Face Hallucination using Eigen Transformation in Transform Domain

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Abstract

Faces often appear very small in surveillance imagery because of the wide fields of view that are typically used and the relatively large distance between the cameras and the scene. In applications like face recognition, face detection etc. resolution enhancement techniques are therefore generally essential. Super resolution is the process of determining and adding missing high frequency information in the image to improve the resolution. It is highly useful in the areas of recognition, identification, compression, etc. Face hallucination is a subset of super resolution. This work is intended to enhance the visual quality and resolution of a facial image. It focuses on the Eigen transform based face super resolution techniques in transform domain. Advantage of Eigen transformation based technique is that, it does not require iterative optimization techniques and hence comparatively faster. Eigen transform is performed in wavelet transform and discrete cosine transform domains and the results are presented. The results establish the fact that the Eigen transform is efficient in transform domain also and thus it can be directly applied with slight modifications on the compressed images.

Keywords: Face hallucination, Super resolution, Eigen transformation, wavelets, discrete cosine transform.

1. INTRODUCTION

In most electronic imaging applications, images with high spatial resolution are desired. High resolution (HR) means that pixel density within an image is high, and therefore an HR image can offer more details than its low resolution counter part. The performance of face recognition or detection in computer vision can be improved if an HR image is provided. The direct solution to increase spatial resolution is to reduce the pixel size by sensor manufacturing techniques. As the pixel size decreases, however, the amount of light available also decreases, which generates shot noise that degrades the image quality severely. Also to reduce the pixel size, there exists a minimum limit, which is already achieved. An alternate approach is to use signal processing techniques to obtain an HR image from one or more low-resolution (LR) images. Recently, such a resolution enhancement approach has been one of the most active research areas, and it is called super resolution (SR) image reconstruction or simply Super resolution. The major advantage of the signal processing approach to improve resolution is that it is less costly and the existing LR imaging systems can be still utilized. The SR image reconstruction has wide fields of application like medical imaging, Synthetic zooming, forensics, satellite imaging and video applications. Another application is in the conversion of an NTSC video signal to HDTV format.

There are two different types of super resolution approaches. In the first type, more than one low resolution images are used to produce a high resolution image. It is generally called multi-frame super resolution. In multi-frame super resolution, HR image is synthesized from input images alone, so these are also called reconstruction based super resolution. Another type of super resolution uses a single low resolution image as the input to produce a high resolution image. This method is called single frame super resolution. Most of the single frame image super-resolution algorithms use a training set of HR images and the additional details of the HR image to be synthesized is learnt from these HR training set. Such algorithms are called learning based super resolution algorithms.

The simplest signal processing technique to increase resolution is the direct interpolation of input images using techniques such as nearest neighbor, cubic spline, etc. But it does not add any extra information to the image. Also its performance become poor if the input image is too small in size.

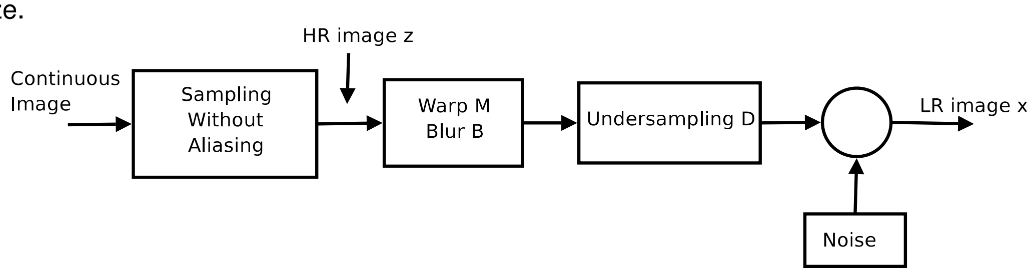

FIGURE 1: A digital low resolution image acquisition model

1.1 LR Image Formation Model

A LR image formation model is shown in Figure 1, the observed LR images result from warping, blurring, and subsampling operations performed on the HR image ***z***. Assuming that LR image is corrupted by additive noise, we can then represent the observation model as

$$x = DBMz + \eta \tag{1}$$

Where ***D*** is the decimation or subsampling matrix, ***B*** is the blur matrix and $\boldsymbol{\eta}$ represents noise vector. The motion that occurs during the image acquisition is represented by warp matrix ***M***. It may contain global or local translations, rotations and so on. Blurring may be caused by an optical system (e.g., out of focus, diffraction limit, aberration, etc.) and the point spread function (PSF) of the LR sensor. Its effects on HR images are represented by the matrix ***B***. The subsampling matrix D generates aliased LR images from the warped and blurred HR image.

Face hallucination, the term coined by Baker and Kanade [1] is the super resolution of face image, which is the process of synthesizing a high resolution face image from low resolution observation. Figure 2 shows the schematic of face hallucination algorithm. Face hallucination techniques can be useful in surveillance systems where the resolution of a face image is normally low in video, but the details of facial features which can be found in an HR image may be crucial for identification and further analysis. The standard super resolution techniques may also introduce some unwanted high frequency components. However, hallucinating faces is more challenging because people are so familiar with the face image. This specialized perception of faces requires that a face synthesis system be accurate at representing facial features and the process should not introduce many unwanted details. A small error, e.g. an asymmetry of the eyes, might be significant to human perception [17], whereas for super resolution of generic images the errors in textured regions, e.g. leaves, grasses, etc. are often ignored.

