Unknown Face Occlusion Removal by Fuzzy Principal Component Analysis

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Abstract: *This paper proposes an iterative face occlusion removal algorithm based on accumulative error compensation and fuzzy principal component analysis (FPCA).The originality of this work is two folds. First, instead of successive error, normalized accumulated absolute error was used as an image fusion weight in recursive error compensation. Second, gappy PCA with bi-value mask was extended to fuzzy PCA with continuous mask between 0~1. The value of the fuzzy mask vector is also defined by normalized accumulated error, which indicates the probability of being occluded of face region. Experimental results shown that our new reconstruction algorithm could remove unknown occlusion with various shape effectively, and outperform classical iterative PCA based algorithm.*

Keywords: *Face occlusion, Face reconstruction, Principal component analysis (PCA), Gappy principal component analysis (GPCA), Fuzzy principal component analysis (FPCA)*

基于模糊主分量分析的脸部未知遮挡物去除

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摘 要：本文提出一种基于累积误差和模糊主分量分析(FPCA)的迭代人脸遮挡物去除算法。创新之处有两点：首先，在迭代误差补偿过程中，使用归一化的累积绝对误差而不时连续两次迭代误差作为图像融合权值；其次，将采用离散二值掩模的缺口主分量分析(GPCA)推广到采用 0-1 之间连续值掩模的模糊主分量分析(FPCA)。模糊掩模向量值取归一化的累积绝对误差，表示脸部区域被遮挡的概率。实验结果表明，本文提出的算法可有效去除人脸上的各种形状的未知遮挡物，优于经典的 PCA 迭代算法。

关键字：人脸遮挡，人脸重建，主分量分析(PCA)，缺口主分量分析(GPCA)，模糊主分量分析(FPCA)

1 Introduction

Face occlusions (such as glasses, respirator, scarf, etc.) are unavoidable in real world face image processing. But it can degrade the performance of face recognition and face animation evidently. Reconstruction of partially occluded face quickly and automatically becomes one of research hotspot 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, image inpainting cannot reconstruct the eye image, and result face will have only one eye.

The dominated methods of reconstruct damaged face are based on analysis and synthesis techniques. Such as principle component analysis (PCA), gappy principal component analysis (GPCA), etc. In PCA based techniques, 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, reconstruction face is obtained by linear combinations of prototypes.

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 estimate 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 space were obtained by maximizing posteriori probability of V.

Both Park [3] and Du [4] used PCA based recursive error compensation algorithms to reconstruct face area occluded by glasses. Result face was obtained by weighted sum of original face and reconstructed face. The weights for compensation were determined by error between successive reconstructed results.

Hwang do PCA analysis on face shape model and face texture model respectively [5]. His algorithm can reconstruct very natural human face, but has two shortcomings: the exact displacement among pixels in an input face which correspond to those in the reference face is known (which is difficult to obtain in practice), and the positions of the pixels in the damaged regions on an input face are known.

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

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].

There are some restrictions in current algorithms. First, occluded region is often supposed to be known, or has some specific shapes (such as eye glasses). Second, when occlude region is unknown, compensation weight calculated from successive error is more likely to be spoiled by noise, which makes some blur and overall gray level difference compare with original un-occluded face image.

In this paper, we proposed a novel face occlusion reconstruction algorithm based on normalized accumulated absolute error and fuzzy PCA (FPCA). Error between successive reconstructed faces image was normalized not only by their maximum value, but also with accumulate error. GPCA is extended to fuzzy PCA which use masks with continued value between 0~1. The continuous mask vector works as the probability of being occluded.

The remainder of this paper is organized as follows: Section 2 briefly introduces the iterative PCA based face reconstruction. Section 3 gives PCA recursive error compensation with normalized accumulated error. Section 4 gives the definition of fuzzy PCA. Experimental results are given in section 5. At last, section 6 is conclusion.

