Reconstruction of Partially Occluded Face by Fast Recursive PCA

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Abstract

This paper proposes a fast recursive PCA (Principal Component Analysis) algorithm to remove face occlusions. In training phase, all faces are normalized by two eye centers and two mouth corners, and eigenvectors (eigenfaces) were obtained by PCA analysis. In test phase, face occlusion is removed by iteratively perform two steps of analysis and synthesis. New damaged face is first normalized by clicking four feature points, and PCA coefficients are obtained in analysis step. In synthesis step, reconstructed face is obtained by linear combining eigenfaces, and coefficients error between two successive analyses is used for fast PCA compensation. Experimental results on training and test faces show that the proposed algorithm convergences faster than classical PCA compensation and reconstructed faces are natural.

1. Introduction

Face occlusions (such as glasses, respirator, scarf, etc.) can degrade the performance of face recognition and face animation evidently. How to remove occlusions on face image quickly and automatically becomes one important problem in face image processing.

As human face is one kind of special image, common image inpainting techniques cannot be used to remove face occlusions. Image inpainting reconstruct damaged image region by its surrounding pixels, which doesn't consider the structure of face. For example, if an eye is occluded, the inpainted face cannot reconstruct the eye image, and the result face will have only one eye.

The dominated methods of reconstruct damaged face are based on analysis and synthesis techniques. Such as PCA (Principle Component Analysis), GPCA (Gappy Principal Component Analysis), etc. Faces are modeled by linear combinations of prototypes. In analysis step, optimal coefficients are estimate from damaged face by project to face space (eigenfaces) in the sense of least-square minimization (LSM). In synthesis step, reconstructed face is obtained by linear combinations of prototypes. If corresponding points in each face are known, reconstructed faces can be very natural and plausible like real photos.

Saito first used PCA techniques in eye glasses remove [1]. First, project face image with glasses onto eigenface space created from faces *without* glasses, and obtained corresponding coefficients. Then, new face was reconstructed by linear combinations of no glasses faces with these coefficients. Wu used a PCA extended algorithm to remove glasses in human face [2]. They estimated the joint distribution of faces with and without glasses through a hidden variable V. After obtain the optimal coefficients by project on eigenfaces with glasses, corresponding coefficients of eigenfaces without glasses were obtained by maximizing posteriori probability of V.

Both Park [3] and Du [4] used recursive PCA algorithm to reconstruct face area occluded by glasses. Result face was obtained by weighted sum of original face and reconstructed face.

Hwang do PCA analysis on face shape model and face texture model respectively [5]. His algorithm can reconstruct very natural human face, but need to known the exact displacement among pixels in an input face which correspond to those in the reference face, which is difficult to obtain in practice.

Kurita use multi-layer perceptron as an auto-associative memory to reconstruct damaged face, which is similar to PCA method in principle [6]. It can realize non-linear analysis, but more difficult to train and with high computation complexity.

Recently, there are many PCA extended face reconstruction algorithms. Colombo use GPCA to reconstruct 3D damaged face, where only un-occluded pixels are used in analysis phase [7], which makes the analysis more precisely. Wu use Tensor PCA to reconstruct super-resolution face from low resolution face, preserve some spatial information in analysis phase [8]. Smet use PCA to reconstruct 3D damaged face form shape, texture and histogram information [9].

The main problems of current algorithms are: (1) need to know the exact correspondence between original face and reference face; (2) slow convergence and high computation complexity.

In this paper, we proposed a robust and fast face occlusion reconstruction algorithm based on recursive PCA compensation. In face normalization, we only need to know the position of two eyes and two mouth corner approximately. By compensate with the PCA coefficients difference between successive analyses, we can accelerate the convergence speed evidently.

