Glasses Removal from Facial Images with Recursive PCA Reconstruction

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ABSTRACT

This paper proposes a new glasses removal method from color frontal facial image to generate gray glassless facial image. The proposed method is based on recursive PCA reconstruction. For the generation of glassless images, the occluded region by glasses should be found, and a good reconstructed image to compensate with should be obtained. The recursive PCA reconstruction provides us with both of them simultaneously, and finally produces glassless facial images. This paper shows the effectiveness of the proposed method by some experimental results.

Keywords: Glasses Removal, Face, Facial Image, Recursive, PCA, Reconstruction.

1. INTRODUCTION

Automatic face recognition has been one of the active research issues since it has a wide range of potential applications such as access control, human-computer interaction and automatic search in visual databases. One of the important requirements for face recognition systems is robustness to various environments, which include facial expression, lighting and glasses. The robustness can be obtained either by making the systems insensitive to the environmental variations or by eliminating the variations in the preprocessing stage. In this paper, we consider glasses occlusion and present a new glasses removal method.

Glasses are most common occluding objects that affect the performance of a face recognition system. Recently glasses detection and extraction has been studied by some researchers[1-4]. Belhumeur et al.[1] showed that their Fisherface method can tell “wearing glasses” from “not wearing glasses”. Jiang et al.[2] introduced a glasses detection method that used edge information under and between eyes. Jing et al.[3] extracted glasses using deformable contour. Further, glasses removal from facial images was also tried. Lanitis et al.[4] showed that their flexible model (now called as Active Appearance Model) could be used to remove small occlusion such as glasses. However, the results were not good enough with the remaining trace of glasses frame in the generated facial images. This paper proposes a glasses removal method from frontal face images by recursive application of the PCA (Principal Component Analysis) to obtain natural looking glassless facial images.

2. GLASSES DETECTION

The Principal Component Analysis (PCA) computes the basis of a space which is represented by its training vectors. The basis vectors are the eigenvectors of the covariance matrix of the training vectors. When the PCA is applied to facial images, the basis vectors define face space, and are called as “eigenface”. Let the training set of face image be Γ_i , $i = 1,2,...,M$, each of which is represented as a column vector. The covariance matrix is given by

$$C = \frac{1}{M}\sum_{i=1}^{M}(\Gamma_i - \Psi)(\Gamma_i - \Psi)^T , \qquad (1)$$

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i , \qquad (2)$$

where Ψ is an average vector. Then, the eigenfaces u_i are the eigenvectors of *C*. Once the eigenfaces are obtained, a new face image Γ can be represented by the eigenfaces as follows,

$$\omega_k = u_k^T(\Gamma - \Psi) , \qquad (3)$$

where ω_k is the PCA coding for the new image. The reconstructed image with the PCA coding can be obtained by

$$\hat{\Gamma} = \Psi + \sum_{k=1}^{M'}\omega_k u_k . \qquad (4)$$

In the PCA reconstruction, it is general to use only M' eigenvectors corresponding to the M' largest eigenvalues to reduce the dimensionality of the space.

The PCA is to find the vectors that best account for the distribution of training images. Thus, the representational power of the PCA depends on the training set. If some object is not contained in the training images, reconstructed image by Eq. (4) does not contain the object. For instance, if training images do not contain glasses, reconstructed image does not contain glasses, either. Therefore, by computing and thresholding the Euclidean distance between the input image and the reconstructed image, we can detect the glasses present in the image,

$$\varepsilon = \left| \Gamma - \hat{\Gamma} \right| > \theta , \qquad (5)$$

where θ is a given threshold. Fig. 1 shows the reconstruction differences for both the cases of "wearing glasses" and "wearing no glasses". Here the client indicates a person in the training set while the impostor indicates a person who is not included in the training set.

