-occluded image patches. Let us denote the feature vectors from the non-occluded patches as X^c and the feature vectors from the occluded patches as X^s. The data set S can be then written as: $S = \{X_1^c, X_2^c, \dots, X_{M/2}^c, X_{M/2+1}^s, \dots, X_M^s\}$, where M is the size of the training dataset.

The mean vector $\bar{X}$ of feature vectors in S is computed as:

$$\bar{X} = \frac{1}{M}\sum_{m=1}^{M} X_m \quad (8)$$

The covariance matrix C can be written as:

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T = AA^T \quad (9)$$

where $\Phi_i = X_i - \bar{X}$, $A = [\Phi_1, \Phi_2, \dots, \Phi_M]$. The eigenvectors and of the covariance matrix C are thus computed to describe the eigenspace. The Gabor wavelet based features are then projected into the computed eigenspace for dimensionality reduction.

C. *SVM based Occlusion Detection*

Occlusion detection can be considered as a two-class classification problem. Since support vector machines (SVM) are proven to be a powerful tool for discriminating 2 classes of data, we adopted then an SVM classifier for occlusion detection. Let us consider a training set consisting of N pairs $\{x_i, y_i\}_{i=1}^N$, where x_i refers to a reduced feature vector of a facial component i, and $y_i \in \{-1,1\}$ is the label which indicates if the sample x_i is occluded or not. SVM finds the maximum-margin hyper-plane to separate the data by:

$$f(x_i) = \mathrm{sign}\left(\sum_{j=1}^{N} \alpha_i y_i K(x_i, x_j) + b\right) \quad (10)$$

where $\{x_j, j \in [1, N]\}$ are the support vectors. Non-linear SVM applies kernels to fit the maximum-margin hyper-plane in a transformed feature space. In our experiments, the Radial Basis Function (RBF) kernel is used. The implementation of the non-linear SVM is provided by LIBSVM [21].

IV. BLOCK-BASED FACE REPRESENTATION AND RECOGNITION USING LBP

We adopted the local binary patterns for representing the non-occluded facial components and thus recognizing the face. In the LBP approach, a face image is divided into several regions from which the LBP features are extracted and concatenated into an enhanced feature histogram which is used as a face descriptor. LBP provides state-of-the-art results in representing and recognizing face patterns. The success of LBP in face description is due to the discriminative power and computational simplicity of the operator, and its robustness to monotonic gray scale changes caused by, for example, illumination variations. The use of histograms as features also makes the LBP approach robust to face misalignment and pose variations.

The original LBP operator forms labels for the image pixels by thresholding the 3×3 neighborhood of each pixel with the center value and considering the result as a binary number. The histogram of these $2^8 = 256$ different labels can then be used as a texture descriptor. Each bin (LBP code) can be regarded as a micro-texton. Local primitives which are codified by these bins include different types of curved edges, spots, flat areas, etc.

The calculation of the LBP codes can be easily done in a single scan through the image. The value of the LBP code of a pixel (x_c, y_c) is given by:

$$\mathrm{LBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \qquad (11)$$

where g_c corresponds to the gray value of the center pixel (x_c, y_c), g_p refers to gray values of P equally spaced pixels on a circle of radius R, and s defines a thresholding function as follows:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases} \qquad (12)$$

The occurrences of the LBP codes in the image are collected into a histogram. The classification is then performed by computing histogram similarities. For an efficient representation, facial images are first divided into several local regions from which LBP histograms are extracted and concatenated into an enhanced feature histogram. Fig. 4 shows an example of an LBP based facial representation for the non-occluded region. In such a description, the face is represented in three different levels of locality: the LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face. This locality property, in addition to the computational simplicity and tolerance against illumination changes, are behind our choice of adopting LBP for representing the non-occluded facial components for robust face recognition.

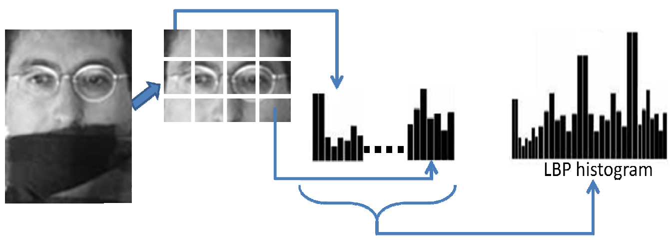

Figure 4. Example of extracting the LBP histogram from the non-occluded facial regions.

V. EXPERIMENTAL ANALYIS

To assess the performance of our proposed approach, we performed a set of experiments on AR face database [22] and compared our results against those of three different methods including PCA [1], LBP [18] and S-LNMF [15]. While PCA and LBP methods do not explicitly address occlusion analysis, S-LNMF method is closely related to our approach as it also considers occlusion detection and reports the performance on the AR face database as well.

