Rangsit Journal of Arts and Sciences, July-December 2011 RJAS Vol. 1 No. 2, pp. 149-158

A novel tensor framework for face hallucination

Kanjana Boonim[1]* and Parinya Sanguansat[2]

[1]Faculty of Information Technology, Rangsit University, Patumthani 12000, Thailand
E-mail: kboonim@yahoo.com
[2]Faculty of Engineering and Technology, Panyapiwat Institute of Management, Nonthaburi 11120, Thailand
Email: sanguansat@yahoo.com

*Corresponding author

Submitted 8 August 2011; accepted in final form 27 November 2011

Abstract

Normal regression analysis methods can be used to find a relationship between high-resolution (HR) and low-resolution (LR) features. Previous work neglected to use regression analysis methods in finding a relationship between the error of face reconstruction and the LR feature in tensor objects. Because of this limitation, the image as a featured matrix is transformed into one-dimensional vectors, causing a loss of spatial information. By using our method this problem is eliminated. In our proposal we have developed a new face hallucination framework, using a Tensor Regression Analysis (TRA) to further enhance the quality of an image. Error estimation of in the validation system providing the correct final result is further applied into our framework through regression analysis. In doing this, we present our framework based on a two-tier approach. First a global step and second a local step. In the global step, we apply the TRA in order to find a relationship between the features of LR and HR based on multilinear Principal Component Analysis (PCA). The regression coefficients are acquired through the relationship between featured HR and LR. In the local step, the TRA is used to find the relationship between the LR features and the error of validation process, obtained from the global step. Experimental results obtained from a well-known face database show that the resolution and quality of the hallucinated face images obtained with our proposed method are greatly enhanced and improved in comparison with the traditional methods used.

Keywords**:** *Tensor Regression Analysis, face hallucination, super-resolution*

1. Introduction

The important of image processing is in the assistance in the perception and interpretation between humans and computers. Image feeds occur around us and may be extremely weak causing error in perception and interpretation. Nowadays, Closed-Circuit Television (CCTV) is the most widely used; for example, a snapshot obtained from a surveillance video is cropped and magnified for closer inspections. To perceive a snapshot on a finite spatial resolution of images imposes limits on human interpretation. A Low-Resolution (LR) image is one of the most difficult problems commonly encountered in various kinds of image processing (Park & Lee, 2008). An assessment of the image depends on the resolution of the images obtained, from the quality of the images and equipment that highly influences face recognition by humans and computers. Factors affecting image quality of have several distorting processes such as warping, blurring and additive noise (Farsiu, Elad & Milanfar, 2006). Therefore, limited information of image, identification, and reconstruction and expression analysis is a challenge to both humans and computers. For this reason, many methods have been proposed in super-resolution (SR) (Baker & Kanade, 2002; Elad & Feuer, 1997; Freeman & Pasztor, 1999; Hardie, Barnard & Armstrong, 1997; Park, Park & Kang, 2003) in order to combine multiple LR images and provide a higher resolution one. To reconstruct the High-Resolution (HR) image from the LR images, available SR techniques can be performed in three manners (Hua & Shutao, 2009). Firstly, interpolation-based (Hsieh & Andrews, 1978; Jian, Zongben & Heung-Yeung, 2008; Xin & Orchard, 2001) uses LR input only in one image for reconstruction HR output. Secondly, reconstruction-based is degradation using only one LR image, as the input for the reconstruction HR image (Elad & Feuer, 1997; Farsiu & others 2006; Hardie & others 1997; Kimmel, 1999). Finally, learning-based uses a lot of training samples for the reconstruction of an

DOI : 10.14456/rjas.2011.17

HR image, which the image does not necessarily use the same object.

The simple method of SR is interpolation-based (Jian, ongben & Heung-Yeung, 2008; Xin & Orchard, 2001). Conventional linear interpolation schemes (e.g., bilinear and bicubic) based on space-invariant models failure to capture the fast evolving statistics around edges, and therefore, produce interpolated images with blurred edges and annoying artifact (Xin & Orchard, 2001). However, New Edge-Directed Interpolation (NEDI) achieves better. Xin and Orchard (2001) applied the NEDI to reconstruct the global face of the LR input. However, we found that the NEDI method is time consuming and does not result in significant improvement in face hallucination. Jian and others (2008) observed approaches are effective in preserving the edges in the zoomed image by an exploration of the gradient of the prior profile for local image structures and applied it to SR. By this method the limitation of sample is in the small amount of information, therefore, the number of samples must be increased. The interpolation-based is limited in modeling the visual complexity of the real images and the quality of such direct interpolations is usually poor since no new information is included into the process (Wang & Tang, 2005). For natural images with fine textures or smooth shading, these approaches tend to result in images which are similar to the artifact image (Park & Lee, 2008).

