Eigentransformation with Error Regression Model for Face Hallucination

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Summary

Generally, a high-resolution (HR) face image is reconstructed only from low-resolution (LR) face image. However, previous researches neglected to gain benefits from error of face reconstruction. This paper proposes a new face hallucination technique for face image reconstruction using Eigentransformation with error regression model. In order to improve the performance of facial image reconstruction, the error information is included in our framework to correct the final result. In this way, the regression analysis is used to find the error estimation which can be obtained from the existing LR in eigen space. Our framework can work with both grayscale and color images. However, to handle with color images, each color channel in RGB model must be separately processed. The framework consists of learning and hallucinating process. In learning process is from the mistakes in reconstruct face images of the training dataset by Eigentransformation, then finding the relationship between input and error by regression analysis. In hallucinating process uses normal method by Eigentransformation, after that the result is corrected with the error estimation. Experimental results from the well-known facial databases show that the final resolution and quality are greatly enhanced over the sole Eigentransformation method

Key words:
Eigentransformation, error regression model, Face hallucination, Principal Component Analysis (PCA)

1. Introduction

Image resolution is contingent on the quality of image and equipment, which has highly influence to face recognition by human and computer. The quality of images are affected from several distorting processes that acquired by commercial digital cameras. These important distortions effects are warping, blurring and additive noise. As in video surveillance, the faces of interest are often appear of small size and blurred because of the large distance between the camera and the people. Beside, a real image is seen to be warped at the camera lens because of the relative motion between the scene and camera. The imperfections of the optical lens results in the blurring of this warped image which is then subsampled at the image sensor [1]. The additive readout noise at the image sensor will further degrade the quality of captured images [1]. In order to synthesis the high-resolution (HR) image from the low-resolution (LR) image, the computation can be performed in two manners: reconstruction-based [2], [3], [4] and learning-based [5], [6], [7]. In this paper, we focus on the second approach which applied to human face images, is also known as ***face hallucination*** [3].

In [5], Principal Component Analysis (PCA) was utilized as feature extraction and maximum a posteriori (MAP) estimation framework is incorporated to explore the underlying statistical structure of the face images. In [6], they developed a two-step statictical modeling approach that integrates both a global parametric model and local nonparametric model. The global constraint assumes a Gaussian distribution learnt by PCA. The local constraint utilizes a patch-based nonparametric Markov network to learn the statistical ralationship between the global face image and the local features. In [7] the Eigentransformation, PCA was used to fit the input face image as a linear combination of the LR face images in the training set. The HR image was rendered by replacing the LR training images with HR ones, while retaining the same combination coefficients. Afterwards, in [8], they approach also adopts a two-step strategy [6]. PCA was applied on both HR and LR, and the global image, which was similar to the original HR image, was reconstructed under a MAP criterion. Second, a linear model between the residual image (the difference between the original image and the global image) and the LR residual image (the difference between the LR input and the manually down-sampled global image) are built, and following a Markov Random Field (MRF) prior, the optimal residual image was estimated under a MAP criterion again. Beside, in [9], the global and local faces are both important in face hallucination. Therefore, they included both the reconstructions of the global face and local face. PCA was used to represent the global face as a linear combination of HR training samples and to calculate the combination coefficients. Moreover, they applied an interpolation based

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method called "new edge-directed interpolation" (NEDI) [10] to reconstruct the global face of the low-resolution input. However, we found that making interpolation by NEDI method is slow and no significant improvement in face hallucination. Therefore, we use bicubi-interpolation in our framework, because it is more simple and faster. All above works, no error information was used to reconstruct the HR image.

Recently, many research approaches attempted to propose frameworks that improve quality of face hallucination, by reconstructing HR face image from LR face image. This paper proposes an alternative framework, which consists two-phases, there is learning and hallucinating phase. An important issue is that we take advantage of the error; the others were not interested in it. Therefore, the error is added in training phases for improving face image reconstruction. In the first phase, learning process is learning the error of the training dataset in face image reconstruction by Eigentransformation. Considering the error of reconstruction, the system does not only learn the correct information but it also learn to correct the wrong information then builds error regression model for learning. Moreover, face image is reconstructed from correct data while error data are corrected by recognizing from the error regression model. In this model, this is finding the relationship between input and error by regression analysis. In the second phase, hallucinating process estimates the error from LR feature via regression coefficients, including the imformation from bicubic-interpolation of LR face image, then combined with images to reconstruct the final HR image by Eigentransformation.