This work studies the feasibility of Eigen transformation based super resolution in transform domain for synthesizing high resolution face images. Advantage of Eigen transformation based technique is that, it does not require iterative optimization, which considerably reduces the processing time. Eigen transform is performed in wavelet transform and discrete cosine transform domains and the results are presented. This work establishes the fact that the Eigen transform is efficient in transform domain and thus it can be directly applied to the compressed images.

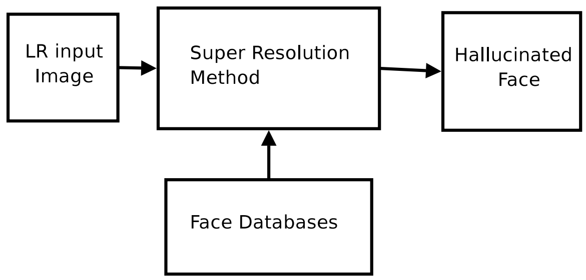

FIGURE 2: block schematic of face hallucination system

2. RELATED WORKS

In the paper "Hallucinating Faces", Kanade and Baker introduced the term face hallucination for super resolution of face image [1][2]. They use a single LR observation to synthesize an HR face image, making use of a training set of HR face images. High frequency details of the HR face image are learned by identifying local features from the training set. In the above hallucination approach, a Gaussian image pyramid is formed for every image in the training set as well as for the LR observation. A set of features are computed for every image in the image pyramid resulting in a feature database. The feature vector for hallucinated image is learned from these feature vector database. Hallucinated face is estimated using maximum a posteriori (MAP) framework, which uses leaned prior in its cost function. The final gray level image is then obtained by gradient descent optimization to fit the constraints learned from the facial features. So here the high frequency part of the face image is purely fabricated by learning the properties from the similar HR images.

The images hallucinated by Baker and Kanade appear to be noisy at places, especially where the test image and training set images have significantly different features. As the magnification increases the noise increases as well. Liu, Shum and Zang [3] argued that face hallucination algorithms should consider the following constraints.

i. The result must be very close to the input image when smoothed and down sampled.
ii. The result must have common characteristics of human face, *e.g* eyes, mouth, nose, symmetry, etc.
iii. The result must have specific characteristics of this face image with realistic local features.

Baker and Kanade considered the first condition but not focused on the next two. Liu, Shum and Zhang [3] proposed a two step approach to take the above constraints into account. It is done by incorporating the local features of face image as well as the global structure. Local features are learned by using a patch based method. Global structure of the face is determined by learning principal component coefficients. Locally learned patches are then combined with the global face structure to give the hallucinated face image.

Capel and Zisserman proposed a principal component analysis (PCA) based learning method for face image super resolution [6]. A collection of registered face images are used as the training set and the image is modeled using PCA basis computed from these training images. In this method the face image is divided in to six regions or subspaces. The intuition here is that these regions are relatively uncorrelated and that, by considering small regions, better models can be learnt than would be by performing PCA on the whole face. Each of the subimages is separately super resolved using PCA based learning method. The reconstructed subspaces are combined to give hallucinated face.

Jiji et al. [8] proposed a wavelet based single frame super resolution method for the super resolution of general images. It makes use of a training set consist of HR images from different categories. In this method, observed image as well as the images in data base are decomposed using wavelet transform. Wavelet coefficients of the super resolved image are learned from the coefficients of images in the database. The HR image is estimated under a MAP frame work using the learned wavelet prior. An edge preserving smoothness constraint is used to maintain the continuity of edges in the super resolved image. This method is applied on face images, but as it is formulated for general images, it does not consider the structural properties of face image and therefore the results are not good for higher magnification factors.

A promising approach for face hallucination is proposed by Wang and Tang [13][14]. This method is based on the face recognition using Eigen faces [11] and it is computationally much efficient than any previous algorithms. It does not require iterative optimization techniques. A registered HR face image training set is used here and a corresponding LR training set is prepared by down sampling the HR images. If the blur matrix is known, it can be incorporated by filtering the HR images with blur matrix, before down-sampling it to produce LR training set. LR observation image is then represented as the linear combination of LR database images. The linear combination coefficients are determined from the PCA coefficients. The super resolution is achieved by finding the linear combination of the HR images with the same coefficients. To avoid abnormalities in the image, regularization is done with respect to Eigen values. Besides other methods, Eigen transformation based method give better results even with higher magnification factors.

3. EIGEN TRANSFORMATION BASED SUPER RESOLUTION

Eigen transformation (ET) based super resolution makes use of a registered set of HR face images as training set. PCA models are formulated for HR and LR image space using the respective training sets. This section discusses the PCA in brief followed by super resolution using Eigen transformation.

