Super-resolution Reconstruction for Facial Images Based on Local Principal Component Analysis

He Jinping[1], Su Guangda[2] and Chen Jiansheng[2]

[1]Beijing Institute of Space Mechanics & Electricity, Beijing, 100094, China

[2]Department of Electronic Engineering, Tsinghua University, Beijing, 100084, China

hjping@mail.tsinghua.edu.cn

Abstract - In order to improve the ghosting effect appearing the reconstruction results which are obtained through applying Principle Component Analysis (PCA) on the whole images, a novel algorithm which is reconstructed through applying PCA on local image patches is proposed. The new method firstly proposes the image patch model with overlapping areas. Then the input low-resolution patches are projected on the sample patches through PCA. And the weights can be obtained. Furthermore, the corresponding high-resolution patches are linearly combined through these weights to output the fusion patches. Now the best results are 16×12 reconstructions with the magnification of 8×8. Experimentations show that our method can reconstruct ultra-low resolution faces of 8×6 pixels with the magnification of 16×16, and the similarity with the original high-resolution images is higher.

Index Terms - Super-resolution reconstruction, Hallucinating faces, Local Principal Component Analysis.

I. Introduction

Principal Component Analysis (PCA) is a classical linear method for feature extraction and data representation. It has been widely applied in the field of pattern recognition and machine vision. The purpose of calculating the principal components is projecting the high-dimensional data to the low-dimensional space.

The most representative application for super-resolution (SR) reconstruction based on PCA is hallucinating face by eigentransformation which is proposed by Wang [1] in 2005. This method keeps the high-dimensional and low-dimensional weighted coefficients consistent, and nonlinearly limits the high-dimensional coefficients according to the threshold. Finally, the optimal high-resolution (HR) image can be obtained. This method belongs to a global algorithm. It would produce the ghost phenomenon. The illuminations of reconstruction before and after are different. If keeping the illuminations constant through changing the nonlinear limited parameter, there will be a lot of loss of high-frequency information. It is very difficult getting the tradeoff between the illumination and the high-frequency detail.

The method for hallucinating faces based on Tensorpatch and coupled residue compensation was proposed by Wei Liu [2] from Chinese University of Hong Kong in 2005. This method utilized PCA to reducing dimensions in order to make the residue compensation more suitable for the traditional multiple linear regression models. Parinya Sanguansat[3] from Rangsit University proposed face hallucination using bilateral-projection-based two-dimensional principal component analysis in 2008. However, this method needed a large amount of calculation, because each image in training set will be bilaterally projected to the feature space. The face hallucination method through KPCA proposed by Yan [4] from Zhongshan University in 2009 was also faced with the large calculated amount. The face hallucination algorithms based on interpolation and PCA was proposed by Shen Hua [5] from Hunan University in 2010. This method used PCA to calculate the weight coefficients of local detail images. Because the manner of using PCA was the same as Wang's, the ghost phenomenon will also happen.

In conclusion, in the above face SR algorithms including PCA, PCA was used to project the whole faces into the feature space, or to fuse with other transformation in order to reduce dimensions. The ghost phenomenon will appear when using PCA to the whole face images. It will greatly affect the quality of image reconstruction. So the operation of using PCA to the local image patches is hoped to be implemented, in order to decrease its lack in the whole application.

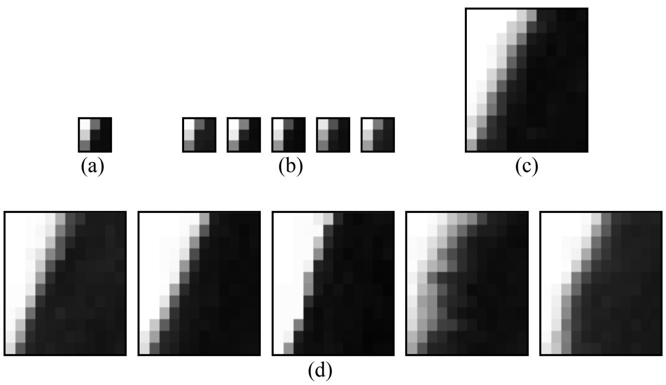
II. The algorithm of face SR based on Local PCA

The action scope of Wang's method was the whole image. It utilized the overall similarity of faces. As shown in Fig.1, the first line is the result of Wang's. It can be gotten that the center field of naked faces is clear, but the neighborhood has the worse ghost phenomenon. It affects the whole quality. The main reason of leading to the ghost is that the similarity of the input image and training set in the naked face area are higher than the neighborhood. Inspired by this phenomenon, a new method in which PCA acts on the local image patches is proposed in this paper.