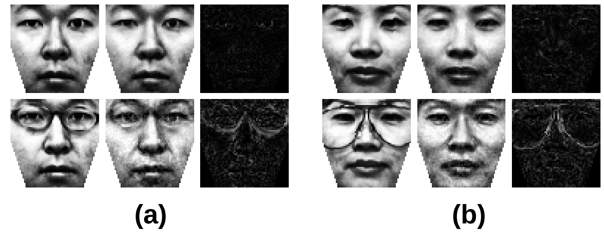


Figure 1. Reconstruction errors for faces wearing no glasses (upper line) and faces wearing glasses (lower line) (a) Client (left:input, middle:reconstruction, right:error) (b) Impostor (same).

3. GLASSES REMOVAL

The PCA reconstruction generates a reconstructed image as close as possible to the input image within the face space defined by its eigenfaces. When an input image contains glasses, the PCA tries to represent the "glasses" region in the reconstructed image. However, if the eigenfaces are obtained from a training set of glassless facial images, the PCA cannot reproduce the "glasses" properly. This error spreads out to the whole reconstructed image, which results in a degradation of reconstruction and remaining trace of glasses frame in the image. Therefore, even with eigenfaces that obtained from a training set of glassless facial images, simple PCA reconstruction cannot generate natural looking glassless facial images for input faces wearing glasses. This can be seen in [4] or in Fig. 1.

In order to remove glasses and to generate natural looking glassless facial images, we need to do two kinds of works: to find the occluded regions by glasses and to make an image for compensating the regions with. The occluded regions by glasses include not only the frame of

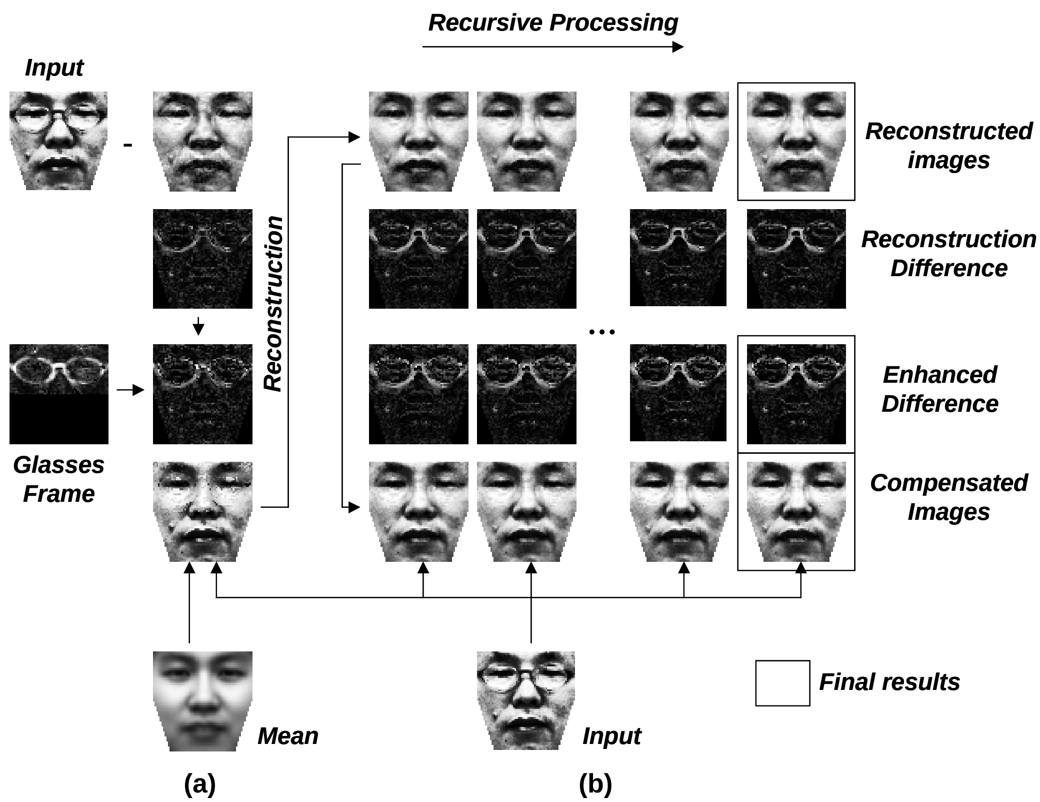


Figure 2. Recursive PCA reconstruction. (a) the 1st reconstruction, (b) the 2nd to *n*th reconstructions. Upper most row: reconstructed images, the 2nd row: reconstruction differences, the 3rd row: enhanced differences, the 4th row: compensated images.