3.1 Principal Component Analysis

PCA is a powerful tool for analyzing data by performing dimensionality reduction in which the original data or image is projected on to a lower dimensional space. An image in a collection of images can be represented as the linear combination of some basis images. Let there be M images with N pixels each, in a collection, all images in the collection are arranged into column vectors by scanning them in raster scan order. Let $\boldsymbol{x_i}$ be the individual image vectors and $\overline{x}$ be the mean image vector, and then the mean removed image is given by

$$L_i = x_i - \overline{x} \tag{2}$$

All the mean removed images are arranged in columns to form the matrix $\boldsymbol{L = [l_1, l_2, \ldots, l_M]}$ Covariance matrix of $\boldsymbol{L}$ can be found as

$$C = L \times L^T \tag{3}$$

Let $\boldsymbol{E}$ be the matrix of Eigen vectors of the matrix $\boldsymbol{C}$ and $\boldsymbol{S}$ be the Eigen values. The Eigen vectors are arranged in such a way that respective Eigen values are in decreasing order. A given image can be projected on to these Eigen vectors and the coefficients $\boldsymbol{w}$ thus obtained are called PCA coefficients.

$$w = E^T \times (x_i - \overline{x}) = E^T \times l_i \tag{4}$$

The mean removed image can be reconstructed as $\hat{l}_i = E \times w$. Adding the mean image vector to $\hat{l}_i$ gives the actual image vector. In the discussions followed, image is considered as the mean removed image unless otherwise mentioned. An important fact about PCA coefficients is that the image can be reconstructed with minimum mean square error, using only the first few coefficients.

3.2 Super resolution with Eigen Transformation

Here we discuss the use of PCA for super resolution. First we determine the significant Eigen vectors of ***C*** as described in [11]. Define the matrix $K = L^T \times L$. Let ***Λ*** be the diagonal matrix consisting of the Eigen values and ***V*** is the matrix containing Eigen vectors of ***K***. Most significant ***M*** Eigen vectors of ***C*** can be determined by

$$E_M = L \times V \times \Lambda^{-1/2} \tag{5}$$

M significant PCA coefficients of $\boldsymbol{l_i}$ can be found by projecting it on to $\boldsymbol{E_M}$, ie. $w_l = E_M^T \times l_i$. The reconstructed image $\hat{l}$ is then obtained as

$$\hat{l} = E_M \times w_l = L \times c \tag{6}$$

where

$$c = V \times \Lambda^{-1/2} \times w_l \tag{7}$$

In the super resolution process, we use databases of registered HR images and corresponding LR images. Let ***H*** be the matrix of mean removed image vectors of HR images in database, corresponding to the matrix ***L*** discussed above. The given LR image is represented as the linear combination of the image vectors as shown in equation (6). Hallucinated face image can be determined by using the same coefficients but by using the HR image vectors ***H***

$$h_{SR} = H \times c \tag{8}$$

where $\boldsymbol{h_{SR}}$ is the hallucinated face image. It means that if LR image is the linear combination of image vectors in the LR face images, then the corresponding HR image will be linear combination of the respective HR image vectors while keeping the same coefficients. If the test image is a very low resolution image, then the hallucinated image will have lot of artifacts. We minimize these artifacts by applying a constraint based on the Eigen values. Let ***Q*** be the resolution enhancement factor and ***α*** be a positive constant. To apply the constraint, PCA coefficients $\boldsymbol{w_h}$ of the super resolved image is found. Let $\boldsymbol{E_h}$ be the Eigen vectors of HR image space, then constrained PCA coefficients, $\boldsymbol{\hat{w}_h(i)}$ of the $\boldsymbol{i}^{th}$ eigen vector is given by

$$\hat{w}_h(i) = \begin{Bmatrix} w_h(i) \text{ if } |w_h(i)| < \lambda_i^{1/2} \alpha / Q^2 \\ sign(w_h(i)) \lambda_i^{1/2} \quad \text{otherwise} \end{Bmatrix} \tag{9}$$

where the $\boldsymbol{\lambda_i}$ are the eigen values corresponding to $\boldsymbol{E_h}$. These new coefficients, $\boldsymbol{\hat{w}_h}$ is used to reconstruct the super resolved images from HR eigen vectors. Super-resolved image $\boldsymbol{x_h}$ is given by

$$x_h = E_h \times \hat{w}_h + \bar{x}_h \tag{10}$$

$\bar{x}_h$ is the mean of HR images in the database. As the value of ***α*** increase, super resolved image may have more high frequency details. This may introduce spurious high frequency components also. On the other hand, when ***α*** is reduced, the super resolved image tends towards mean face image.

4. EIGEN TRANSFORMATION IN WAVELET TRANSFORM DOMAIN

In this section we discuss the use of Eigen transformation in the wavelet transform domain for face hallucination.

4.1 Discrete Wavelet Transform

Wavelets are functions defined over a finite interval and are used in representing data or other functions. The basis functions used are obtained from a single mother wavelet, by dilations or contractions and translations. The Discrete Wavelet Transform (DWT) is used with discrete signals. Wavelet coefficients of an image are determined using filters arranged as shown in Figure 3. ***g(n)*** and ***h(n)*** are the half band high pass and low pass filters respectively.