Fig.1 The reconstruction results of Wang

A. The model of image patches

From the above analysis of experimental results, the bigger the similarity of the input image and training set is, the better the reconstruction quality is. So we can reduce the difference of the input image and training set through shrinking the action scope of PCA. Suppose the size of low-resolution (LR) faces is $m \times n$ pixels. It can be divided into square patches with the same size. Suppose the size of the local LR patch is $n_l \times n_l$ ($n_l < m$, and $n_l < n$). Because the texture features of local patches are more simple than the whole face image's, we can get that the similarity of patches are better than the similarity of the input image and training set as show in Fig.2(a) and Fig.2(b).



(a) one target LR patch with the size of 3×3;
(b) five nearest LR patches to (a) with 12×12size selecting from 10 training images;
(c) the ground true HR patch corresponding to (a) with 4×4 magnification;
(d) the five HR patches corresponding to (b).

Fig.2 An illustration of local patches' similarity:

The HR faces are divided into the patches with the same number of LR faces. Each pair of LR and HR patches forms the one-to-one relationship. $P^l(i,j)$ is defined as the LR patch with the center (i,j) and the $n_l \times n_l$ (n_l is the odd number) size. And $P^h(i,j)$ is the corresponding patch of $P^l(i,j)$ in HR space. Its size is $n_h \times n_h$. The amplification factor is $R = n_h / n_l$. The overlapping width of each direction between the LR patch and neighbor patches is $(n_l - 1)/2$. As shown in Fig.3, each patch $P^l(i,j)$ and its neighbor patches $P^l(i-\Delta, j)$, $P^l(i+\Delta, j)$, $P^l(i, j-\Delta)$ and $P^l(i, j+\Delta)$ are overlapping, and $\Delta = (n_l + 1)/2$.

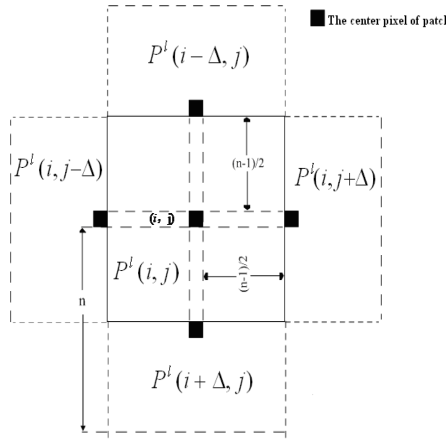


Fig.3 The illustration of overlapping patches' model

B. The reconstruction algorithm based on local PCA

The basic assumption of the proposed new method in this paper is that the patches in the LR and HR space have the same local topological structure. As shown in Fig.4, ω is the weighted coefficients of linear combination and $NB(P(i,j))$ is the neighbor patches of $P(i,j)$. There is an one-to-one relationship between $NB(P^l(i,j))$ and $NB(P^h(i,j))$. And they keep the local zoom feature unchanged ($w_l = w_h$). The assumption in this paper is the same as the Chang's [6] based on Linearly Local Embedding (LLE).

Firstly, the alignment pretreatment of eyes and the low jaw of training face set is implemented. Then suppose the patch of the input LR face l_{in} centered at point (i,j) is $P^l_{in}(i,j)$. The LR training patch set can be expressed by $\{P^l_k(i,j)\}_{k=1}^N$. The corresponding HR training set are $\{P^h_k(i,j)\}_{k=1}^N$. Specific algorithm is described as follows:

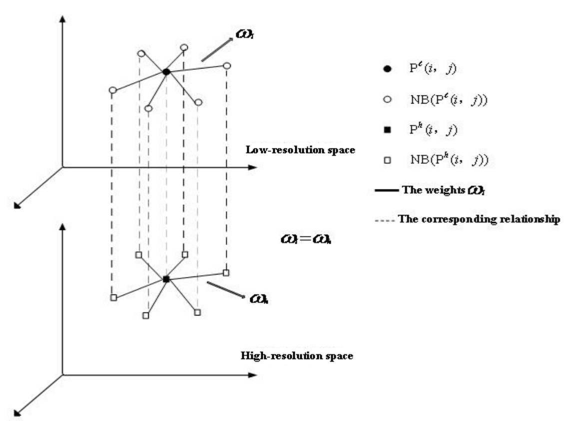


Fig.4 The local topology of patches

Step1: Projection feature space is constructed in LR space. Then the weighted coefficients of the input patch $P^l_{in}(i,j)$ can be obtained.