Information compensation of an image is also known as reconstruction-based (Elad & Feuer, 1997; Hardie, Brnrd & rmstrong, 1997; Kimmel, 1999). Elad and Feuer (1997) examined a technique for estimating a high-resolution image with reduced aliasing, from a sequence of undersampled frames. Moreover, the registration parameters are iteratively updated along with the high-resolution image in a cyclic coordinate-descent optimization procedure. Hardie et al (1997) utilize three main tools as the Maximum Likelihood (ML) estimator, the Maximum a Posteriori Probability (MAP) estimator and the set theoretic approach using Projection onto Convex Sets (POCS) to improve resolution image, which is restored from several geometrically warped, blurred, noisy and downsampled measured images. Kimmel's proposed method involves two successive steps, the first step is motivated by Coke template matching technique, while the second step uses steerable inverse diffusion in color (Kimmel, 1999). However, the performance of these algorithms degrades apace when the ambition magnification factor is large or the number of available input images is small (Baker & Kanade, 2002). Hence, the above method is suitable only for aerial photography. Interpolation and reconstructed-based methods have limited information, in this way, to increase details of the input image must be increased the number of the same object. In practical, the sample cannot be available. Moreover, human face images have identically common features.

To eliminate the problems in using reconstruction-based, learning-based is proposed in (Baker & Kanade, 2002; CeLiu, Heung-YeungShum & Zhang, 2001; Wang & Tang, 2005; Wei, Dahua & Xiaoou, 2005). Baker and Kanade (2002) were the first to propose a "recognition-based" image pyramid used to learn the prior on the spatial distribution of image gradient for frontal face image. However, the gradient pyramid based prediction introduced with this does not directly model the face initially and the pixels are predicted individually, causing discontinuities and artifacts (Yang, Wright, Huang & Ma, 2010). Liu et al (2001) proposed a two-step approach integrating a parametric global model with Gaussian assumptions and linear inference, and a nonparametric local model based on MRF. However, the methods of Baker and Kanade (2002), and Liu et al (2001) rely on an explicit resolution reduction function, which is sometimes unavailable in practice. Wang and Tang (2005) propose 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. However, the method only utilizes global information without paying attention to the local details and results in images which are similar to the artifact image. Therefore, a learning-based method is suitable for facial image reconstruction. The characteristics a face images has in a common structure which can be learned and used as prior in superresolving face images (Kumar & R.Aravind, 2008). In particular, facial features such as eyes, a nose, and mouth become more difficult to discern. Hence, all problems associated with them are only limited to the facial feature image. To raise the performance of a face recognition system it is often useful to render an HR face image from an LR one, which refers to face hallucination (Liu, Lin & Tang, 2005). For face hallucination, domain knowledge about facial images was used to generate the HR facial images.

The main object of our proposal is learning-based as this method suitable for facial image reconstruction. A face image has a common structure which can be learned and used as prior in super resolving face images (Kumar & R.Aravind, 2008; Liu, Shum & Freeman, 2007). In particular, facial features such as the eyes, nose, and mouth become more difficult to discern. Hence, these problems are only limited to the facial feature image. To raise the performance of a face recognition system it is often useful to render an HR face image from an LR one, which refers to face hallucination (Liu, Lin, & Tang, 2005).

Unlike the previously mentioned method, we proposed in this paper a novel face hallucination approach to utilize a Tensor Regression Analysis (TRA) with multilinear Principal Component Analysis (PCA) which is learning-based. For most of the facial image reconstruction, we found that regression analysis can be used to find a relationship between the HR and LR features. It is not of interest to utilize regression analysis between the error of face reconstruction and the LR feature in a tensor object. With this limitation, the matrices feature images are transformed into one dimensional vectors causing a loss of spatial information. Therefore, in this paper we proposed a novel framework including TRA with multilinear PCA to analyze the two data set relationships. Moreover, the error information is added into our framework in order to correct the final result. The first is the relation between HR and LR features, and the second is the relationship between the error reconstruction in learning and the LR feature. Therefore, all images in our framework does not transform to the vecterization. Thus, data can be preserving.

The remainder of this paper is organized as follows. Section 2 presents the objectives of our proposal. Section 3 describes the related works. In section 4, tensor regression analysis is proposed that includes an algorithm for processing. Our framework is proposed in Section 5. In Section 6, experimental results are presented for the face image database to demonstrate the effectiveness of our proposed techniques. Section 7 is discussion and finally, conclusions are presented in Section 9.

2. Objectives

The proposal is for a novel tensor framework in order to improve the quality of facial image reconstruction, which utilizes a face image matrix not necessarily transformed previously into a vector. The frameworks include Tensor Regression Analysis with multilinear PCA to analyze two data relationship.

3. Related works

In the manner of face hallucination, many frameworks have been famously used; for example, bicubic-interpolation, NEDI, Eigentransformation and a two-step approach. In this paper we select these methods for comparison in the experimental results.