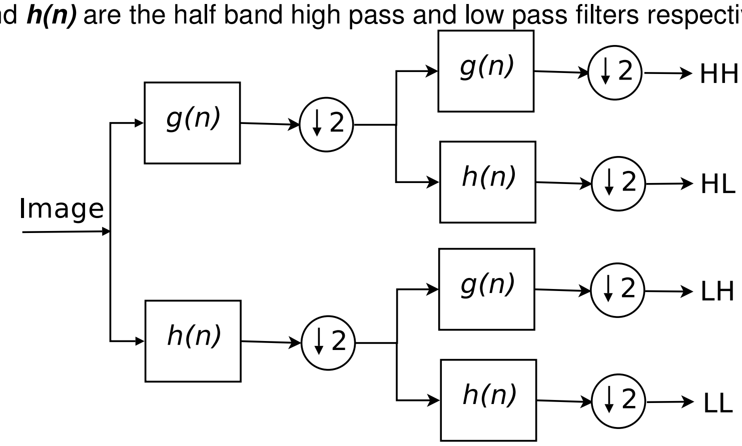

FIGURE 3: Filter structure for the wavelet decomposition of an image.

Resulting wavelet subbands of a face image are depicted in figure 4. Perfect reconstruction of the image is possible from the wavelet coefficients, using inverse DWT (IDWT). Wavelet subbands preserve the locality of spatial and spectral details in the image [18]. This property of spectral and spatial localization is useful in problems like image analysis, especially in super resolution. The type of filters used for ***g(n)*** and ***h(n)*** is determined by the wavelet associated. Face recognition experiments performed by Wayo Puyati, Somasak W. and Aranya W.[15] claims that Symlets give better performance in PCA based face recognition, over other wavelet. In this work, we have tested the proposed algorithm with Coiflets, Symlets and Daubechies wavelets.

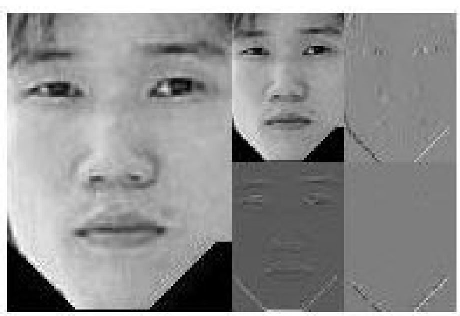

FIGURE 4: Single level wavelet decomposition of face image.

4.2 Why Eigen Transformation in Wavelet Domain?

Face image has a specific structure and this prior information is utilized in face hallucination algorithms. In a specific class of properly aligned face images, contours, patterns and such facial features will be closely aligned. Discrete wavelet transform (DWT) decomposition of face image splits the image into four spectral bands without losing spatial details. Details in respective subbands will be more similar for different face images. It can be observed from Figure 5 that in any given subband other than LL subband, the patterns are similar for all images. Therefore, using very less number of Eigen images we will be able to capture the finer details accurately.

Hence a PCA based super resolution scheme in wavelet domain will be more efficient and computationally less expensive. Another importance of such transform domain approach is that, all images are stored in compressed format and most of the popular image compression techniques are in transform domain. Wavelet based compression is used in JPEG2000, MPEG4/H.264 and in many other standard image and video compression techniques. Therefore, the proposed algorithm can be directly applied on compressed images. This will considerably reduce the computational cost.

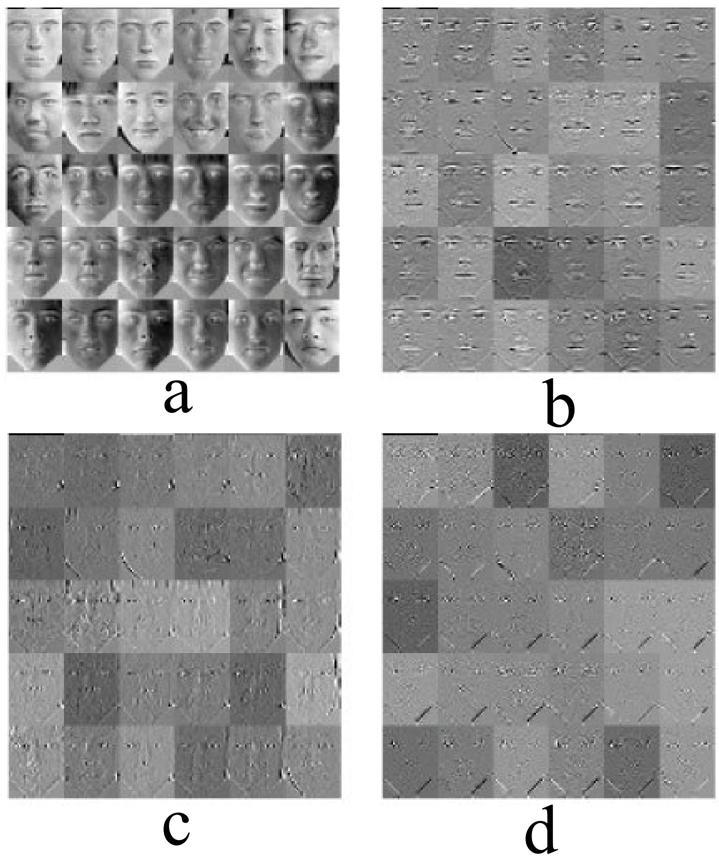

FIGURE 5: Wavelet subband images of face images in the training set. (a) LL subband, (b) LH subband, (c) HL subband and (d) HH subband images.