The remainder of this paper is organized as follows: in Section 2, the hallucinating faces by Eigentransfomation concept are firstly described. Our proposed error regression model is proposed in Section 3, beside face hallucination Framework is presented 4. In Section 5, experimental results are presented for the face image databases to demonstrate the effectiveness of our proposed techniques. Finally, conclusions are presented in Section 6.

2. Hallucinating faces by Eigentransformation

In this section, the face hallucination problem is briefly described and then the Eigentransformation is presented here to solve the problem.

2.1 Face Hallucination

The face hallucination is view as the inverse problem of the getting of LR image from HR image. The HR image can be generated the LR images in million ways. Only the downsample, blurred and noise one mostly interested [3].

The process of getting a LR face image from the HR face image can be formulated as

$$\mathbf{l} = \mathbf{B}\mathbf{h} + \eta \tag{1}$$

Give, $\mathbf{h}$ is the HR face image vector to be rendered, with length n as the total pixel number. $\mathbf{l}$ is the observed LR face image vector with length $s^2 n$, where s is is the downsampling factor $(0 < s < 1)$. $\mathbf{B}$ is the transformation matrix involving blurring and downsampling process, and η is the noise perturbation to the HR face image captured by camera.

2.2 Eigentransformation

In [7], they applied PCA to the LR face image and representation, different frequency components are uncorrelated. They could extract the maximum amount of facial information from the LR face image and remove the noise. The HR image is rendered by replacing the LR training images with HR ones, while retaining the same combinationcoefficients.

From [7], the eigenfaces are used to represent the face images. A face $\mathbf{r}_l$ can be reconstructed from the K eigenfaces $\mathbf{E}_l = [\mathbf{e}_1, \mathbf{e}_2, ...\mathbf{e}_k]$. μ_l is mean of LR. $\mathbf{w}_l$ is weight vector and $\mathbf{r}_l$ is reconstruction image of LR.

$$\mathbf{r}_l = \mathbf{E}_l \mathbf{w}_l + \mu_l \tag{2}$$

Let $\mathbf{L}$ is set of $\mathbf{l}$, according to singular value decomposition theorem, $\mathbf{E}_l$ also can be computed from,

$$\mathbf{E}_l = \mathbf{L}\mathbf{V}_l \Lambda_l^{-1/2} . \tag{3}$$

Where $\mathbf{V}_l$ and Λ_l are the eigenvector and eigenvalue matrix for $\mathbf{L}^{\mathbf{T}}\mathbf{L}$. From (2) and (3), the reconstructed face image can be represented by

$$\mathbf{r}_l = \mathbf{L}\mathbf{V}_l \Lambda_l^{-1/2} \mathbf{w}_l + \mu_l = \mathbf{L}\mathbf{c} + \mu_l . \tag{4}$$

Where $c = \mathbf{V}_l \Lambda_l^{-1/2} \mathbf{w}_l = [c_1, c_2, \ldots c_M]^{\mathbf{T}}$. c describes the weight that each training face contributes in reconstructing the input face can be rewritten as,

$$\mathbf{r}_l = \sum_{i=1}^{\mathbf{M}} c_i \mathbf{l} + \mu_l \tag{5}$$

This shows that the input LR face image can be reconstructed from the optimal linear combination of the $\mathbf{M}$ LR training face images. Let μ_h is mean of HR. Replacing each LR image l' by its HR sample $\mathbf{h}$, and replacing μ_l with the HR mean face μ_h , we get $\mathbf{x}_h$, which is expected to be an approximation to the real HR face image.

$$\mathbf{x}_h = \sum_{i=1}^{\mathbf{M}} c_i \mathbf{h} + \mu_h \tag{6}$$

Let $\mathbf{E}_h$ and Λ_h be the eigenface, $\mathbf{E}_h = \mathbf{H}\mathbf{V}_h \Lambda_h^{-1/2}$ and eigenvalue matrixes computed from the HR training images. The principal components of $\mathbf{x}_h$ projecting on the HR eigenfaces are

$$\hat{\mathbf{w}}_h = \mathbf{E}_h^{\mathbf{T}} (\mathbf{x}_h - \mu_h) \tag{7}$$