2 Face Reconstruction Based on PCA

Due to the special structure of human face, the most successful reconstruction algorithms were PCA based. The basic idea of PCA can be described as following:

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

where $\mathbf{x} = [x_1, x_2, ..., x_n]^T$ is the input face image with n pixels, $\mathbf{e}$ is the approximation error, and quantity of ||**e**|| is called DFFS (Distance From Face Space). $\mathbf{m} = [\bar{x}_1, \bar{x}_2, ..., \bar{x}_n]^T$ is the mean face, $\mathbf{v}_i$ is the ith reserved N eigenfaces (eigenvectors of the covariance matrix of **x**), and y_i is the coefficient for linear combination, which can be estimated in analysis step by:

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

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

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

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

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

Weight w is between 0 and 1. If occlude region is known, weight value in occluded region is 1, and in other region is 0. If occluded region is unknown, weight can be estimated by normalized error between temporal face and original face used in analysis. x1 is result face after first analysis and synthesis cycle.

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

3 Weighting with Normalized Accumulated Error

After the *k*th cycle of analysis and synthesis, a temporal reconstructed face is obtained, the absolute error between successive results can be calculated by:

$$|\mathbf{e}| = \left|\mathbf{m} + \sum_{i=1}^{N} y_i^k \mathbf{v}_i - \mathbf{x}^k\right| = \left|\mathbf{x}^{k+1\prime} - \mathbf{x}^k\right| \qquad (5)$$

For every pixel, if value of |**e**| is larger, it is more far away from face space, and it is more likely to belong to occluded regions. So the normalized value of |**e**| (between [0 1]) can be approximated as the probability of being occluded. Then we can estimate the sum weight **w** in (4) from |**e**|, that is:

$$\mathbf{w} = 1 - norm(|\mathbf{e}|) = 1 - |\mathbf{e}| / \max(|\mathbf{e}|) \qquad (6)$$

But this will result some problems. With the progress of iterative analysis and synthesis, successive error |**e**| becomes smaller and smaller, and the normalized result will contain many noises. (See experimental result image in section 5) Many un-occluded pixels were weighted as occluded pixels with relatively high probability. This will result in gradual changing of un-occluded regions, blur the reconstructed result, and introduce some noises.

We define a new normalized accumulated error:

$$\mathbf{w}^k = 1 - norm(|\mathbf{e}|^k \cdot \mathbf{w}^{k-1}) \qquad (7)$$

Weight (normalized error) in last cycle will be considered in current synthesis step. This accumulated effect will prevent unlikely non-occluded pixels in early iteration steps become more likely occluded pixel in latter iteration steps. It gives more precisely prediction of occluded regions. We called it accumulative PCA.

4 Fuzzy PCA

In classical PCA, both un-occluded and occluded region are used in the analysis step, which makes the analysis result not very precise. Gappy PCA is proposed to over this problem. Gappy PCA is desired to PCA analysis with incomplete pattern **x** (i.e., an occluded face). First, gappy inner product was defined as [7]:

$$(\mathbf{u}, \mathbf{v})_z = \sum_{i=1}^{d} u_i v_i z_i \qquad (8)$$

where **u**, **v** are eigenfaces, **z** is a vector with same length of pixel number which indicate whether a pixel is occluded (=0) or not (=1). According to LSM rule, we should minimize the $\|\mathbf{e}\|_z$, which obtained:

$$\frac{\partial \|\mathbf{e}\|_z^2}{\partial y_i} = -2(\mathbf{x} - \mathbf{m}, \mathbf{v}_i)_z + 2\sum_{j=1}^{N} y_j (\mathbf{v}_j, \mathbf{v}_i)_z = 0 \qquad (9)$$

If we write it into formula of matrix:

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

Then the counterpart analysis procedure of (2) becomes:

$$\mathbf{y} = (\mathbf{v}^T, \mathbf{v})_z^{-1} \cdot (\mathbf{v}^T, \mathbf{x} - \mathbf{m})_z \qquad (11)$$

If there is no occlusion, $\mathbf{z}=[1,1,\ldots,1]^T$. $(\mathbf{v}^T, \mathbf{v})_z = \mathbf{v}^T \cdot \mathbf{v} = \mathbf{I}$, formula (11) becomes identical with (2).