A. *Experimental Data and Setup*

For our experimental analysis, we considered the AR face database [22] which contains a large number of occluded faces. The database is commonly used in many other works on face recognition under occlusions. It contains more than 4000 face images of 126 subjects (70 men and 56 women) with different facial expressions, illumination conditions, and occlusions (sun glasses and scarf). The images were taken under controlled conditions but no restrictions on wear (clothes, glasses, etc.), make-up, hair style, etc. were imposed to participants. Each subject participated in two sessions, separated by two weeks (14 days) time. The original image resolution is 768x576 pixels. Some examples of face images from the AR face database are shown in Fig. 5. Using the eye coordinates, we cropped, normalized and down-sampled the original images into 128x128 pixels. Some results can be seen from Fig. 6.

Figure 5. Example of images from the AR face database.

For occlusion detection, we randomly selected 150 non-occluded faces, 150 faces occluded with scarf and 150 faces wearing sunglasses for training. The upper parts of the faces with sunglasses are used to train the SVM-based sunglass detector while the lower parts of the faces with scarf are used to train the SVM-based scarf detector. The 150 non-occluded faces are used in the training of both classifiers.

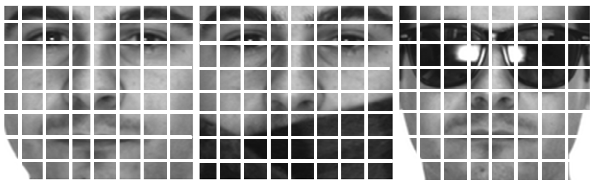

Figure 6. The face images are divided into 64 block and the LBP histograms are extracted using $\mathrm{LBP}_{8,2}^{u2}$.

For face recognition, the LBP-based representation is adopted. The face images are then divided into 64 blocks as shown in Fig. 6. The size of each block is 16x16 pixels. The LBP histograms are extracted using the operator $\mathrm{LBP}_{8,2}^{u2}$ (using only uniform patterns, 8 equally spaced pixels on a circle of radius 2) yielding in feature vector histograms of 3776 bins. In case of non-occluded faces, all these 3776 bins are used for matching using the Chi-square distance (χ^2). For occluded faces, however, the feature vector histograms are extracted only from the non-occluded parts as shown in the example in Fig.4. The occluded faces are thus represented with histograms of 1888 bins, corresponding to the 32 non-occluded blocks. This means that when a face is occluded by a scarf, the upper 32 blocks are selected, while the lower 32 blocks are used when the face is occluded by sunglasses. The faces which are occluded with both sunglasses and scarf are naturally rejected.

B. *Experimental Results and Analsysis*

We first selected 240 non-occluded faces from session 1 of the AR database as the templates images. These non-occluded faces correspond to 80 subjects (40 males and 40 females), with 3 images per subject under neutral expression, smile and anger. For evaluation, we considered the corresponding 240 non-occluded faces from session 2, the 240 faces with sunglasses of session 1 and the 240 faces with scarf of session 1, under three different illuminations conditions.

Table 1 shows the results of the occlusion detection as a confusion matrix. Note that only 2 images from the non-occluded faces are wrongly classified as faces with scarf. This assesses the efficiency of our occlusion detection method.

TABLE I. RESULTS OF OCCLUSION DETECTION

	no-occlusion	Scarf	Sunglass	Detection Rate
no-occlusion	**238**	2	0	99,17%
Scarf	0	**240**	0	100%
Sunglass	0	0	**240**	100%

Fig. 7 shows the face recognition performance of our approach on three different test sets: non-occluded faces, face occluded with scarf and faces occluded with sunglasses. For comparison, we also report the results of eigenfaces (i.e. PCA) and basic LBP methods. Since PCA and LBP methods do not address occlusion detection, we implemented a third baseline approach for comparison. We thus combined our occlusion detection module with eigenfaces and call this approach FA-PCA (facial accessories robust PCA). In FA-PCA, three eigenspaces are computed during the training stage. The first one is computed using the whole face images, while the second and third eigenspaces are computed using the upper and lower facial regions, respectively. During the recognition phase, the non-occluded components are projected into the corresponding eigenspace when partial occlusions are detected.

The results in Fig. 7 clearly show that our proposed approach (it could be denoted by FA-LBP) significantly outperform all other methods. On the non-occluded faces, our approach and LBP yielded equal performance (94.83%) while the Eigenface method (with and without occlusion detection) yielded much lower performance (75.83 %). On the test set of faces with scarves, our proposed approach gave best results (92.08%), followed by LBP (60.83%), and then by PCA-based methods (34.17% and 5.42%). Note that LBP performed quite well even under occlusion, thus confirming the earlier findings stating that local feature-based methods are more robust against occlusions than holistic methods. Comparing the results on the test sets of faces with sunglasses and scarves, we notice that most methods are more sensitive to sunglasses than to scarf. This is an interesting conclusion which is in agreement with the psychophysical findings indicating that the eye regions play the most important role in face recognition.

