# Improved Two-Step Human Face Hallucination with Coupled Residue Compensation

**HAJU MUHAMED MUHAMED NALEER*, YAO LU**, AND ZUBAIR AHMED MEMON*****

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## ABSTRACT

**This paper presents a face hallucination using training data sets as low and high - resolution patch pairs for an input low-resolution face image. It is complicated to be acquainted with details from a low-resolution image since of severe aliasing and unfortunate face image quality, hence gratitude from the low resolution face image may effect in false gratitude decision. In order to get better gratitude performance, the anticipated expansion method is adopted. Considering the coupled PCA compensation algorithm, this capably exploits the local distribution structure in the training samples. The first and second steps were generate global features the main characteristics of the real image and produces residual image to compensate the outcome of the first step respectively. Experiments give an idea about that the anticipated method generate higher quality face image than recent several methods.**

**Key Words:** **Hallucination, Super Resolution, Training Images, Example Based.**

## 1. INTRODUCTION

Baker, et. al. [1], pioneer developer used "hallucination technique" by means of Bayesian formulation. In this technique high-resolution image frequency is obtained via parent structure and the local feature set as pixel support.

In topical years, the ordinary learning-based face super resolution algorithms frequently involve two-steps. The first step generates global structure of real image by means of probabilistic method in MAP (Maximum a Posteriori) frame or manifold learning method such as LLE (Locally Linear Embedding), the second step produces residual image to compensate the results of the first step. However, the two-step framework or residue compensation may not be indispensable in all circumstances. Since the local model has higher [2].

The above all methods were involved with manifold learn model or probabilistic model. But the two step method with coefficient learning using the example-based is described in [2]. In this method; Step1: reconstructed the global image. Step 2: the local face image could be reconstructed (residual image) and these two steps results could be added collectively to outward appearance the ending outcome.

In our study , a innovative technique is anticipated which is hallucination method based on coefficient learning [2], we also use the coefficient learning frame proposed by Xiang, et. al. [2], our approach is patch-based [3-5]. In addition, we have the PCA coupled residual compensation for local feature model and by experimental result show that improvement of low-resolution image.

* Department of Mathematical Science, Faculty of Applied, Sciences, South Eastern University of SriLanka, SriLanka.
** Beijing Laboratory of Intelligent Information Technology, School of Computer Science, Beijing Institute of Technology, Beijing, 100081, China.
*** Associate Professor, Department of Electrical Engineering, Mehran University of Engineering & Technology, Jamshoro

The rest of this paper is well thought-out as follows. The interconnected global linear model and local residual based on coupled residual compensation was surveyed in the next section. In Sections 4 and 5 were represented the experimental setup and results, and conclusions respectively.

## 2. GLOBAL LINEAR MODEL OF FACE

We presume the input low-resolution image $I_L$, and high-resolution images $\left(T_H^i\right)_{i=1}^n$ for training images related low-resolution images $\left(T_L^i\right)_{i=1}^n$. Where the quantity of training images related to *n*. The structural likeness of individual face could be obtained from the following equation [6,2]. It has given as:

$$I_H \approx \sum_{i=1}^{n}\left(\varepsilon_i * \tilde{T}_H^i\right) = \tilde{I}_H \tag{1}$$

Where $I_H$ and $\left(\tilde{T}_H^i\right)_{i=1}^n$ are the yield of interpolated to the identical resolution space of the high-resolution training face images of $I_L$ and $\left(T_L^{i+1}\right)_{i=1}^n$ respectively. And $\varepsilon_i$ are the reconstruction coefficients.

$$\varepsilon = \arg\min \left\| I_H - \sum_{i=1}^{n} \varepsilon_i * \tilde{T}_H^i \right\|^2 \tag{2}$$

$$I'_H = \sum_{i=1}^{n}\left(\varepsilon_i * T_H^n\right) \tag{3}$$

The maximum weight of high-resolution face image reconstruction residual depends on minimization of reconstruction error is defined in Equation (2). And Equation (3) is described that $I'_H$ is the linear equation of the high-resolution face image [2] and is the result of global model face.