Gappy PCA can only be used when occluded region is known. Because vector **z** has only two values (0 or 1), indicate un-occluded and occluded regions respectively. We extended it to unknown occluded reconstruction with continuous value between [0 1]. Compare with original GPCA, bi-value mask vector is replaced by a fuzzy mask. We called it fuzzy principal analysis (FPCA). Clearly, GPCA is just a special case of our FPCA.

Similar to the weight sum process, if one pixel is more likely to be occluded, it should contribute less to analysis step. So we can just define values of **z** the same with weight **w**:

$$\mathbf{z}^k = \mathbf{w}^k \qquad (12)$$

Fuzzy inner product and FPCA analysis step also have the same definitions with (8) and (11). The only difference is that vector **z** has continuous value between [0 1]. After we define the fuzzy **z** vector, we can do iterative FPCA in the second and following analysis according to formula (8), (3) and (4).

5 Experimental Results

We use BioID face database as training face image [10]. The BioID database contains 1521 faces. 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.

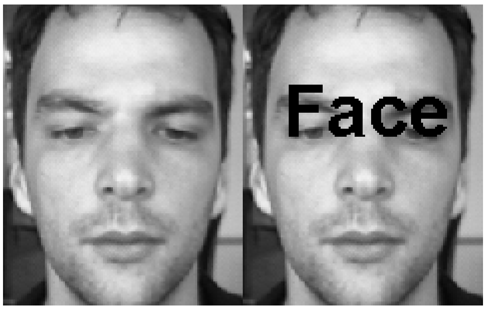


Figure 1: Original and occluded face

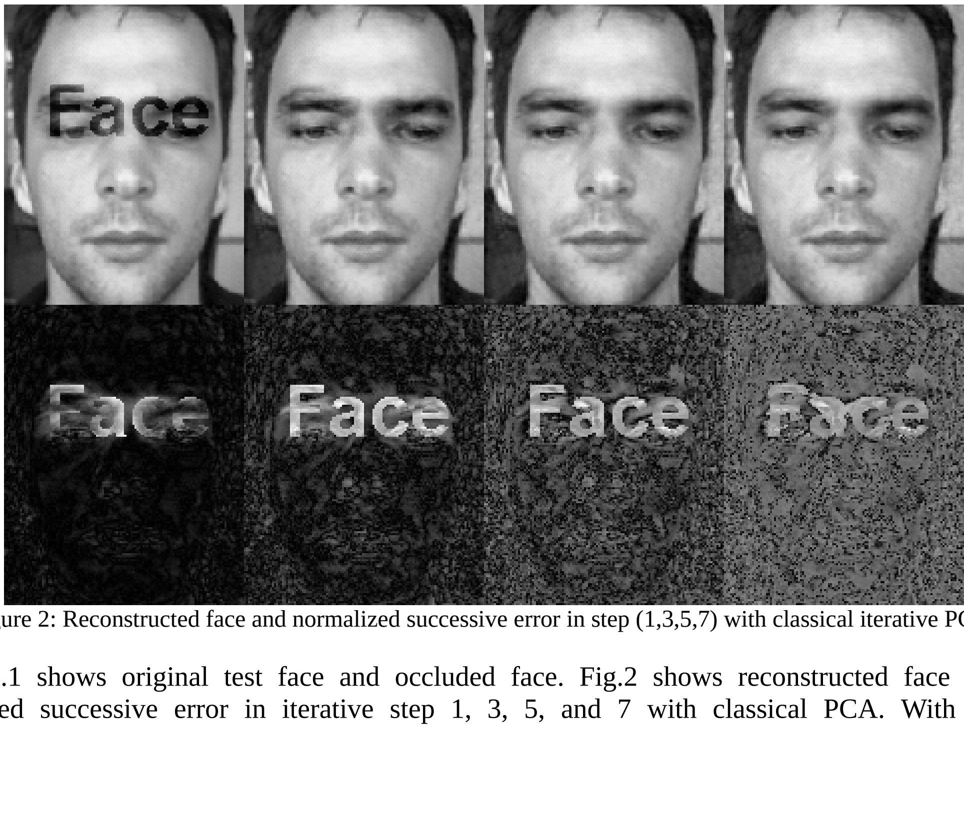


Figure 2: Reconstructed face and normalized successive error in step (1,3,5,7) with classical iterative PCA

Fig.1 shows original test face and occluded face. Fig.2 shows reconstructed face and normalized successive error in iterative step 1, 3, 5, and 7 with classical PCA. With the development of analysis and synthesis, successive error becomes noisy. Almost all of pixels have some probability of being occluded. This results in gradual changing of un-occluded regions (more dark than original face). It also blurs the reconstructed result, and introduces some noise in background regions.