3.1 Bicubic-interpolation

Bicubic-interpolation is often chosen over bilinear interpolation or nearest neighbor in image resampling. Images resampled by bicubic-interpolation are smoother and have fewer interpolation artifacts (Wikipedia, 2011). All digital photos have image interpolation at some stage whether this is in bayer demosaicing or in photo expansion occurring anytime, when you resize or remap your image from one pixel grid to another. Image resizing is essential, when you need to increase or decrease the total number of pixels, whereas remapping can occur under a wider variety of scenarios: correcting for lens distortion, changing perspective, and rotating an image (McHugh, 2011). Although the same image resizes or remap is performed, the results can vary significantly depending on the interpolation algorithm. It is only an approximation; therefore, an image will always lose some quality each time interpolation is performed. For a better understanding, the aim is to provide methods for varying results which will help to minimize any interpolation-induced losses in image quality.

In the original image, a new pixel is a bicubic function using 16 pixels in the nearest 4 x 4 neighborhood of the pixel, which is the method most commonly used by image editing software, printer drivers and many digital cameras for resampling images (Zhang, 2008). Bicubic-interpolation improves the model of the brightness functions by approximating that, locally by a bicubic polynomial surface; traditionally 16 neighboring points are used for interpolation (Nuno-Maganda & Arias-Estrada, 2005).

3.2 NEDI

The New Edge Directed Interpolation (NEDI) also known as "covariance-based adaptive interpolation" which is an estimate local covariance coefficient from an LR image, and then use these covariance estimates to adapt the interpolation at a higher resolution based on the geometric duality between the LR and the HR covariance (Xin & Orchard, 2001). In order to be adaptive, a hybrid approach of switching between bilinear interpolation and covariance-based interpolation is proposed to alleviate the burden of the computational complexity. Geometric duality refers to the correspondence between the HR and the LR covariance that couple the pair of pixels at the different resolution, but along the same orientation. In NEDI, the covariance is used that between pixels and their four nearest neighbors along the diagonal directions. It also assumes that the new pixel in the super-resolution image is obtained by blending the four diagonals with calculated coefficients. The optimal coefficients can be determined to match arbitrarily oriented edges by using local covariance (Hua & Shutao, 2009).

3.3 Eigentransformation

The LR input is approximated by a linear combination of the LR image using the PCA method, and the eigenvector and eigenvalue of LR which is then replaced with the same of HR, and then a new HR face image can be synthesized. The synthesized face image is projected onto the HR eigenface and reconstructed with constraints on the principal component. This transformation procedure is called Eigentransformation, since it uses the eigenfaces to transform the input image to the output result (Wang & Tang, 2005). The eigenfaces are used to represent the face images. A face, $\mathbf{r}_l$ can be reconstructed from the *K* eigenfaces, $\mathbf{E}_l$ = [e1, e2,…,e*k*]. ^1l is mean of LR. $\mathbf{w}_l$ is weight vector and r*l* is reconstruction image of LR.

$$\mathbf{r}_l = \mathbf{E}_l \mathbf{w}_l + \boldsymbol{\mu}_l \tag{1}$$

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

$$\mathbf{E}_l = \mathbf{L}\mathbf{V}_l \boldsymbol{\Lambda}_l^{-1/2} \tag{2}$$

Where $\mathbf{V}_l$ and $\boldsymbol{\Lambda}_l$ are the eigenvector and eigenvalue matrix for $\mathbf{L}^T\mathbf{L}$. From Eq. (1) and Eq. (2), the reconstructed face image can be represented by

$$\mathbf{r}_l = \mathbf{L}\mathbf{V}_l \boldsymbol{\Lambda}_l^{-1/2} \mathbf{w}_l + \boldsymbol{\mu}_l = \mathbf{L}\mathbf{c} + \boldsymbol{\mu}_l \tag{3}$$

Where $\mathbf{c} = \mathbf{V}_l \boldsymbol{\Lambda}_l^{-1/2}, \mathbf{w}_l = [\mathbf{c}_1, \ \mathbf{c}_2, \dots \mathbf{c}_m]^T$

$\mathbf{c}$ describes the weight that each training face contributes in reconstructing the input face can be rewritten as,

$$\mathbf{r}_l = \sum_{i=1}^{M} \mathbf{c}_i \mathbf{l} + \boldsymbol{\mu}_i \tag{4}$$

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 $\boldsymbol{\mu}_h$ is mean of HR. Replacing each LR image $\mathbf{l}'$ by its HR sample $\mathbf{h}$, and replacing $\boldsymbol{\mu}_l$ with the HR mean face $\boldsymbol{\mu}_h$, we get $\mathbf{x}_h$, which is expected to be an approximation to the real HR face image.

$$\mathbf{x}_h = \sum_{i=1}^{M} \mathbf{c}_i \mathbf{h} + \boldsymbol{\mu}_h \tag{5}$$

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

$$\hat{\mathbf{w}}_h = \mathbf{E}_h^T (\mathbf{x}_h - \boldsymbol{\mu}_h) \tag{6}$$

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

$$\tilde{w}_h(i) = \begin{cases} \hat{w}_h(i) & |\hat{w}_h(i)| \le d\sqrt{\lambda_i} \\ sign(\hat{w}_h(i)) * d\sqrt{\lambda_i}, & |\hat{w}_h(i)| > d\sqrt{\lambda_i} \end{cases} \tag{7}$$

It uses $d\sqrt{\lambda_i}$ to bind the principal components. Here, d is a positive scale parameter. The final hallucinated face image is reconstructed by

$$\hat{\mathbf{X}}_h = \mathbf{E}_h \tilde{\mathbf{w}}_h + \boldsymbol{\mu}_h \tag{8}$$

From experimental results, we found that the eigenvector number (*K*) controlled the detail level of the reconstructed face. When *K* is increased, the details of the image could be increased, but the face image was a similar artifact. However, the limitation of this method presents two issues: it could handle only an image that had a little difference and the result image was similar to the non-realistic image.