## 3. LOCAL RESIDUAL BASED ON COUPLED RESIDUAL COMPENSATION

We bring into being the face image with high frequency along with the use of coupled PCA in residue compensation. The coupled PCA will be initiate, because the human face image obtained by the global linear model is gone to astray some feature of human face image. The relation between low- and high- resolution images were represented as image patches is express by the coupled PCA.

In the training stage, we have to set up the training low and high-resolution training data patch pair's sets for the purpose of residue compensation in the step two. Therefore we setup, for the low and high-resolution training face images sets $\left(M_L^i\right)_{i=1}^n$ and $\left(M_H^i\right)_{i=1}^n$ respectively according to the following Equations (4-5):

$$\left(M_L^i\right)_{i=1}^n = \left(T_L^{i+1}\right)_{i=1}^n - D\left(\tilde{T}_H^i\right)_{i=1}^n \tag{4}$$

$$\left(M_H^i\right)_{i=1}^n = \left(T_H^i\right)_{i=1}^n - \left(\tilde{T}_H^i\right)_{i=1}^n \tag{5}$$

We hallucinate low-resolution patches using global linear model as explain in section 2. Then the patch sample for each low- and high-resolution image could be constructed for residue compensation. The set of small patches with overlap could be obtained from training image patches. The patch $\left(M_L^i\right)_{i=1}^n$ with its adjacent patches. Then these two spaces were trained with help of coupled PCA.

Consider $x_i$ and $y_i$ are indicate the vectors in $\left(M_L^i\right)_{i=1}^n$ and $\left(M_H^i\right)_{i=1}^n$ respectively and correspondent to the identical vector $q_i$ in the unseen space. Then the Equation (6) is show that the relation between $\left(M_L^i\right)_{i=1}^n$ and $\left(M_H^i\right)_{i=1}^n$.

$$y = \left(\frac{y_i}{q_i}\right)\left(\frac{x_i}{q_i}\right)^T x \tag{6}$$

$\left(M_L^i\right)_{i=1}^n$ and $\left(M_H^i\right)_{i=1}^n$ were greater than the dimension of common hidden space. The Equation (7) could be solved by least square and minimization of Equation (7) may help to formulate the PCA.

$$\phi = \sum \left\| y_i - \left(\frac{y_i}{q_i}\right)\left(\frac{x_i}{q_i}\right)^T x_i \right\|^2 \tag{7}$$

In addition, by subtracting the down sampled version of the $\tilde{I}_H$ from original low-resolution image input the residual compensation for input image is obtained.

$$S_L = I_L - D\left(\tilde{I}H\right) \quad (8)$$

Infer the super-resolution residue of $S_L$ obtained by Equation (8). The absolute hallucinated image is formed by adding inferred residue image and the result of global model. The process of the system is shown as shown in Fig. 1.

Experiments give an idea about that, by means of Coupled Residue Compensation, the hallucination excellence can be remarkably improved and also concluding consequence improved.

## 4. EXPERIMENTAL SETUP AND RESULTS

We conduct experiments on a FERET database over randomly selected 480 image pairs with low-resolution and high-resolution and the size of the face image was 96x128. We selected 370 images for training from these samples and remaining part for testing.

In addition to that, all low-resolution images were generated from their high-resolution images by degradations (i.e. down sampling). As well as using affine transformation to fix the position of centers eyes and mouth all the training and testing images are normalized by manually. We compare our system with Xiang, et. al. [2] has been shown in Fig. 2(a-d).

## 5. CONCLUSIONS

In this paper we proposed improvements of two-step hallucination face system based on coupled PCA compensation. Specifically, we modeled the aggradations in the term of local features. There features are extracted by coupled PCA. Experiments on FERET face data base validate our proposed system. We clearly argue from the comparison; our proposed system is shown the significant improvement of two-step face hallucination method.