To reduce the distortion, we apply constraints on the principal components according to the eigenvalues:

$$\tilde{\mathbf{w}}_h(i) = \begin{cases} \hat{\mathbf{w}}_h(i), & |\mathbf{w}_h(i)| \le d\sqrt{\lambda_i} \\ \mathbf{sign}(\hat{\mathbf{w}}_h(i)) * d\sqrt{\lambda_i}, & |\mathbf{w}_h(i)| > d\sqrt{\lambda_i} \end{cases} \tag{8}$$

They use $d\sqrt{\lambda_i}$ to bound the principal components. Here, d is a positive scale parameter ($d > 0$). The final hallucinated face image is reconstructed by

$$\hat{\mathbf{x}}_h = \mathbf{E}_h \tilde{\mathbf{w}}_h + \mu_h \tag{9}$$

3. Error Regression Model

In traditional method, HR images are reconstructed from LR images only. None of these works interested to take advantage of the reconstruction error

$$\mathbf{\Phi} = \mathbf{h} - \hat{\mathbf{x}}_h \tag{10}$$

Therefore, we propose a new technique for face image reconstruction by using the error to be useful information. In error estimation, we can use the existing LR features in eigen space or LR training dataset for regression analysis. From the experimental results, we found that the estimation error by using LR features in eigen space improved face image reconstruction better than LR training images.

In order to describe the mathematical procedure for the reconstruction method above, the following notations are defined. Firstly, the reconstruction error of learning phase is computed by the following equation:

$$\mathbf{\Phi} = \mathbf{R}\mathbf{\Gamma}_l \tag{11}$$

where $\mathbf{\Phi}$ is the reconstruction error, $\mathbf{R}$ is regression coefficient. Γ_l is LR features in eigen space of learning phase.

The regression coefficient $\mathbf{R}$ can solve by least squares estimator

$$\mathbf{R} = \mathbf{\Phi}\mathbf{\Gamma}_l^{T} (\mathbf{\Gamma}_l \mathbf{\Gamma}_l^{T})^{-1} \tag{12}$$

Practically, regression coefficient cannot be computed by this equation because the invert term does not exist. Therefore, error regression model adopt the regularization parameter to solve this problem. The regression coefficient $\mathbf{R}$ is defined by the following equation:

$$\mathbf{R} = \mathbf{\Phi}\mathbf{\Gamma}_l^{T} (\mathbf{\Gamma}_l \mathbf{\Gamma}_l^{T} + \alpha \mathbf{\Gamma}_l)^{-1}, \tag{13}$$

thus, the singularity problem is avoided by suitable regularization parameter, $\alpha > 0$. While actual error $\mathbf{\Phi}$ can obtain from validation. For this reason, the estimated reconstruction error $\hat{\mathbf{\Phi}}$ is presented by the following equation:

$$\hat{\mathbf{\Phi}} = \mathbf{R}\tilde{\mathbf{\Gamma}}_l \tag{14}$$

from (10) where $\tilde{\Gamma}_l$ is LR features in eigen space of input data.

Actually, the high resolution should remove the error by $\hat{\mathbf{\Phi}} + \hat{\mathbf{x}}_h$. However, the result of this method cannot provide the satisfied image, as shown in Fig 1 (e). In our framework, in Figs. 2 and 3, the bicubic-interpolation is used to improve this image. Additional information from interpolated image can produced more accurate image, as shown in Fig 1 (f)

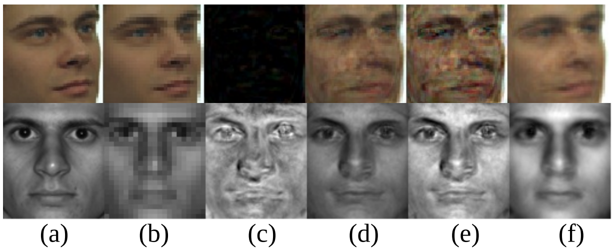

Fig 1 The Basic concept of face hallucination compare with our proposed. The upper row is color while the lower one is grayscale image. (a) HR image $\mathbf{h}$ (b) LR input (c) Error estimation $\hat{\mathbf{\Phi}}$ (d) Eigentransformation $\hat{\mathbf{x}}_h$ (e) $\hat{\mathbf{\Phi}} + \hat{\mathbf{x}}_h$. (f) Result of our proposed approach.

4. Proposed Framework

In this section, we delineate workflow as shown in Figs. 2 and 3 by separating the proposed face hallucination process into two-phase that show as follows.