3.4 A two-step approach

A two-step algorithm is developed to hallucinating faces, the first applied PCA to model HR images and used Maximum a Posteriori (MAP) estimate to reconstruct the global image. Then they built a nonparametric Markov Network between the residual images and the global images in order to estimate the residual image with patch based sampling (CeLiu & others 2001).

Let $\mathbf{l}$ and $\mathbf{h}$ denote the HR and LR images respectively. If $\mathbf{l}$ is $s2$ times smaller than $\mathbf{h}$, $\mathbf{l}$ can be computed as

$$\mathbf{l}(a,b) = \frac{1}{s^2}\sum_{i=0}^{s=1}\sum_{j=0}^{s=1}\mathbf{h}(sa+i, sb+j) \quad (9)$$

where s is always a positive integer and n is the random noise. For notation simplification, if $\mathbf{h}$, $\mathbf{l}$ and n are respectively $\mathbf{n}$-$\mathbf{d}$ and $\mathbf{m}$-$\mathbf{d}$ vectors $\left(\mathbf{m} = \mathbf{n}/s^2\right)$, Eq. (9) can be rewritten as

$$\mathbf{l} = \mathbf{D}\mathbf{h} + \boldsymbol{\eta} \quad (10)$$

For a given $\mathbf{l}$, based on the MAP criterion the optimal $\mathbf{h}$ can be found by maximizing the posterior probability $\mathbf{P}\left(\mathbf{l}|\mathbf{h}\right)$, i.e.

$$\mathbf{h} = \arg\max \mathbf{P}\left(\mathbf{l}|\mathbf{h}\right)\mathbf{P}\left(\mathbf{h}\right) \quad (11)$$

Experiments indicate that our approach is insensitive to the down-sampling model, that will be shown in Eq. (10) Likelihood can be derived from the relationship between $\mathbf{l}$ and $\mathbf{h}$ such as Eq. (11). Finally, the hallucinating face is given by

$$\mathbf{h} = \mathbf{h}^g + \mathbf{h}^l \quad (12)$$

where $\mathbf{h}^g$ is global image and $\mathbf{h}^l$ is residual image with patch based sampling.

However, the global image obtaining from applying PCA and local image receiving from the optimal residual image are estimated under a MAP criterion. Thus, the limitation of this method is the input image which would be transformed into a vecterization.

4. Tensor Regression Analysis

In this section, the regression analysis is briefly described, and then the ridge regression is presented to solve this problem. Most previous face hallucination does not take into interest the regression analysis in tensor. Generally regression analysis can be used to find the relationship between HR and LR feature only. Therefore, all images must be transforming into vecterization, for this reason it causes a loss of spatial information. Inspired by this limitation, our proposal takes regression analysis in the tensor.

In order to describe the mathematical procedure for the reconstruction method above, the following notations are defined. The regression coefficient R can solve by least squares estimator

$$\mathbf{R} = \mathbf{h}\boldsymbol{\Gamma}_l^T\left(\boldsymbol{\Gamma}_l\boldsymbol{\Gamma}_l^T\right)^{-1} \quad (13)$$

Where $\mathbf{h}$ is a HR image, $\boldsymbol{\Gamma}_l$ is a LR feature. Practically, regression coefficient cannot be computed by the above equation shown in Eq. (13) because the invert term does not exist. Therefore, tensor regression analysis adopts the regularization parameter to solve this problem. The regression coefficient R is defined by the following equation:

$$\mathbf{R} = \mathbf{h}\boldsymbol{\Gamma}_l^T\left(\boldsymbol{\Gamma}_l\boldsymbol{\Gamma}_l^T + \lambda\mathbf{I}\right)^{-1} \quad (14)$$

thus, the singularity problem is avoided by a suitable regularization parameter¸ λ >0, I is the identity matrix.

In (Wei, Dhu & Xiaoou, 2005), the coupled PCA algorithm is used for learning the relation between HR and LR residue, which is utilized for compensating the error residue in facial images hallucination. (Senjian, Wanquan & Venkatesh, 2007), an HR patch is obtained from learning by using Orthogonal Locality Preserving Projections (OLPP) in the first step. In the second step, Kernel Ridge Regression (KRR) is used learning the relationship between residual patches of LR and HR. The global images of these frameworks are not interested in utilizing regression analysis in the tensor. It was still on a vector form.