But, our proposed method is slightly worst when we were considering the computational cost because, the patches making the sparse matrix during the experimental for compensation stage. And this work also limited to frontal low-resolution input image as well as low- and high-resolution training images, Therefore, we glad to say two

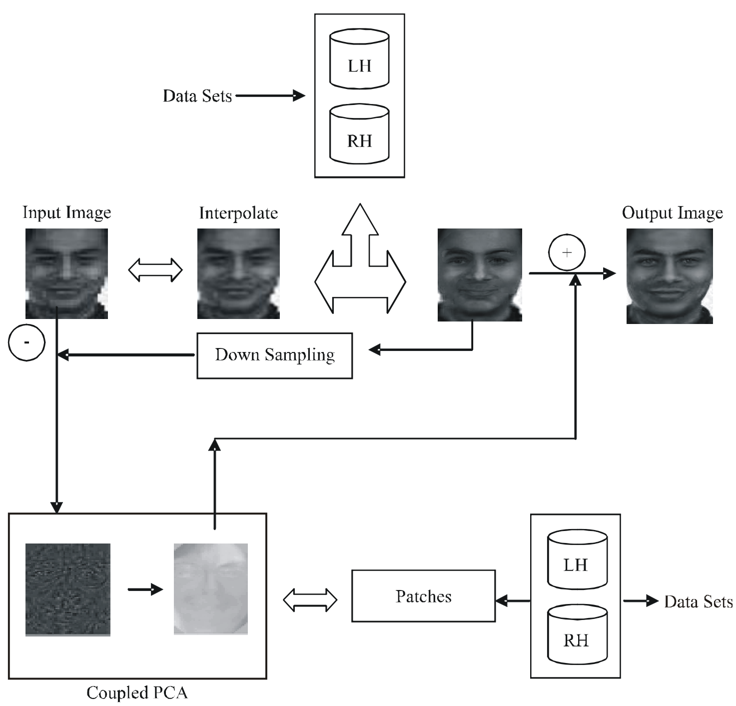
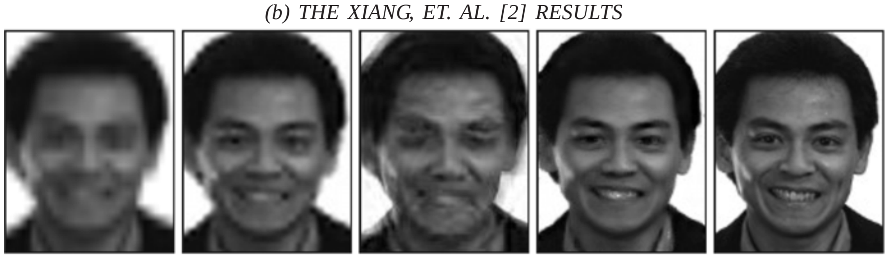


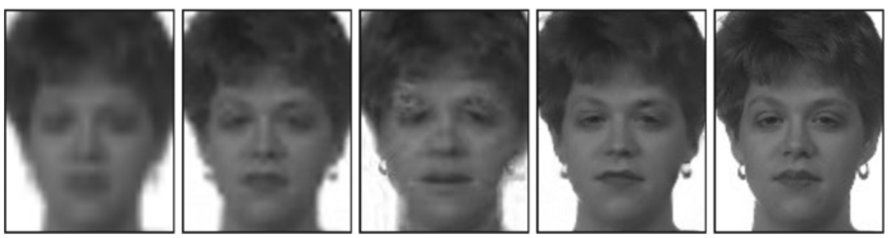

*FIG. 1. THE PROPOSED PROCESS OF THE SYSTEM*

*(a) THE FIRST FRAME OF LOW RESOLUTION INPUT IMAGES SERIES (24x32)*

*(b) THE XIANG, ET. AL. [2] RESULTS*



*(c) OUR SYSTEM RESULTS*



*(d) THE ORIGINAL IMAGES*

*FIG. 2. FACE HALLUCINATION BY XIANG, ET. AL. [2] AND OUR PROPOSED SYSTEM*

direction of future research will focus on computational cost and different face pose input low-resolution image.

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