Phase 1: Learning phase

1. HR training images degraded to obtain theirs LR.
2. After that, this LR training set is used to train PCA to obtain the eigenvalues $\mathbf{V}_l$ and eigenvectors Λ_l of LR space.
3. HR training set is used to train PCA to obtain the eigenvalues $\mathbf{V}_h$ and eigenvectors Λ_h of LR space.
4. Validation process picks up LR from training set for face hallucination by Eigentransformation method.
5. The reconstruction error is received from reconstruction image in the previous step and original image of itself.
6. The regression coefficients $\mathbf{R}$ is acquired form relationship between LR space with error by regression analysis.

Phase 2: Hallucinating phase

1. HR face image is reconstructed from LR testing set by bicubic-interpolation.
2. HR face image is reconstructed from LR testing set by Eigentransformation.
3. The error estimation is computed from LR feature space and regression coefficient.
4. The result image is obtained from the computations that subtracts the error estimation image form image in step 1, and then add to step 2.

In hallucination of color facial image, it must be separated to red, green and blue channel image before using as training sets. Along the procedures, each color channel image will be processed separately.

5. Experimental Results

In this section, we examined the impact of training set upon the hallucination performance by our approach comparing with Eigentransformation [7]. Experimental results demonstrate the performance of our face hallucination method to verify its potential. We find an appropriate setting of regularization parameter $\boldsymbol{\alpha}$ = 0.01 for good performance in experimental result. Besides, we use 3 enhancement methods which are bicubic-interpolation, Eigentransformation, and our proposed method to increase image quality. YaleB [11] and FERET [12] databases are chosen to be the set of simulated experiments.

5.1 YaleB database

The YaleB database were manually cropped and resized to 96×84 pixels. The database contains 38 subjects that are mostly frontal images with different 9 poses and illumination directions. All images of one subject are selected as testing data, while the rest 37 subjects are training data. LR image are downsampled by 4 and 6 respectively. The results of this algorithm for several subjects are shown in Fig.5. Our results have obvious better quality comparing with LR inputs, bicubic-interpolation, and Eigentransformation.

5.2 FERET database

For FERET database, the images were manually cropped and resized to 60×60 pixels and we selected images of 19 subjects. Each image is assigned a different expression such as the center-light, wearing glasses, happy, left-light, without glasses, normal, right-light, sad, surprised and wink. In experiments, all images of one subject are selected as testing data while the rest 18 subjects are training data. LR image are downsampled by 4 and 6 respectively. The images in Figs. 6 and 7 show examples of 60x60 HR grayscale facial images that are reconstructed from 15x15 and 10x10 respectively, while Figs 8 and 9 show examples HR color facial images. The results of this algorithm for several subjects are shown in Fig.4. Moreover, Eigentransformation method is not robust with non-frontal view whereas our results provide better visual quality.