From Eq. (14), we cannot solve $\mathbf{R}$ more than two variables. Therefore, in this paper we apply regression analysis into tensor object, which both of the input and the outputs were tensor. To overcome these problems, in this paper, we proposed a novel framework including the TRA technique in order to improve the quality of the facial image. We can compute the feature matrix of the HR image as follows:

$$\mathbf{B}_h = \mathbf{R}_1 \mathbf{B}_l \mathbf{R}_2 \tag{15}$$

Where $\mathbf{B}_h$ is feature matrix of HR image, $\mathbf{B}_l$ is feature matrix of LR image, $\mathbf{R}_1$ and $\mathbf{R}_2$ are regression coefficient in tensor. Thus, $\mathbf{R}_1$ and $\mathbf{R}_2$ can be defined by tensor regression analysis.

However, Tensor regression analysis can be implemented to the following theorem.

Theorem: The above defined tensor regression analysis for improvement reconstructive image. Proof: Let $A_h \in \mathbb{R}^{I_1 x I_2}$ and $A_l \in \mathbb{R}^{I_1 x I_2}$ be the image pair of high resolution and its corresponding low resolution, as the second order tensor.

Let $f\left(\mathbf{R}_1, \mathbf{R}_2\right) = \sum_{n=1}^{N} \left\| \mathbf{A}_h - \mathbf{A}_l \times_1 \mathbf{R}_1 \times_2 \mathbf{R}_2 \right\|$ be an objective function, where N is the number of image pairs.

Forcing $\frac{\partial}{\partial \mathbf{R}_1} \mathbf{f}(\mathbf{R}_1, \mathbf{R}_2) = 0$, we have

$$\mathbf{R}_1 = \left(\sum_{n=1}^{N} \left(\mathbf{A}_l\right)^T \mathbf{R}_2 \mathbf{R}_2^T \mathbf{A}_l \right)^{-1} \sum_{n=1}^{N} \left(\mathbf{A}_l\right)^T \mathbf{R}_2 \mathbf{A}_h \tag{16}$$

Forcing $\frac{\partial}{\partial \mathbf{R}_2} \mathbf{f}(\mathbf{R}_1, \mathbf{R}_2) = 0$, we have

$$\mathbf{R}_2 = \left(\sum_{n=1}^{N} \mathbf{A}_l \mathbf{R}_1 \mathbf{R}_1^T \left(\mathbf{A}_l\right)^T \right)^{-1} \sum_{n=1}^{N} \mathbf{A}_l \mathbf{R}_1 \left(\mathbf{A}_l\right)^T \tag{17}$$

From above equation, TRA can be manipulated to an algorithm as follow

Table 2 Tensor Regression Analysis (mode 2) Algorithm

Input : $\mathbf{A}_h, \mathbf{A}_l$
Output: $\mathbf{R}_1, \mathbf{R}_2$

Step1: Obtain initial $\hat{\mathbf{R}}_1$ and set i←1
Step2: while not convergent do
Step3: compute from equation

$$\mathbf{R}_2 = \left(\sum_{n=1}^{N} \mathbf{A}_l \mathbf{R}_1 \mathbf{R}_1^T \left(\mathbf{A}_l\right)^T \right)^{-1} \sum_{n=1}^{N} \mathbf{A}_l \mathbf{R}_1 \left(\mathbf{A}_l\right)^T$$

Step4: compute from equation

$$\mathbf{R}_1 = \left(\sum_{n=1}^{N} \left(\mathbf{A}_l\right)^T \mathbf{R}_2 \mathbf{R}_2^T \mathbf{A}_l \right)^{-1} \sum_{n=1}^{N} \left(\mathbf{A}_l\right)^T \mathbf{R}_2 \mathbf{A}_h$$

Step5: $\hat{\mathbf{R}}_1 = \mathbf{R}_1$
Step6: end while

TRA as being seen also in Table 2 improved the quality of reconstruction. The TRA with multilinear PCA analyzes the two data relationships, in which the input and output data were the tensor object. The first regression: $\mathbf{TRA}_{HR}$ was the relationship between the HR and the LR feature. While the second one: $\mathbf{TRA}_{error}$ was the relationship between the error reconstruction in the learning process and the LR feature such TRA was carried out continuously in order to observe the change rate until its function was over when its value was changed into non-convergence and then the last two values would be selected.

5. Our framework

In this section, we develop a novel face hallucination framework using tensor regression analysis. Moreover, we add the error estimation of the validation process into our framework. Most previous work on face hallucination does not take such error into account. Therefore, the error estimation is included into our framework by applying TRA with multilinear PCA to analyze the relationships of the two data sets. In this way, Bilateral Two Dimensional Principal Component Analysis (B2DPCA) is incorporated to learn the face subspace of the LR and the HR training. The success of this newly developed framework to achieve this implementation can be described as follows.

5.1 Error estimation

To accurately approximate the prior facial reconstruction of the target HR face, a validation process is necessary. Many previous works neglect this error in facial reconstruction. Thus, the feedback of this error may benefit facial reconstruction. In this paper, we apply regression analysis between the error and LR feature. The error computes from the HR image to subtract with the image reconstructed by TRA. After that, the error and LR training feature are manipulated by the regression analysis.