glasses but also reflection by lens and shades by glasses. These regions cannot be correctly extracted from simple reconstruction difference ε defined in Eq. (5). The reconstruction difference consists of occlusion error and reconstruction error that is generated in the process of reducing dimensionality. Since the occlusion error spreads out to the whole image, it is difficult to classify correctly "occluded" and "non-occluded" regions in the reconstruction difference. This problem may be solved by recursive application of PCA reconstruction and compensation, which is described in Fig. 2.

In Fig. 2(a), the first iteration of the PCA reconstruction and compensation is shown. The upper most image of Fig. 2(a) is the reconstructed image for the input. The difference between the image and the input is in the 2nd row of Fig. 2(a). The difference is enhanced once and then is used to compute a mask for compensation (Fig. 2(a), the 3rd row). The compensated glassless image is generated from the input image with substitution of mean image for the regions of high reconstruction difference (Fig. 2(a), the 4th row). From the 2nd iteration, the compensated image of the previous iteration is used to reconstruct glassless images. The first row shows them. However, the reconstruction difference on the 2nd row is still the difference between reconstructed image and input image rather than the compensated image of the previous iteration. The reconstructed images are also used to compensate the input image from the 2nd iteration. The reason to use mean image in the first iteration is that the first reconstruction has poor quality to be used in compensation. As the iteration evolves, reconstructed image excludes glasses occlusion and the reconstruction difference finds the occlusion regions by glasses. The iteration stops if the differences between reconstructed images become small and almost constant. In this way, the recursive PCA reconstruction does the both of works: to find the occluded regions and to produce a good-quality reconstructed image for compensating the regions with.

In the recursive process, the reconstruction difference provides us with rough information about occluded regions. We need to determine occlusion regions to be compensated. Fig. 3(a) depicts an example of reconstruction difference in 3D graph. As expected, the high values are located in the occlusion regions by glasses.

The low values represent the simple reconstruction error with eigenfaces. Therefore, the reconstruction difference can be classified into 3 parts: non-occlusion, occlusion and uncertain as shown in Fig. 3(b). We determine the thresholds for the classification using the statistics of the difference. The lower threshold, which divides non-occlusion and uncertain, is given by the mean value of reconstructed errors in the skin region. The upper threshold, which divides uncertain and occlusion, is determined by computing the mean value of larger errors

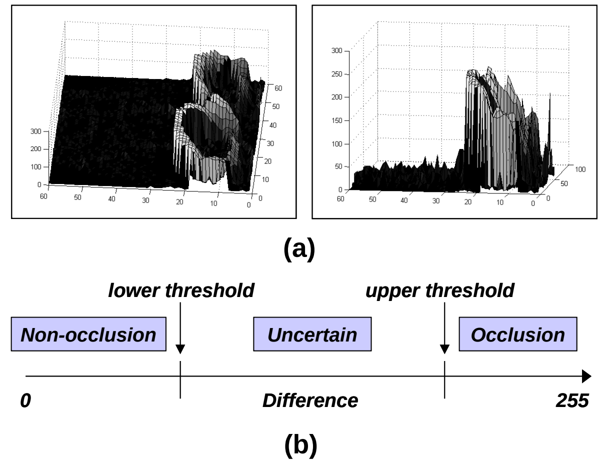


Figure 3. (a) Reconstruction difference image in 3D, (b) Difference classification.

than the lower threshold in the upper part of the face. Then, the uncertain region may include some of occlusion such as occlusion around eyebrows because of color similarity with glasses. This uncertainty can be reduced with the glasses frame information from the original color image. The glasses frame information can be obtained as shown in Fig. 4 with the application of GSCD (Generalized Skin Color Distribution) transform[5,6] and edge detection operation. This information is used to enhance the reconstruction difference by reducing the uncertain regions as shown in the 3rd row of Fig. 2. Both of this glasses frame information and the reconstruction difference may not determine occlusion regions by glasses.