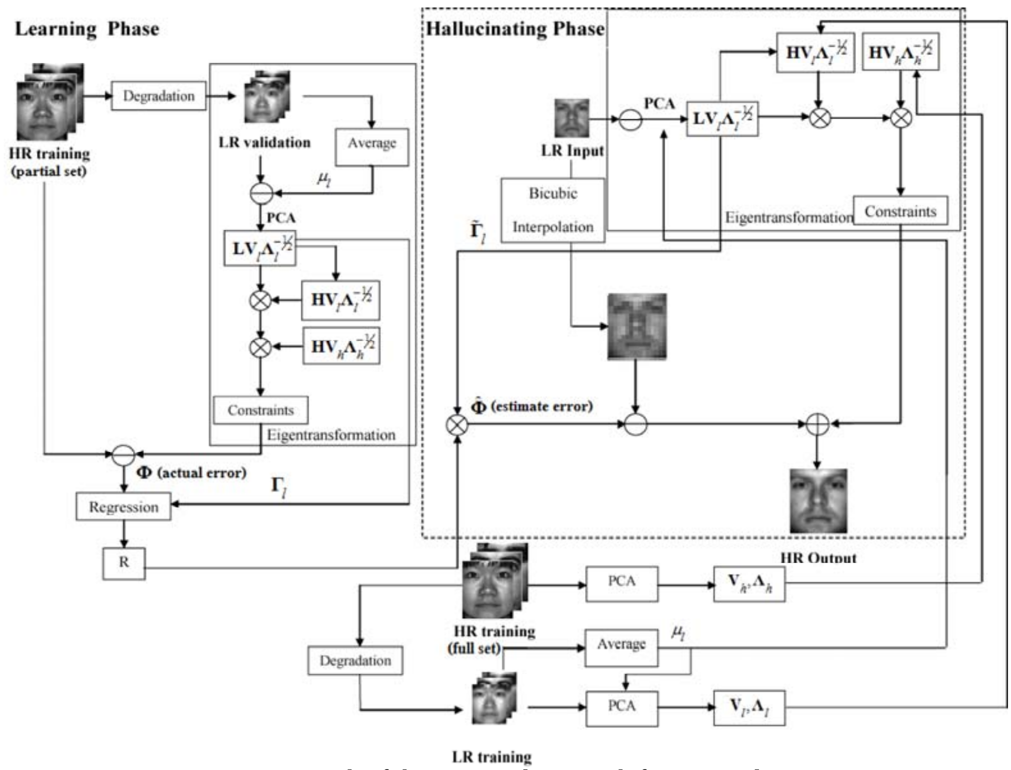

Fig.2 Framework of the proposed approach for grayscale image

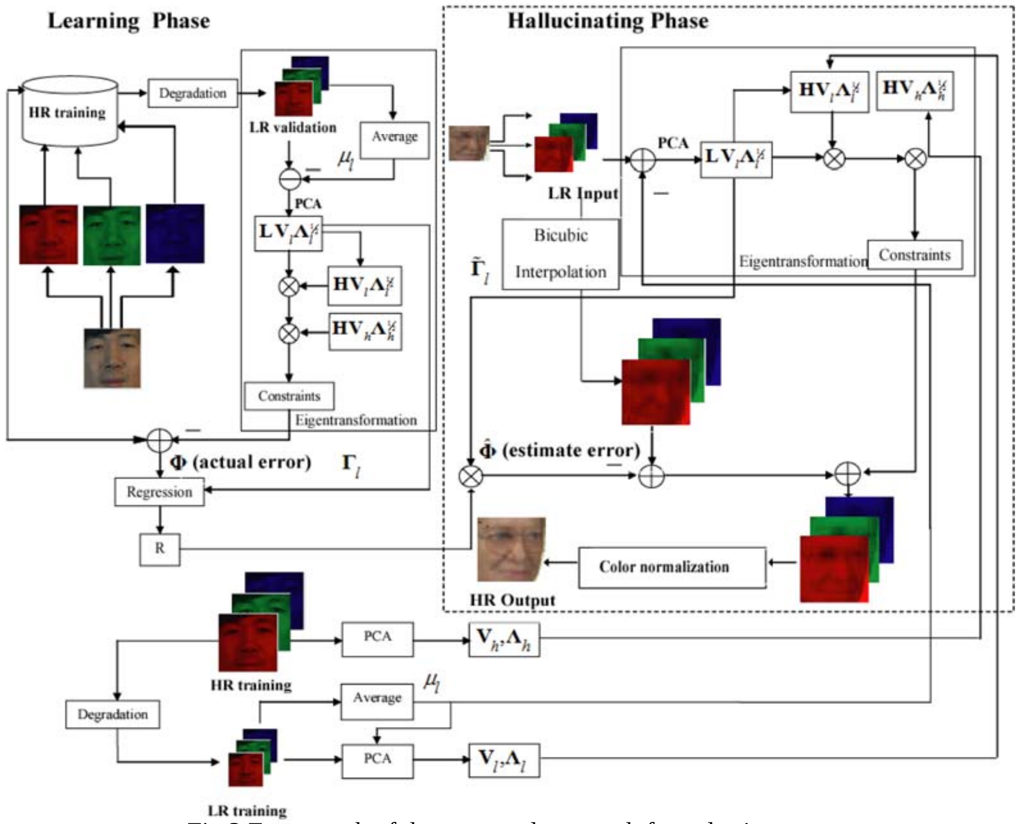

Fig.3 Framework of the proposed approach for color image.