5.2 Patch based processing

In the experiment, the images would be sliced through mirror-image patches to decrease problems from image margins. From the experiments, the optimum values are six slices and twelve overlaps. In this way, we get 36 blocks, although it would be better if we had more data sets used as training samples. However, the amount of data sets used in the training step was often inadequate. Our framework used this method for slicing and overlapping HR and LR training counterparts.

5.3 $\mathbf{TRA}_{HR}$ and $\mathbf{TRA}_{error}$

In this study, we proposed a new alternative framework shown in Figure 1, including the Tensor regression analysis to improve the quality of reconstruction. The first regression: $\mathbf{TRA}_{HR}$ is used for the relationship between the HR and the LR feature. The second one: $\mathbf{TRA}_{error}$ is the relationship between the error reconstruction in learning and the LR feature.

5.4 Bilateral two dimensional principal component analysis (B2DPCA)

For data reduction in our framework we use B2DPCA for HR and LR training. Before this procedure, HR and LR training are sliced and overlapped by patch based processing. We can illustrate the B2DPCA algorithm as follows.

Algorithm B2DPCA

Require: $\left\{\mathbf{A}_{H_k}, \mathbf{A}_{L_k}\right\}_{k=1}^{N}$

Ensure : $\mathbf{V}_h, \mathbf{V}_l, \mathbf{\Lambda}_h, \mathbf{\Lambda}_l$

1: HR and LR image are decomposed that slice and overlap by patch based processing.
2: Compute the image covariance matrices of HR image, $\mathbf{G}_h'$ and $\mathbf{H}_h'$.
3: Compute the image covariance matrices of LR image, $\mathbf{G}_l'$ and $\mathbf{H}_l'$.
4: Compute the eigenvectors of $\mathbf{G}_h' \rightarrow \mathbf{V}_h$.
5: Compute the eigenvectors of $\mathbf{G}_l' \rightarrow \mathbf{V}_l$.
6: Compute the eigenvalues of $\mathbf{H}_h' \rightarrow \mathbf{\Lambda}_h$.
7: Compute the eigenvalues of $\mathbf{H}_l' \rightarrow \mathbf{\Lambda}_l$.
8: for k = 1 to N do
9: Project the HR image to HR feature space,
10: Project the LR image to LR feature space,
11: end for

In Figure 1 illustrates the implementation procedures of our framework for face hallucination base on two-steps as follows.

Step 1: Global Step

1. HR training images degraded to obtain their LR.
2. HR and LR training images are sliced and overlap by patch base processing.
3. HR training is used to train B2DPCA to obtain the eigenvectors $\mathbf{V}_h$ and eigenvalues $\mathbf{\Lambda}_h$ of HR space.
4. After that, this LR training set is used to train B2DPCA to obtain the eigenvectors $\mathbf{V}_l$ and eigenvalues $\mathbf{\Lambda}_l$ of LR space.
5. The regression coefficients $\mathbf{R}_1$ and $\mathbf{R}_2$ is acquired form relationship between feature of HR and LR by $\mathbf{TRA}_{HR}$.
6. Validation process picks up LR feature from training set for face hallucination by TRA method.
7. The reconstruction error is received from the reconstruction image in the previous step and original image of itself.
8. Global image as G recon is reconstructed from LR feature space and regression coefficient in article 5.

Step 2: Local Step

1. The regression coefficients $\mathbf{R}_1$ and $\mathbf{R}_2$ is acquired form relationship between feature of LR and error of validation process from global step by $\mathbf{TRA}_{HR}$.
2. The error estimation is evaluated from the LR feature space and regression coefficient.
3. The resulting HR image is obtained from the computation by adding the error estimation image in article 2 of the local step with the global image from article 8 of the global step.

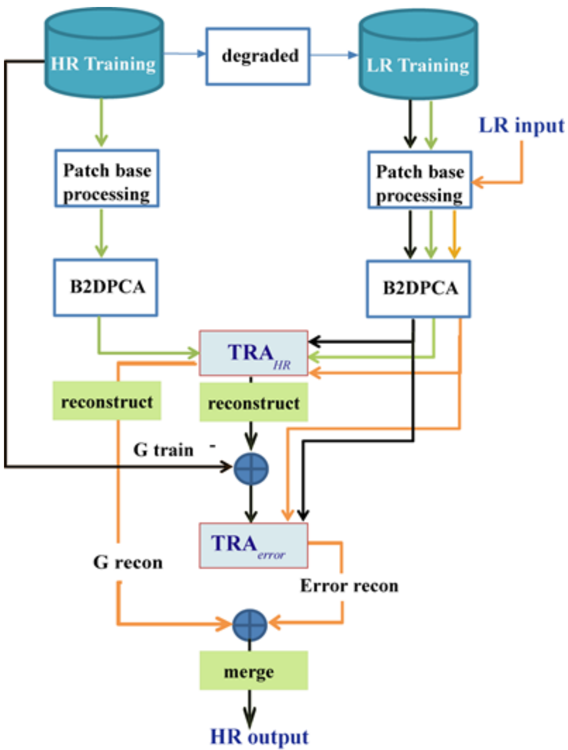

Figure 1 Proposed Frameworks to analyze the relationship of the two data relations by bases with a two step approach