4.3 Super resolution with Eigen Transformation in Wavelet Domain

In this section we describe our face hallucination method using eigen transformation in the wavelet domain. The HR and LR face images in database are decomposed using DWT to form LR and HR wavelet coefficient database.
Define,

$$[L_{xx}] = DWT(L) \tag{11}$$

$$[H_{xx}] = DWT(H) \tag{12}$$

where ***xx*** stands for LL, LH, HL and HH wavelet subbands. The test image is also decomposed with DWT and then ET based super resolution method described in section 3.2 is applied on these wavelet subbands separately. Resulting wavelet coefficients, $\boldsymbol{h_{SR\text{-}xx}}$, are given by

$$h_{SR-xx} = H_{xx} \times c_{xx} \tag{13}$$

where $\boldsymbol{c_{xx}}$ represents the coefficients for linear combination in different subbands, calculated using equation (7). The constraint based on Eigen value, as given in equation (9), is applied individually on all the super resolved wavelet subbands to obtain $\hat{h}_{SR-xx}$. Super resolved face image h_{SR} is computed by determining the IDWT of the coefficients $\hat{h}_{SR-xx}$.

$$h_{SR} = IDWT(\hat{h}_{SR-xx}) \tag{14}$$

The complete algorithm for face hallucination using ET in wavelet domain is summarized below.

Step 1: Prepare the HR and LR image databases and compute the wavelet subbands of all the images in the databases.
Step 2: For all the wavelet coefficients, find the vectors ***L***, the matrix ***K*** and the eigen vectors ***V*** as in section 3.2.
Step 3: Determine the significant Eigen vectors of ***C***
Step 4: Find the PCA coefficients $\boldsymbol{w_l}$ of the test image
Step 5: Compute the coefficients ***c***, using equation (7).
Step 6: The super resolved coefficients are obtained from equation (8).
Step 7: Modify the coefficients by applying the eigen value based constraints using equation (9).
Step 8: Reconstruct the wavelet subbands from the modified coefficients
Step 9: Reconstruct the super resolved images by finding the IDWT of super resolved wavelet coefficients.

5. FACE HALLUCINATION USING EIGEN TRANSFORMATION ON SUBSPACES IN WAVELET DOMAIN

In this section we describe a subspace based method for face hallucination in wavelet domain.

5.1 Super resolution using Eigen Transformation in Subspaces

In the case of a normal face image, some of the portions like eyes, nose, etc. are highly textured and more significant, so it needs more attention during super resolution. Bicubic interpolation will be sufficient for smooth regions like forehead, cheeks, etc. In our subspace based approach, face image is split into four subimages. They are left eye, right eye, mouth with nose and the remaining area as shown in figure 6. These regions are the subspaces of the entire face space.

Eigen transformation based super resolution technique out performs other hallucination methods if the test image is in the column span of Eigen vectors. If sub images are used for super resolution, only small number of images are required in the database compared to the case of whole face image for a given reconstruction error. Eigen transform based hallucination is applied on all the subimages separately and the resulting super resolved regions are combined along with the interpolated version of remaining area. The computational cost associated with this method is much less because it is comparatively easy to compute the Eigen vectors of smaller subspace images.

5.2 Eigen Transformation on Subspaces in Wavelet Domain

The subspace method proposed for face hallucination is an extension of the algorithm propsed in previous section. In this method HR and LR face images in database as well as the LR test image are split in to four regions as shown in figure 6. Then the three textured regions are individually super resolved using the algorithm explained in section 4.3. The fourth region is interpolated using bicubic interpolation and the three super resolved regions are combined with the fourth region to form the hallucinated face image. This subspace technique in wavelet domain for super resolution, reduces computational cost considerably, because the size of the subimages are small and therefore the computation required to determine wavelet coefficients are very less.

PCA in wavelet domain further reduces the memory required for implementation. This method is not suitable where input image resolution is very less, because it is not feasible to split and align test image into subimages when the input image resolution is very less.

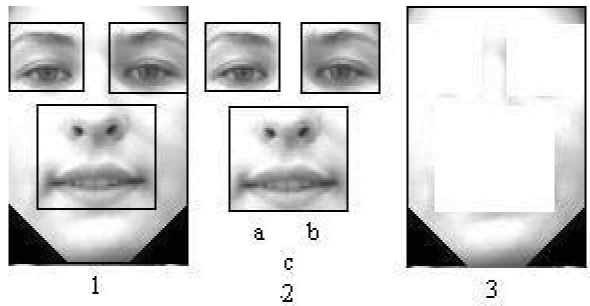

FIGURE 6: Face image divided into subspaces. (1) Entire face image with regions marked, (2 a, b, c) Textured regions, left eye, right eye and mouth with nose respectively. (3) Remaining smooth region.