The image patch set $\{P^l_k(i,j)\}_{k=1}^N$ can be expressed by a one-dimensional column vector $\vec{l}_k$. The average patch of LR training patch set can be calculated by $\vec{m}_l = \frac{1}{N}\sum_{k=1}^{N}\vec{l}_k$. Then the sequence of the image patches with zero mean value can be denoted by $L = [\vec{l}_1 - \vec{m}_l, \cdots, \vec{l}_N - \vec{m}_l] = [\vec{l}_1{}', \cdots, \vec{l}_N{}']$. The eigenvectors corresponding to the K bigger eigenvalues of covariance matrix $C = L(L)^T$ can compose a projection matrix $E = [e_1, \cdots, e_K]$. The weighted vector can be got through projecting the LR vector $\vec{l}_{in}$ on E:

$$\vec{w}_l = (E)^T(\vec{l}_{in} - \vec{m}_l) \qquad (1)$$

However, matrix C size is very big. The eigenvectors of C can be obtained by calculating the eigenvectors of the small matrix $R = (L)^T L$. The eigenvectors' matrix V of R and the eigenvalue matrix Λ can be calculated by

$$(L)^T LV = V\Lambda \qquad (2)$$

Multiplying both sides by L, we have

$$(L(L)^T)LV = LV\Lambda \qquad (3)$$

Therefore, the eigenvector matrix of C is

$$\hat{E} = LV\Lambda^{-\frac{1}{2}} \qquad (4)$$

The K bigger eigenvalues through descending sort are selected out to make their corresponding eigenvectors consist of projection matrix $E = [e_1, \cdots, e_K]$.

Step2: The coefficients x of linear combination in the original space are solved according to the projection coefficients in the feature space.

The projection matrix E can be calculated by

$$E = LV_K(\Lambda_K)^{-\frac{1}{2}} \qquad (5)$$

Where the matrix Λ_K consists of K bigger eigenvalues and V_K is its corresponding eigenvectors matrix. From (1), the input image patch can be expressed by

$$\vec{l}_{in} = E\vec{w}_l + \vec{m}_l = LV_K(\Lambda_K)^{-\frac{1}{2}}\vec{w}_l + \vec{m}_l = Lx + \vec{m}_l \qquad (6)$$

Where $x = [x_1, \cdots, x_N]^T$ is the vector of linear combination coefficients in the original space. The above formula can be written as

$$\vec{l}_{in} = \sum_{k=1}^{N}\vec{l}_k{}' * x_k + \vec{m}_l \qquad (7)$$

Step3: Make the LR patch coefficients of linear combination equal to HR patch's, and the HR patch $P_{out}^h(i, j)$ corresponding to $P_{in}^l(i, j)$ can be estimated.

Each zero-mean patch $\vec{l}_k{}'$ in (7) can be replaced with the HR patch $\vec{h}_k{}'$. And the average vector $\vec{m}_l$ is also replaced with the HR average vector $\vec{m}_h$. Then we have

$$\vec{h}_{out} = \sum_{k=1}^{N}\vec{h}_k{}' * x_k + \vec{m}_h \qquad (8)$$

Where $\vec{h}_{out}$ is the one-dimensional vector of $P_{out}^h(i, j)$.

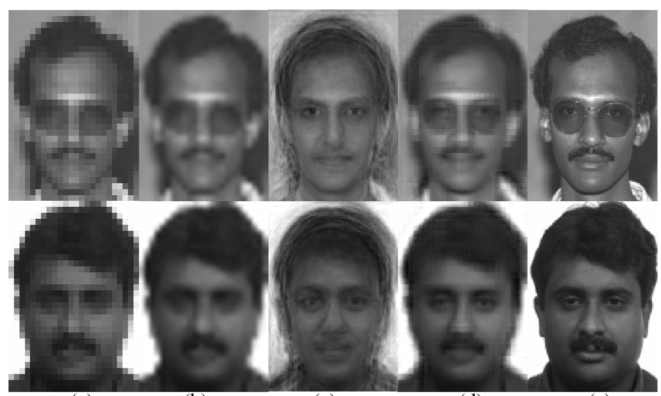
Step4: Step1 to Step2 loop is executed until completing all the LR patches.

Step5: Our algorithm performs the image mosaic of HR patches' overlapping areas through calculating their means.

Step6: Output the HR face image.

III. Experiment

The 549 face images in FERET are used our experiments. Fig.5 shows some SR reconstruction results of FERET. In the experiments, the original HR images are down-sampled to 32×24 pixels as the input LR images. The eyes distance of LR images is 8 pixels. Comparing with the results of different methods, we can get that the ghost phenomenon seriously appears at the field of hairs and the face contours in the Wang's results. And it will directedly affect the reconstruction quality. The results of our method are more objective to the original images. And our reconstruction algorithm adds more high-frequency information than linear interpolation's.