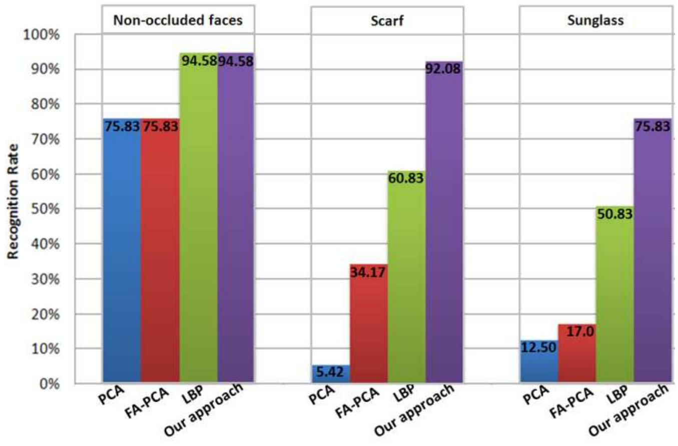

Figure 7. Recognition performance different methods on three test sets: non-occluded faces, face occluded with scarf and faces occluded with sunglasses.

To get insight into our approach, we also considered the recent work of H. J. Oh et al. [15] for comparison. In [15], the authors proposed an approach called Selective LNMF (S-LNMF) that detects the presence of occlusions in pre-defined local patches, and then performs face recognition by selecting LNMF bases from the non-occluded patches. This approach is closely related to our proposed method. The authors evaluated their method also on the AR face database. The reported results showed that the S-LNMF method outperformed several other techniques including PCA [1], LNMF [16], AMM [5] and LFA [4]. Moreover, the authors also studied the robustness of S-LNMF against drastic facial expression caused by screaming and against illumination changes caused by right-lighting, as well.

We compared our proposed approach against S-LNMF using similar protocol under the more challenging scenario in which the gallery face images are taken from Session 1 of AR database while the test sets are taken from Session 2. Note that the two sessions were taken at time interval of 14 days. The comparative results between our proposed approach and S-LNMF are illustrated in TABLE II.

TABLE II. OUR APPROACH VS. S-LNMF [15]

	Sunglass	Scarf	Scream	Right-Light
S-LNMF	49%	55%	27%	51%
Our approach	**54.17%**	**81.25%**	**52.50%**	**86.25%**

The results in TABLE II clearly show that our proposed approach outperforms S-LNMF method in all configurations assessing robustness against sunglasses, scarves, screaming and illumination changes. The robustness of our approach to illumination changes and drastic facial expression is brought by the use of local binary patterns, while the occlusion detection module significantly enhances the recognition of face occluded by sunglasses and scarves.

VI. DISCUSSION AND CONCLUSIONS

We addressed the problem of face recognition under occlusions caused by scarves and sunglasses. Our proposed approach consisted of first detecting potential occlusions and then performing face recognition from the non-occluded regions. The salient contributions of our present work are: (**i**) a novel approach for improving the recognition of occluded faces is proposed; (**ii**) state-of-the-art in face recognition under occlusion is reviewed; (**iii**) a new approach to scarf and sunglasses detection is thoroughly described; and (**iv**) extensive experimental analysis is conducted, demonstrating significant performance enhancement using the proposed approach compared to many other methods under various configurations including robustness against sunglasses, scarves, non-occluded faces, screaming and illumination changes.

Although we focused on occlusions caused by sunglasses and scarves, our methodology can still be extended to other sources of occlusion such as hats, beards, long hairs, etc. For detecting sunglasses and scarves, we divided the face region into an upper and a lower component. Obviously, such an approach may not be optimal for other types of occlusions. A more accurate segmentation of the occluded regions may then be needed. Fig. 8 shows two different segmentations for discarding the effect of the sunglasses. In the left side of the figure, the upper part of the face is considered as the occluded region while in the right side a more accurate segmentation is shown. However, in case of sunglasses and scarf, we noticed that accurate occlusion segmentation is not crucial as only minor performance enhancement can be obtained when using accurate segmentation. This explains our motivations for dividing the facial region into upper and lower components.

Figure 8. Example of two different ways of segmenting occluded regions.

As a future work, it is of interest to extend our approach to address face recognition under general occlusions, including not only the most common ones like sunglasses and scarves but also like beards, long hairs, caps, extreme facial make-ups, etc. Automatic face detection under severe occlusion, such as in video surveillance applications, is also far from being a solved problem and thus deserve thorough investigations.

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