2. Reconstruction on normalized face

2.1 Recursive Reconstruction Based on PCA

The basic idea of PCA can be described as following:

$$\mathbf{x}+\mathbf{e}=\mathbf{m}+\sum_{i=1}^{N} y_i \mathbf{v}_i \qquad (1)$$

Where $\mathbf{x}=[x_1,x_2,\ldots,x_n]^T$ is the input image with n pixels, $\mathbf{e}$ is the approximation error, $\mathbf{m}$ is the mean face, $\mathbf{v}_i$ is the ith reserved N eigenfaces (eigenvectors of the covariance matrix of $\mathbf{x}$), and y_i is the coefficient for linear combination, which can be estimated in analysis step by:

$$\mathbf{y}^0=\mathbf{v}^T\cdot(\mathbf{x}^0-\mathbf{m}) \qquad (2)$$

Here superscript '0' means the original data, to distinguish from following iterative analysis. $\mathbf{x}^0$ is original face, $\mathbf{y}^0$ is the coefficients computed from $\mathbf{x}^0$. The reconstructed face can be obtained in synthesis step by:

$$\mathbf{x}^1{}'=\mathbf{m}+\sum_{i=1}^{N} y_i^0 \mathbf{v}_i \qquad (3)$$

And new face was obtained by weight sum of original face and reconstructed face:

$$\mathbf{x}^1=\mathbf{w}\cdot\mathbf{x}^0+(1-\mathbf{w})\cdot\mathbf{x}^1{}' \qquad (4)$$

Weight value is between 0 and 1. If occlude region is unknown, weight can be estimated by normalized DFFS (Distance From Face Space). If occlude region is known, weight value in occlude region is 1, and in other region is 0. $\mathbf{x}^1$ is result face after first analysis and synthesis cycle.

In recursive method, the new reconstructed face was used in formula (2~4) for a new cycle of analysis and synthesis, until differences between two successive coefficients is less than a predefined threshold.

2.2 Face Normalization

Before PCA analysis and synthesis, we need to normalize all faces. To be convenient, we suppose face image is only under affine transforms, such as translation, rotation and scaling. So face normalization can be performed through four distinct points: two eye centers and two mouth corners. Suppose coordinates for one point in normal face are (x, y), then the corresponding point (x', y') in original face can be calculated by following formula [10]:

$$\begin{pmatrix} x' \\ y' \end{pmatrix}=\begin{pmatrix} s\cos\theta & -st\sin\theta \\ s\sin\theta & st\cos\theta \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix} \qquad (5)$$

Let $P_1(x_{le},y_{le})$ and $P_2(x_{re},y_{re})$ be positions of two eye center, parameters in formula (5) can be obtained by:

$$\theta=arctg\frac{y_{re}-y_{le}}{x_{re}-x_{le}} \qquad (6)$$

$$s=\frac{W}{W_0} \qquad (7)$$

$$t=\frac{H}{W}/\frac{H_0}{W_0} \qquad (8)$$

Where W is the distance between two eyes, H is the distance between middle point of two eyes and middle point of two mouth corner, and W_0 and H_0 is the corresponding values in standard face.

Similarly, we can calculate coordinates of original face from normal face by following formula:

$$\begin{pmatrix} x \\ y \end{pmatrix}=\begin{pmatrix} \frac{1}{s}\cos\theta & \frac{1}{s}\sin\theta \\ -\frac{1}{st}\sin\theta & \frac{1}{st}\cos\theta \end{pmatrix}\begin{pmatrix} x' \\ y' \end{pmatrix} \qquad (9)$$

In training phase, all faces are normalized and eigenfaces are computed from the covariance matrix of training faces.

In test phase, give a new face with occlusion, we only need to click the points of two eyes center and two mouth corner with mouse. Even if parts of eye or mouth are occluded, it is not difficult to estimate the position of eye center and mouth corner. Then the occluded face will be normalized automatically. After normalization, face can be reconstructed by recursive PCA analysis and synthesis.