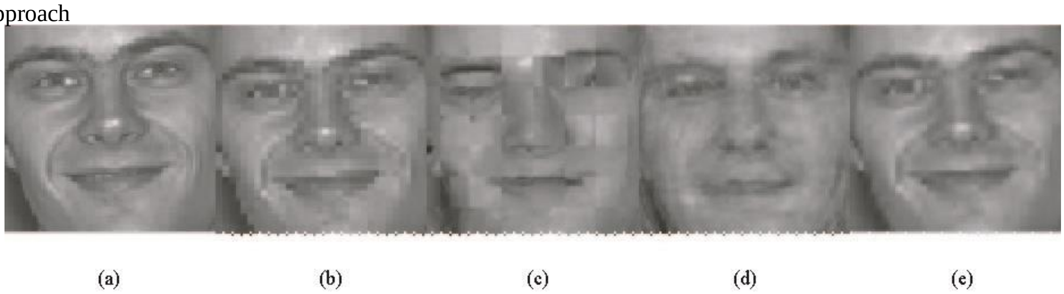

Figure 2 HR facial images reconstructed by the different regression analysis (a) High-resolution 60x60 (b) Low-resolution input 30x30 (c) None Regression Analysis (d) Normal Regression Analysis (e) Tensor Regression Analysis

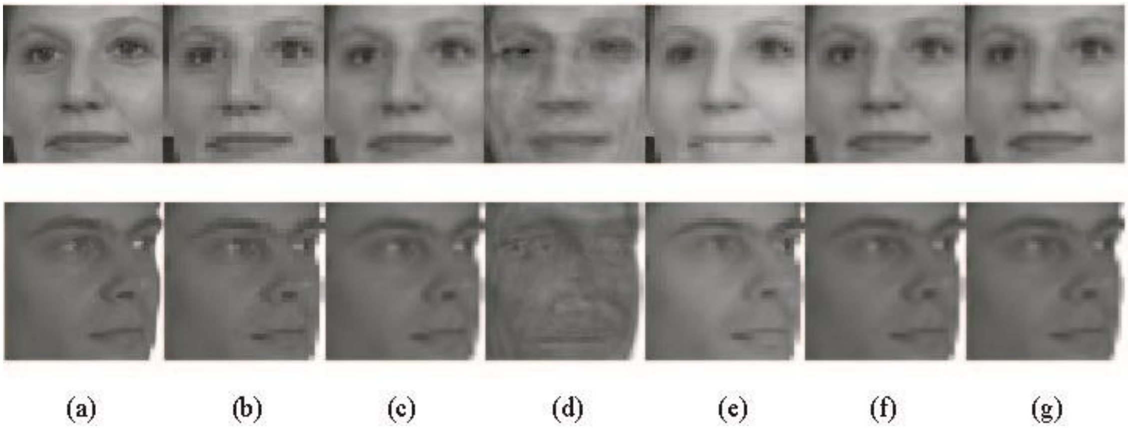

Figure 3 HR facial images reconstructed by the different methods using a magnification a) High-resolution 60x60 (b) Low-resolution input 30x30 (c) Bicubic-interpolation (d) Eigentransformation (e) NEDI (f) Image is reconstructed by our proposal as TRA (g) Image is reconstructed by our proposal as TRA combine with error

6. Experimental results

In our experiments, we examined the impact of training sets upon the hallucination performance by our approach comparing bicubic-interpolation (Nuno-Maganda & Arias-Estrada, 2005), Eigentransformation (Wang & Tang, 2005) and NEDI (Xin & Orchard, 2001). The FERET database was manually cropped and resized to 60 × 60 pixels, which are contains 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. The leave-one-out strategy is used to evaluate our technique; all images of one subject are selected as testing data while the remaining 18 subjects are training data. The images in Figure 2 show examples of 60x60 HR facial images, which are reconstructed from 30x30. The image in Figure 2 (c) cannot discernible causing a checkerboard effect because the image does not using regression analysis. Image in Figure 2 (d) can be discernible, but it is not better than the image in Figure 2 (e) with the success that resulted from TRA. In Figure 3, the results of this algorithm show that the non-frontal view, with the Eigentransformation method in Figure 3 (d) is not accurate with a non-frontal view whereas our results in Figures 3 (f) and (g) provide better visual quality. Therefore, the experimental results of our framework, which uses the FERET database, shows that reconstruction outputs are better than the traditional method. When comparison with the results generated from traditional methods: bicubic-interpolation, Eigen-transformation and NEDI, the results created by applying TRA with multilinear PCA are looking better. Outputs created from Eigentransformation are simply artifacts while ones generated from NEDI have over light in the middle of the image and take great time to process.