After reducing the uncertain regions, the remaining uncertain region is compensated with linear combination of input and reconstructed (or mean) image using weights. Thus, the weights for compensation are given by the graph as in Fig. 5. The recursive PCA reconstruction

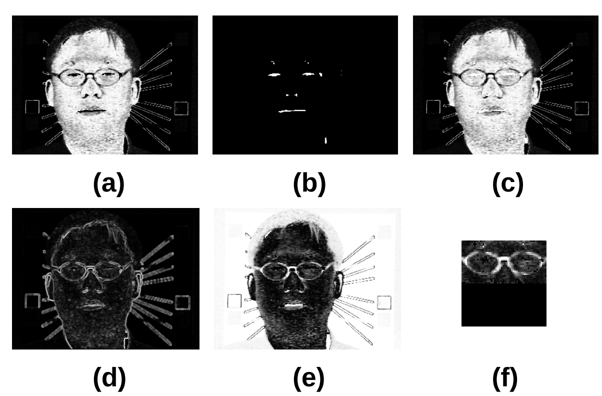


Figure 4. Extraction of additional glasses frame information (a) GSCD image, (b) Components in the face, (c) (a)+(b), (d) edge detection for (c), (e) inversion of (a), (f) glasses region of (d)||(e) (OR operation) with lowe half masked.

with these operations can remove the occlusion of glasses and produce facial images wearing no glasses.

As a whole, an automatic system for glasses detection and removal can be described in a flow chart shown in Fig. 6. In the off-line process, eigenfaces are generated with training facial images without glasses. In the on-line process, the algorithm detects glasses in the test facial images by a simple PCA reconstruction. If it detects glasses, it starts the process of glasses occlusion compensation with the recursive PCA reconstruction as shown in Fig. 2. The compensation process uses the

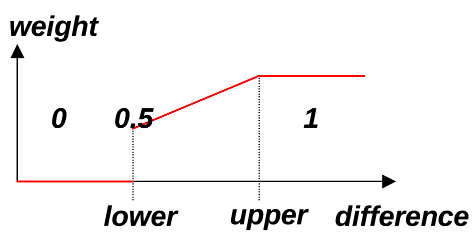


Figure 5. Weights for compensation with reconstructed (or mean) images

result of additional glasses frame extraction from original color image in order to increase the quality of first reconstruction.

4. EXPERIMENTS

In the experiments, we first constructed eigenfaces with a training set of glassless facial images. The training images were captured by a Sony digital camera (PC-100). The original color image was 320x240 pixels in size. The images were converted to gray images and normalized automatically to 60x60 in size. The training images were captured for 33 people with 8 photos each including facial expressions.

In order to see the performance of glasses removal, we tested the proposed method with facial images that were overlapped by artificially generated glasses. The glasses were obtained from real images by leaving glasses and erasing other regions. In this way, we could compare the results of glasses removal and original input images. Fig. 7 shows some of the comparison. In the figure, the numbers represent the Euclidean distances. The proposed method was also applied to many people wearing various glasses. Some of them were in the training set (clients), and others were not (impostor). Fig. 8 shows some of the results. The upper row is inputs, and the lower row is outputs. Though there were a little bit unnatural parts in output images for impostors, we could obtain natural glassless facial images in most of cases.