3. Fast PCA compensation

In classical PCA recursive compensation algorithm, we can summarize the analysis and synthesis cycle as:

$$\mathbf{y}^n=(\mathbf{x}^n-\mathbf{m})\cdot\mathbf{v} \qquad (10)$$

$$\mathbf{x}^{n+1}{}'=\mathbf{m}+\sum_{i=1}^{N} y_i^n \mathbf{v}_i \qquad (11)$$

$$\mathbf{x}^{n+1} = \mathbf{w} \cdot \mathbf{x}^{n} + (1-\mathbf{w}) \cdot \mathbf{x}^{n+1\prime} \qquad (12)$$

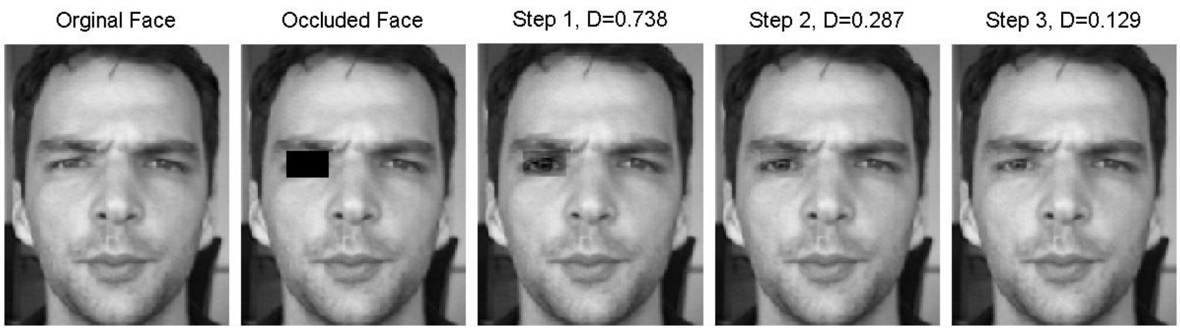
The iteration stops if the maximum absolute difference between successive coefficients becomes less than a given threshold:

$$D = \max(| y_i^{n+1} - y_i^{n} |) < \varepsilon \qquad (13)$$

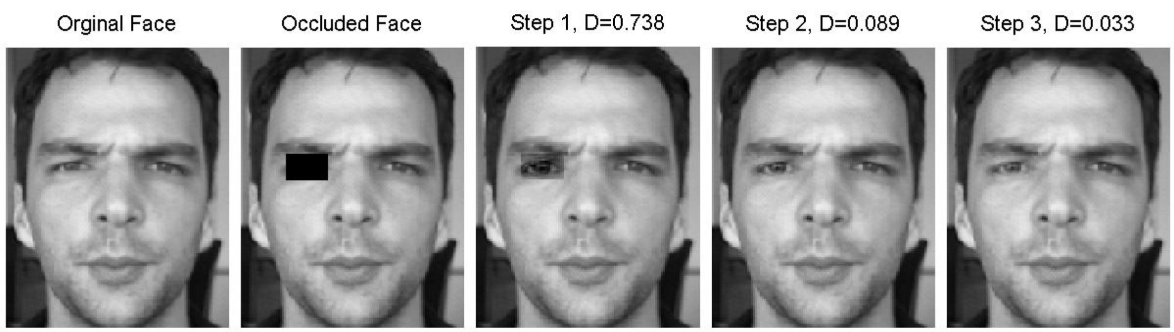
To accelerate the convergence speed, the difference between successive coefficients is used for compensation the second and after synthesis step. So the second step is revised as:

$$\mathbf{x}^{n+1\prime} = \mathbf{m} + \sum_{i=1}^{N} \left[y_i^{n} + \alpha \cdot (y_i^{n} - y_i^{n-1}) \right] \mathbf{v}_i \qquad (14)$$

Here 0<α<1 is a compensation constant, typical value is 0.5. If α=0, it becomes classical PCA compensation algorithm. Values greater than 1 would results in oscillation. With new iterative algorithm, the iteration steps can be reduced to about half of original recursive PCA.