7. Conclusion

TRA with multilinear PCA is used in the framework to analyze the relationship of the two data sets. The first relationship is the relationship between the HR and LR features, and then the second ones is the relation between error reconstruction in learning and LR feature. From the experimental results, we found that the result from our proposed method can perform face reconstruction better than the traditional methods. When compared with the Bicubic-Interpolation, Eigentransformation and New Edge-Directed Interpolation (NEDI), the results show that our proposed techniques provide better output than conventional algorithms. The results from Eigentransformation are only artifacts and non-robust with non-frontal view image while ones generated from NEDI have over light in the middle of image.

8. Acknowledgements

This study is supported by Rangsit University, and the Institute of Physical Education Bangkok Campus. Additionally, the invaluable recommendation and supervision from anonymous reviewers are much appreciated.

9. References

Baker, S., & Kanade, T. (2002). Limits on super-resolution and how to break them. In *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 24, 1167-1183.

Elad, M., & Feuer, A. (1997). Restoration of a single superresolution image from several blurred, noisy, and undersampled measured images. In *IEEE Transactions on Image Processing*, 6, 1646-1658.

Farsiu, S, Elad, M., & Milanfar, P. (2006) Multiframe demosaicing and super-resolution of color images. In *IEEE Transactions on Image Processing, 15,* 141-159.

Freeman, W. T., & Pasztor, E. C. (1999). Learning low-level vision. In *7th IEEE International Conference on Computer Vision*, 1182-1189.

Hardie, R. C., Barnard, K. J., & Armstrong E. E. (1997). Joint MAP, registration and high-resolution image estimation using a sequence of undersampled images. In *IEEE Transactions on Image Processing*, 6, 1621-1633.

Hsieh, H., & Andrews, H. (1978). Cubic splines for image interpolation and digital filtering. In *IEEE Transactions on Acoustics, Speech and Signal Processing*, 26, 508-517.

Hua, S., & Shutao, L. (2009). Hallucinating faces by interpolation and principal component analysis. In *Second International Symposium on Computational Intelligence and Design (ISCID)*, 295-298.

Jian, S., Zongben, X. & Heung-Yeung, S. (2008). Image super-resolution using gradient profile prior.In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1-8.

Liu, C., Shum, H-Y., & Zhang, C-S. (2001). A two-step approach to hallucinating faces: Global parametric model and local nonparametric model.In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 1*, 192-198, 2001.

Kimmel, R. (1999). Demosaicing: image reconstruction from color CCD samples. In *IEEE Transactions on Image Processing, 8,* 1221-1228.

Kumar, B. G. V., & Aravind, R. (2008). A 2D model for face superresolution. In *19th IEEE Conferences*, 1-4. DOI: 10.1109/ICPR.2008.4761072

Liu, C., Shum, H.-Y., & Freeman, W. (2007). Face hallucination: Theory and practice." *International Journal of Computer Vision*, 75, 115-134.

Liu, W., Lin, D., & Tang, X. (2005). Neighbor combination and transformation for hallucinating faces. In *IEEE International Conference on Multimedia and Expo (ICME)*, 1-4.

McHugh, S. (n.d.). Digital Image Interpolation. [On line] Retrieved 15 March 2011 from http://www.cambridgeincolour.com/tutorials/image-interpolation.htm

Nuno-Maganda, M. A., & Arias-Estrada, M. O. (2005). Real-time FPGA-based Architecture for bicubic interpolation: An application for digital image scaling. In *International Conference on Reconfigurable Computing and FPGAs (ReConFig)*, 1-8.

Park, J-S., & Lee, S-W. (2008). An example-based face hallucination method for Single-frame, low-resolution facial images. In *IEEE Transactions on Image Processing*, 17, 1806-1816.

Park, S. C., Park, M. K., & Kang M. G. (2003) Super-Resolution Image Reconstruction. In *IEEE Signal Processing Magazine*,Vol, 21-36.

Senjian, A., Wanquan, L. & Venkatesh, S. (2007). Face recognition using kernel ridge regression. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1-7.

Wang, X., & Tang, X. (2005). Hallucinating face by eigentransformation. In *IEEE Transactions on Systems, Man and Cybernetics*, 35, 425-434.

Wei, L., Dahua, L., & Xiaoou, T. (2005). Hallucinating faces: Tensor patch super-resolution and coupled residue compensation. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, 478-484.

Wikipedia. (n.d.). Bicubic Interpolation.[On line] Retrieved 15 March 2011from: http://en.wikipedia.org/wiki/Bicubic_interpolation

Xin, L., & Orchard, M. T. (2001). New edge-directed interpolation. In *IEEE Transactions on Image Processing, 10,* 1521-1527.

Yang Jianchao, Wright John, Huang Thomas S. & Ma Yi. "Image Super-Resolution Via Sparse Representation." *IEEE Transactions on Image Processing*. 19 (2010): 2861-2873.

Zhang, X-g. (2008). A new kind of super-resolution reconstruction Algorithm based on the ICM and the constrained cubic spline interpolation.In *International Symposium on Intelligent Information Technology Application Workshops*, 530-534.