The steps involved in this method for face are listed below:

Step 1: Split all the face images in the HR and LR databases into mouth with nose, left eye, right eye and remaining area.

Step 2: Determine the wavelet coefficients of eyes and mouth with nose.

Step 3: Repeat steps 2 to 9 of the algorithm described in section 4.3 on all the three textured portions.

Step 4: Combine the super resolved regions with interpolated version of remaining part to form the hallucinated face image.

6. EIGEN TRANSFORMATION IN DISCRETE COSINE TRANSFORM DOMAIN

In this section, we explain the usefulness of Discrete Cosine Transform (DCT) for face hallucination using Eigen transformation based approach. The DCT helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the visual quality of the image).

DCT has excellent energy compaction performance and therefore it is widely used in image compression [9]. Block wise DCT is usually used in image compression applications. DCT of image $\boldsymbol{x_i}$ with a DCT block size $\boldsymbol{N \times N}$ is computed as

$$DCT(x_i) = \sum_x \sum_y x_i(x, y) g(x, y, u, v) \quad \text{for } u, v = 0 \text{ to } N-1 \tag{15}$$

where

$$g(x, y, u, v) = \alpha(u)\alpha(v)\cos\left[\frac{(2x+1)\pi u}{2N}\right]\cos\left[\frac{(2y+1)\pi v}{2N}\right] \tag{16}$$

After normalization of the DCT coefficients of LR and HR images, the low frequency side of HR coefficients and DCT coefficients of the corresponding LR images are very close and they represent the low frequency information [7]. The remaining DCT coefficients of HR image correspond to the high frequency information. Thus the process of super resolution in DCT domain is determining these remaining coefficients from the low frequency coefficients of LR image. The super resolution is applied on the block wise DCT coefficients of the image. Let $\boldsymbol{Q}$ be the magnification factor in $\boldsymbol{x}$ and $\boldsymbol{y}$ directions, $\boldsymbol{b \times b}$ be the size of one DCT block for HR image and the $\boldsymbol{b/Q \times b/Q}$ be the size of DCT block used for LR image and test image. Find the block wise DCT of all images in HR and LR databases as well as test image and then all coefficients are normalized with the maximum values in the DCT of each image. Now the values of DCT coefficients in the ***b/Q × b/Q*** block corresponding to the low frequency side of HR image are very close to the corresponding DCT coefficients of LR image as shown in figure 7.

$$x_{dct-i} = DCT(x_i) \tag{17}$$

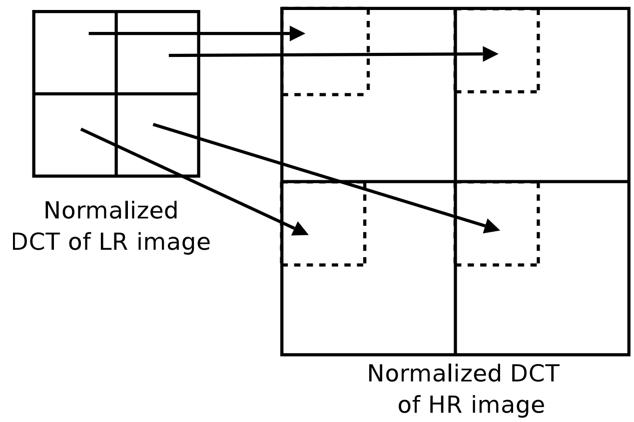

FIGURE 7: Relation between the normalized DCT coefficients of LR and corresponding HR images. Values of the DCT coefficients in the blocks connected by arrows correspond to low frequency details.

To perform ET, compute the matrices L_{dct}, H_{dct} and c_{dct} as explained in equations (2) through (7). The DCT coefficients of the super resolved image are determined as explained in section 3.2. The resulting coefficients are the normalized DCT coefficients of hallucinated face image. Mean of the value used for normalizing the DCT coefficients of HR image is used to find the de-normalized DCT x_{dct-h}. Now compute the inverse DCT to give the hallucinated face image x_h.

$$x_h = IDCT(x_{dct-h}) \tag{18}$$

In this proposed algorithm for face hallucination in DCT domain, images are divided into fixed size blocks and the DCT of these blocks are determined as in the case of JPEG compression. All these blocks are considered together as a single unit for determining the SR image. With minimum modifications, this algorithm can be customized to use directly with different DCT based compression schemes.