(a) Classical PCA compensation algorithm



(b) Fast PCA compensation algorithm

Figure 1 Reconstructed results and maximum coefficient difference on training data

4. Experimental results

We use BioID face database as training face image [11]. The BioID database contain 1521 faces, all face had been labeled with 20 points, including two eyes and mouth corners we needed. We exclude faces with glasses, faces with exaggerative expressions, and faces too close to image border that cannot be normalized. Finally, 853 faces had been selected for training the model. The experimental results include faces in and out of training database respectively.

Fig.1 shows reconstructed results and maximum absolute coefficient difference between two successive steps of classical PCA compensation algorithm and our fast compensation PCA algorithm respectively (α=0.5). The test face image is from training database. The title upon each iteration image shows the iterative steps and maximum error. Clearly, our new algorithm converge faster the classical algorithm.

Fig.2 shows another experimental result on faces out of training face database, which is from AR face database [12]. It shows the result is almost as good as result in Fig.1, and our new algorithm converge much fast than classical PCA algorithm.

Both Fig.1 and Fig.2 demonstrates that our face normalization is good enough for face occlusion remove.

5. Conclusion

Current PCA based face occlusion remove algorithms need face to be normalized. Some algorithms even need to know the precise corresponding relationship of new face and standard face. But this information was difficult to obtain. We give a simple and fast algorithm in this paper. Face is normalized through only 4 salient points in face image. Fast face occlusion remove is realized by PCA coefficient error compensation.

6. References

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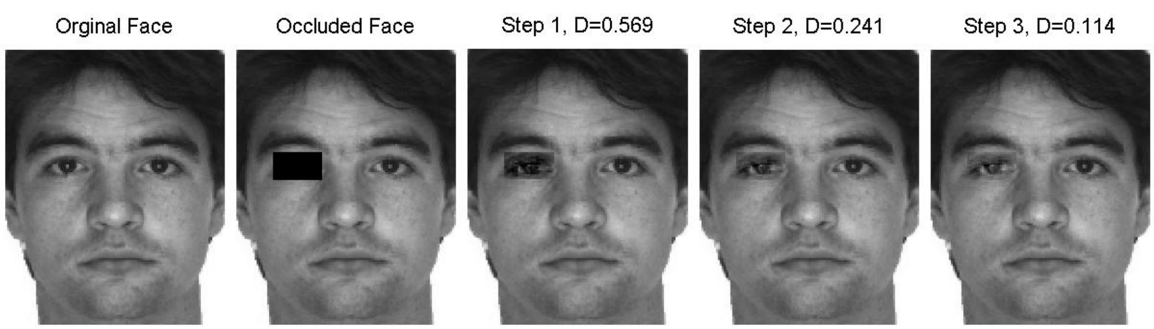
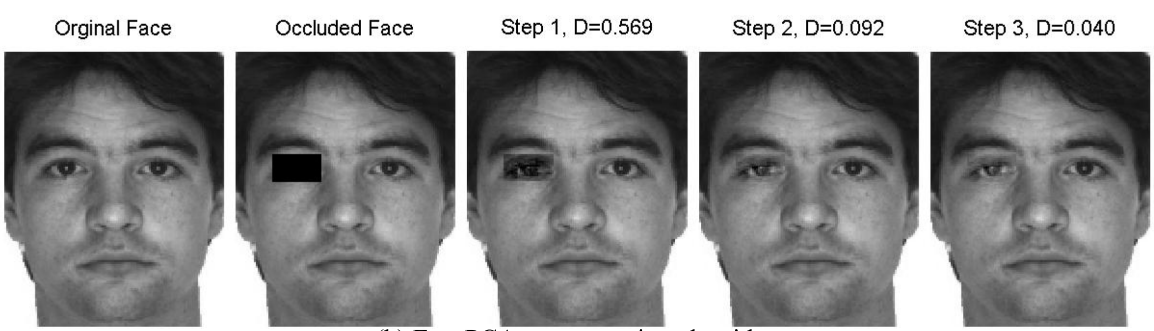


(a) Classical PCA compensation algorithm



(b) Fast PCA compensation algorithm

Figure 2 Reconstructed result and maximum coefficient difference on test data