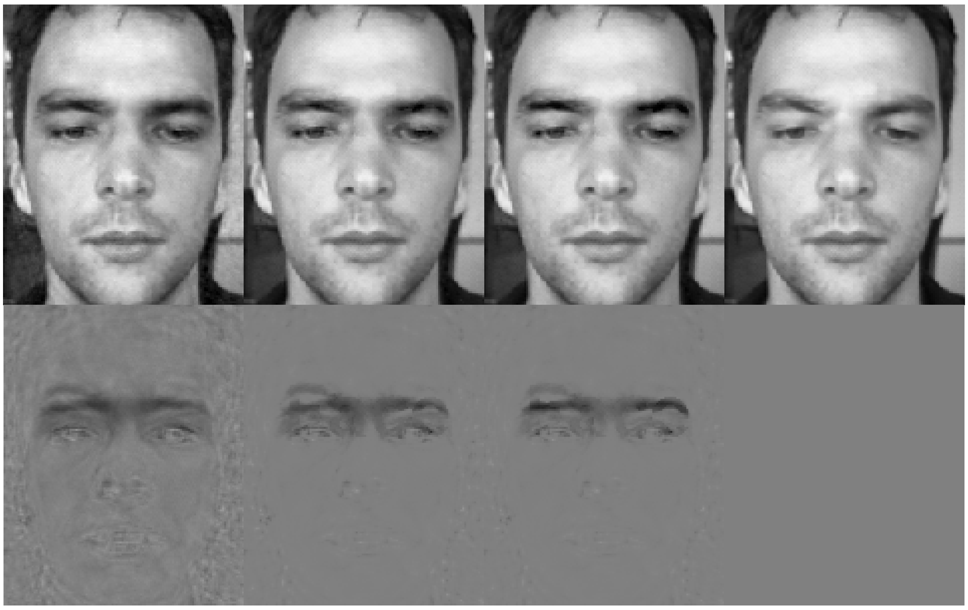
Fig.3 shows reconstructed face and normalized accumulated error in iterative step 1, 3, 5, and 7 with classical PCA. It is clearly that normalized accumulated error can extract occlusion more precisely than normalized successive error. Reconstructed face is more natural than PCA based on normalized successive error.

Figure 3: Reconstructed face and normalized accumulated error in step (1,3,5,7) with iterative PCA

Fig.4 shows results with fuzzy PCA. Reconstructed face of fuzzy is similar with accumulative PCA, but convergence faster than accumulative PCA.

Figure 4: Reconstructed face and normalized accumulated error in step (1,3,5,7) with fuzzy iterative PCA

Fig.5 compares reconstructed faces and errors from original face by different algorithms. Mean absolute error (MAD) is also given in bottom of the figure. Both accumulative PCA and fuzzy PCA give better results than classical PCA, and fuzzy PCA is a little better than accumulative PCA.



Classical PCA, Accumulated PCA, Fuzzy PCA, Original
MAD = 0.0259, 0.0132, 0.0112, 0

Figure 5: Reconstructed face and error (normalized to [-0.3-0.2])

6 Conclusion

Two improvements were made to classical iterative PCA based face image reconstruction. During the process of weigh sum, successive error was replaced by accumulated error, which predict occluded region more precisely. GPCA is extended to FPCA, which can be used in face reconstruction with unknown occlusions.

However, there are some drawbacks in our accumulated error compensation algorithm. Regions where the grey level of occlusion object is close to face image cannot be removed clearly. See regions in eyebrows in Fig. 4. This will be one of our future works.

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