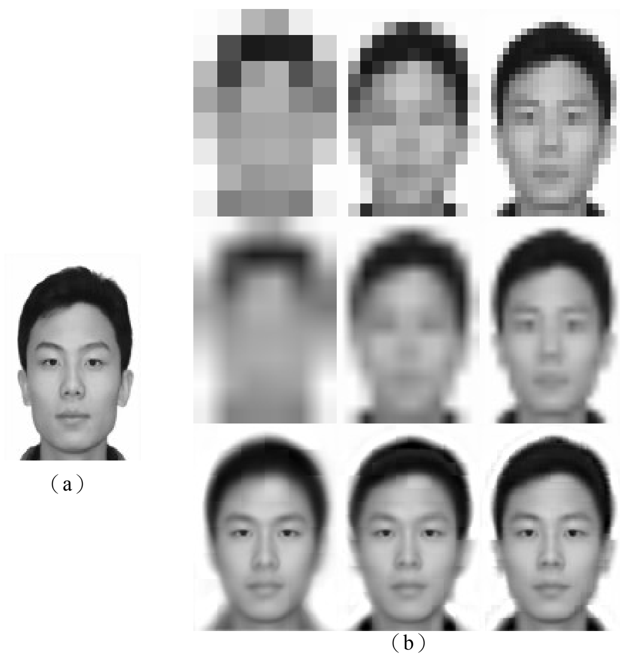
(a) (b) (c) (d) (e)

(a) the input low-resolution images with the size of 32×24;
(b) the results of linear interpolation;
(c) Wang's results;
(d) our method's;
(e) the original high-resolution images with the size of 128x96.

Fig.5 The SR results of FERET database:

The same experiments are implemented at the students' face set of Tsinghua. The results of 32×24 pixels reconstruction are also very well. It shows that our method can adopt different face sets and has certain robustness. The reconstruction experiments for the lower images are further implemented at the students set. The sizes of the original LR images are 32×24, 16×12 and 8×6 pixels. Fig.6 shows the reconstruction results of the same image in different LR levels. The LR image of 32×24 is magnified to 4×4 times, and 16×12 is corresponding to 8×8 times. 8×6 is corresponding to 16×16 times. From the results, the five sense organs in the interpolation's results are completely blur. Yet our method can reconstruct the details of the five sense organs.

100 face images are selected as the training set, and another 100 face images are the test set. Than calculate the average Root Mean Square (RMS) of the reconstruction results with 4×4 zoom times of the 100 test samples which size is 32×24. TABLE I displays the average RMS values of the interpolation results, Wang's and our method's. Our algorithm is obviously superior to the other two methods. The average RMS is biggest because of the ghost at the contours.



(a) the original high-resolution image (128×96) with the eyes distance of 32 pixels;

(b) the first line are the inputs with the eyes distance of 2, 4 and 8 pixels. The second line are the results of linear interpolation. The third line are the results of our method.

Fig.6 The SR reconstruction results with different resolution inputs:

TABLE I The average RMS comparison of 100 test samples

	Linear interpolation	Wang's method	Our method
The average RMS	19.0368	36.7306	16.1530

IV. Conclusion

To reduce the ghost phenomenon which occurs in the global PCA algorithm, a new method based on local PCA for faces SR is proposed. The innovation point is proposing to reduce the action scope of PCA and using this at SR application. The experiment results show its better validity than the global PCA method. It can achieve the 8x6 reconstruction. It will supply the wider application prospect for learning-based SR method in the actual situation.

V. Acknowledgment

This work was supported by National 973 plans projects of China (2007CB310600) and the National Science Foundation for Post-doctoral Scientists of China (20100470295).

References

[1] Wang X, Tang X, "Hallucinating face by eigentransformation", *IEEE Trans Systems, Man and Cybemetics, Part C: Applications and Reviews*. vol. 35, pp. 425-434,2005.

[2] W. Liu, D. Lin and X. Tang, "Hallucinating faces: Tensorpatch super-resolution and coupled residue compensation", *Proc. of IEEE Conf. on CVPR*, vol. 2, pp. 478-484,2005.

[3] P. Sanguansat, "Face hallucination using bilateral-projection-based two-dimensional principal component analysis", *IEEE ICCEE*, pp. 876-880, 2008.

[4] Yan Liang, J.H. Lai and Y.X. Zou et al., "Face hallucination through KPCA", *IEEE CISP*, pp. 1-5, 2009.

[5] Shen Hua, *Researches on face hallucination algorithms based on interpolation and PCA*, Wu Han: Hunan University of Science and Technology, 2010.

[6] CHANG Hong,Dit-Yan Yeung and Xiong Y, "Super-resolution through neighbor embedding",. *Proc. of IEEE Conf. on CVPR*, pp. 275-282, 2004.