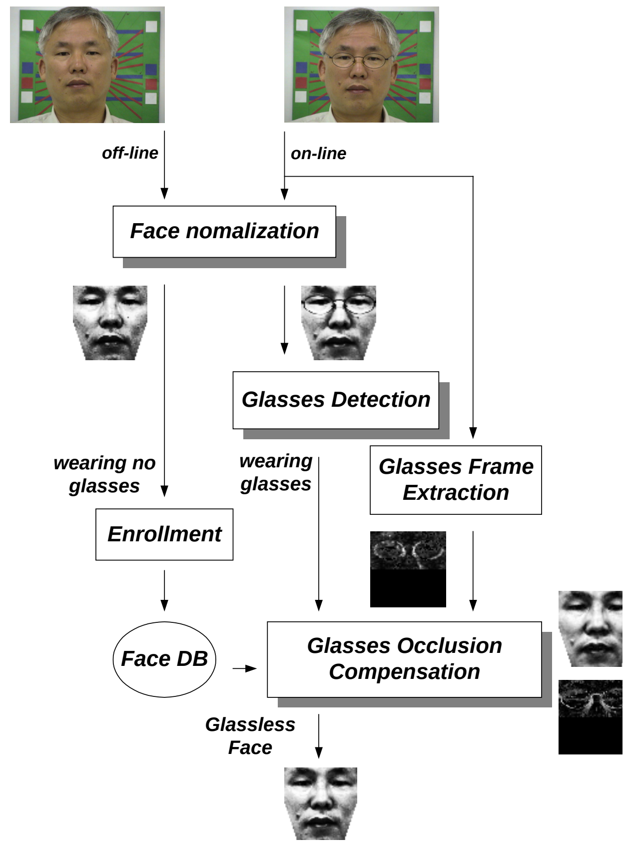


Figure 6. The flow chart of automatic glasses detection and removal

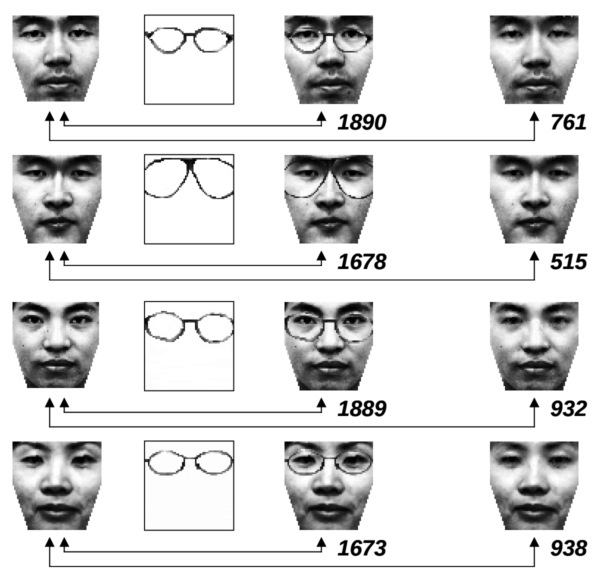


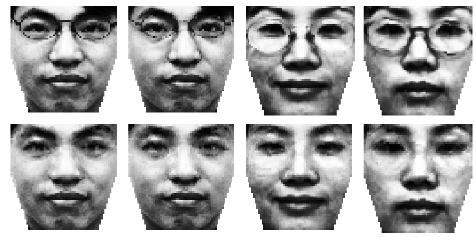
Figure 7. Glasses removal for artificially overlapped glasses

5. CONCLUSION

In this paper, we have proposed a new glasses removal method from color frontal facial image to generate gray glassless facial image. The proposed method is based on recursive PCA reconstruction. Since the PCA representation depends on training data set, the PCA can detect and remove glasses partly in facial images using eigenfaces that are generated with glassless training images. However, simple PCA reconstruction is not enough for generating good glassless images.

In order to generate glassless images, we need to find the occlusion region by glasses and to obtain a good reconstructed image to compensate with. The recursive PCA reconstruction provides us with both of them simultaneously, and finally produces more improved glassless facial images. We believe that this method can be applied to remove other type of occlusion than the glasses with some modification.

(a)



(b)

Figure 8. Generation of glassless facial images (a) Clients, (b) impostor, upper row (input), lower row(output)

6. REFERENCES

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