7. EXPERIMENTAL RESULTS

All experiments in this paper are performed using manually aligned face images taken from PIE, Yale and BioID face databases. 100 front facial images are selected from the above databases. All the images are manually aligned using affine transformation and warping such that the distance between the centres of eyes is 50 pixels. Also the eyes, lip edges and tip of nose of all the images are aligned. Images are then cropped to *128 × 96* pixels. The high resolution images are having a resolution *128 × 96* and the low resolution images are derived from these HR images by subsampling them. Database is formed using these HR and LR images. Test image is also chosen from the LR image database as per leave one out policy, ie. the testing image is excluded from the training set for that particular experiment. Performances of the proposed techniques are quantified in terms of peak signal to noise ratio (PSNR), Mean structural similarity measure (MSSIM) [16] and correlation coefficient (CC). Structural Similarity Measure (SSIM) is defined by the relation

$$SSIM = \frac{(2\mu_x\mu_y)(2\sigma_{xy})}{(\mu_x^2+\mu_y^2)(\sigma_x^2+\sigma_y^2)} \tag{19}$$

SSIM is measured with a local window size of 8×8 pixels. Mean value of SSIM (MSSIM) is used as the metric. Ideal value of MSSIM is 1. Correlation coefficient (CC) between two images is computed by the following relation. Here also the ideal value is unity.

$$CC = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \tag{20}$$

$$\sigma_{xy} = \frac{1}{N_1 N_2} \sum_{\forall i} \sum_{\forall j} (x(i,j) - \mu_x)(y(i,j) - \mu_y) \tag{21}$$

where N_1 and N_2 are the dimensions of the image.

$$\sigma_x^2 = \frac{1}{N_1 N_2} \sum_{\forall i} \sum_{\forall j} (x(i,j) - \mu_x)^2 \tag{22}$$

$$\mu_x = \frac{1}{N_1 N_2} \sum_{\forall i} \sum_{\forall j} x(i,j) \tag{23}$$

7.1 Eigen Transformation in Wavelet Domain

Experimental results of the method described in section 4.3 are shown in figure 8. Experiments are performed; a) to evaluate the visual quality of the hallucinated image, b) to test the performance of the algorithm with noisy observation and c) to find the variation in performance with different types of wavelet functions.

FIGURE 8: Hallucinated faces with the Eigen transformation in wavelet domain. Input, original, Bicubic interpolated and hallucinated images. For magnification factors of four (top), eight (middle) and eleven (bottom).

Figure 8 shows the hallucination result of the Eigen transformation in wavelet domain with magnification factors 4, 8 and 11. Experiments using this method are done with Daub2 wavelet function. Result of hallucination result is much better when the images in database precisely represent the features of the test face. But the result seems to be noisy when the test face is significantly different from those in database. As it can be observed from figure 8, the hallucinated result is much better than the bicubic interpolation, for higher values of ***Q***. But if the number of pixels in the input image is very less, the proposed method fails to find the super resolved image. In our experiment, the resolution of HR image is 128×96 pixels. Therefore, it is observed that when the value of ***Q*** is above 11, size of input image will be less than 11×9 pixels and the algorithm fails to produce correct result. Figure 9 show the result of the proposed algorithm, when the test image not similar to the images in the database.

FIGURE 9: Hallucination result with a test image not similar to the database images. Input, original, Bicubic interpolated and hallucinated face images.

Next we perform the experiment with noisy test image. Gaussian noise is added to the test image. In this case, the test image and its corresponding HR version is included in the LR and HR databases respectively and the corresponding result is shown in Figure 10. This result shows the recognition performance of the algorithm with noisy observations.

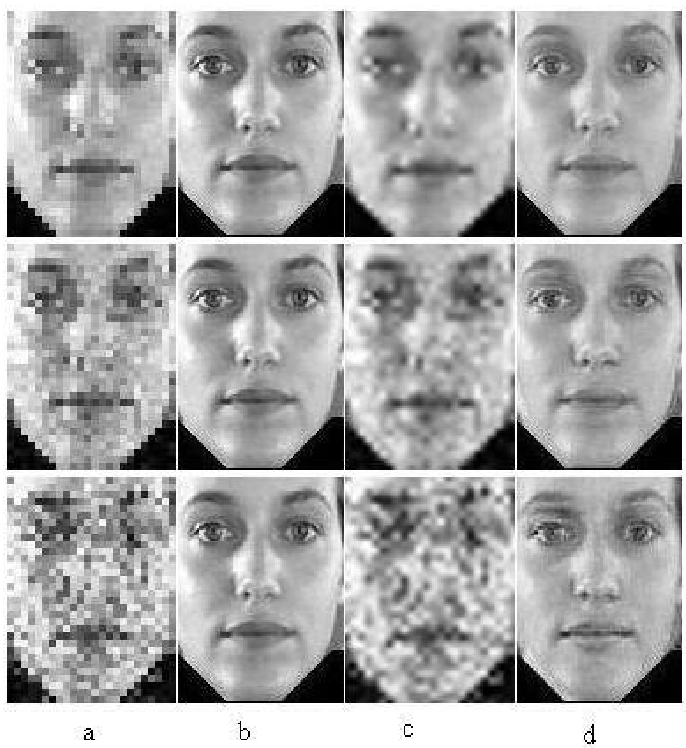

FIGURE 10: {Hallucinated faces using Eigen transformation in wavelet domain, with noisy input image. (a) Input image with Gaussian noise, (b) Original image, (c) Bicubic interpolated image and (d) hallucinated image. Noise variance σ=0.001 (top), σ =0.01 (middle) and σ =0.1 (bottom).