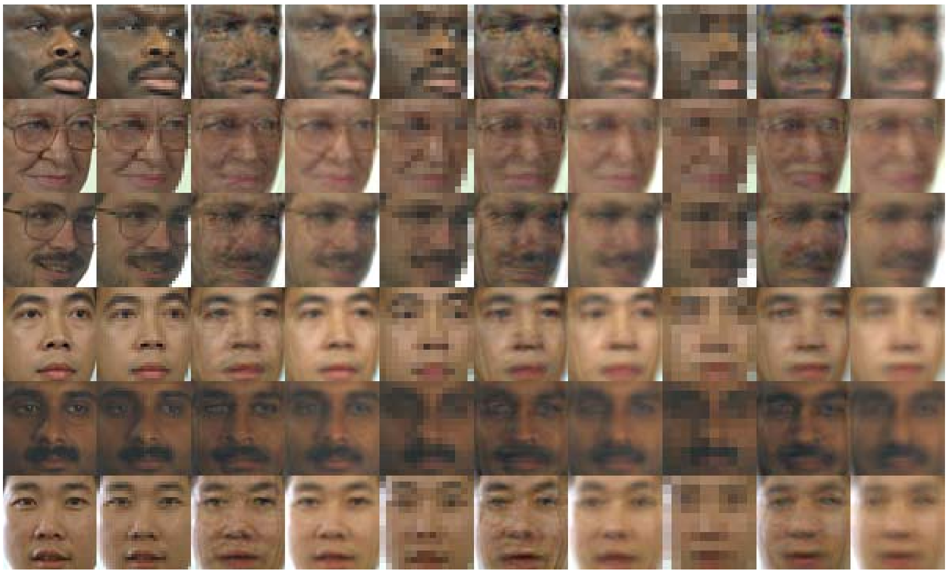

Fig.4 The hallucination result on FERET database. (a) High-resolution 60x60. (b) Low-resolution input 30x30 (2x) (c) Eigentransformation of (b). (d) Eigentransformation with error regression model of (b). (e) Low-resolution input 15x15 (4x). (f) Eigentransformation of (e). (g) Eigentransformation with error regression model of (e). (h) Low-resolution input 10x10 (6x). (i) Eigentransformation of (h). (j) Eigentransformation with error regression model of (h).

Fig.5 The hallucination result on YaleB database. (a) High-resolution 96x84. (b) Low-resolution input 48x42 (2x) (c) Eigentransformation of (b). (d) Eigentransformation with error regression model of (b). (e) Low-resolution input 24x21 (4x). (f) Eigentransformation of (e). (g) Eigentransformation with error regression model of (e). (h) Low-resolution input 16x14 (6x). (i) Eigentransformation of (h). (j) Eigentransformation with error regression model of (h).

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

Fig.6 The hallucination result on FERET database is down-sampled by 4. (a) High-resolution 60x60 (b) Low-resolution input 15x15 (c) Bicubic-interpolation (d) Eigentransformation (e) Eigentransformation with error regression model (f) Difference due HR and image is reconstructed by our propose

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

Fig.7 The hallucination result on FERET database is down-sampled by 6. (a) High-resolution 60x60 (b) Low-resolution input 10x10 (c) Bicubic-interpolation (d) Eigentransformation (e) Eigentransformation with error regression model (f) Difference due HR and image is reconstructed by our propose

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

Fig.8 The hallucination result on FERET database is down-sampled by 4. (a) High-resolution 60x60 (b) Low-resolution input 15x15 (c) Bicubic-interpolation (d) Eigentransformation (e) Eigentransformation with error regression model (f) Difference due HR and image is reconstructed by our propose

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

Fig.9 The hallucination result on FERET database is down-sampled by 6. (a) High-resolution 60x60 (b) Low-resolution input 10x10 (c) Bicubic-interpolation (d) Eigentransformation (e) Eigentransformation with error regression model (f) Difference due HR and image is reconstructed by our propose

6. Conclusions

In this paper, we proposed a novel face hallucination method. Not only reconstruct HR facial image from single LR one, we also apply error estimation to the process to increase the quality of reconstructed facial result. Sample images used in our experiments are from YaleB and FERET databases. The results generated by using our model demonstrate significant improvement better than one generated by traditional Eigentransformation model. The input images for our model can be enhanced up to 6 times of the original size. Moreover, our method has ability to deal with much degraded input images since the reconstruction occurs in LR feature spaces. When working with non-frontal view or different gestures, using our technique also provides finer results than the output from just traditional Eigentransformation method. Not just that, our model can also work well with both grayscale and color images. The only concern which can be further improved is the results from grayscale input image which may have variance in intensity. By the way, they can be corrected by fine tuning parameters in post-processing steps.

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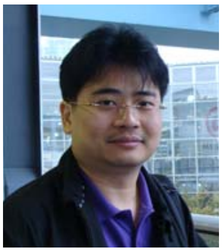

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