The proposed algorithm is then tested for the variation in performance with the different types of wavelets. In this particular case, algorithm increases the resolution by a factor of two both horizontally and vertically (magnification factor is two, ***Q****=2*). Experiments are performed with different types of wavelet functions. Table 1 show that results are better for daubechies2, coiflet5, symlets2 and symlets5 and the best result is obtained for symlet9.

FIGURE 11: Textured regions reconstructed using the algorithm proposed in section 4.4. Hallucinated, original and bicubic interpolated images.

FIGURE 12: Hallucinated face image with subspace PCA in wavelet domain. Hallucinated face, Original face and bicubic interpolated face image.

7.2 Eigen Transformation on Subspaces in Wavelet Domain

Experimental results of the face hallucination technique using Eigen transformation on subspaces in wavelet domain is given here. In order to implement the subspace based super resolution, face image is split in to four regions as explained in section 5. All the images in the database are aligned and thus the coordinates of all the subimages edges are predetermined. All the images in the database as well as the test image are split in to the subimages and the Eigen transformation based super resolution in wavelet domain is separately performed on all the subimages. Super resolved subimages are separately shown in figure 11 along with their original and bicubic interpolated versions. These results are for a magnification factor of two (***Q****=2*). Smooth regions in the image are interpolated and then the super resolved subimages are combined with the interpolated image to form the final hallucinated face. Figure 12 shows the final hallucinated face. Eyes, nose, lips etc are sharper than the bicubic interpolated version. Boundaries of the subimages are barely visible in this image, but it will become more visible as the magnification factor increases.

The proposed algorithm is then tested for the variation in performance with the different types of wavelets. Table 1 gives the change in performance with wavelet types. The subspace based method has best results when symlet7 and coiflet3.

7.3 Eigen Transformation in DCT Domain

Finally we show the results of face hallucination using Eigen transformation in DCT domain. Block wise DCT of all the images are computed. The values of ***b*** are chosen such that the value of ***b/Q*** is at least 2. If this value is less, PCA based super resolution in Eigen Transformation will be weak and the result will be noisy.

Wavelet Type	**ET in Wavelet Domain (PSNR)**	**Subspace ET in Wavelet Domain (PSNR)**
Symlet2	28.777	24.630
Symlet5	28.773	24.046
Symlet7	28.706	25.048
Symlet9	28.794	24.891
Coif3	28.641	25.048
Coif4	28.719	25.029
Coif5	28.765	24.961
Daub2	28.777	24.630
Daub3	28.671	24.802
Daub7	28.684	24.875

TABLE 1: Change in PSNR of hallucinated image for Eigen transformation in wavelet domain with different types of wavelets

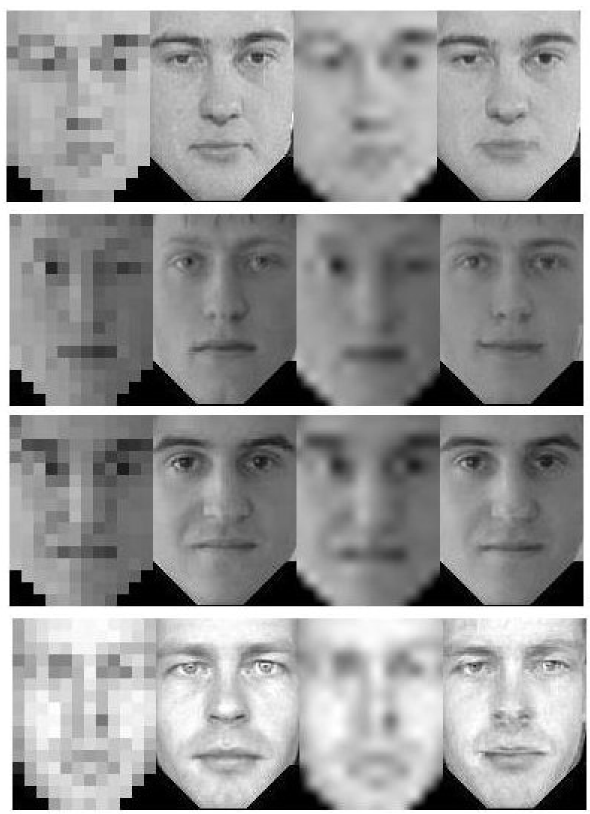

FIGURE 13: Result of hallucination experiments in DCT domain. Input image (first column), original image (second column), bicubic interpolated (third column) and Hallucinated result (Fourth column) for ***Q****=8*.

In our experiment the values of ***b*** is chosen as 16. Computed coefficients are normalized with the maximum values in the DCT of each image. Algorithm represents the DCT coefficients of LR image as the linear combination of DCT coefficients in the LR image database. Resulting images are shown in figure 13 along with the input image, original image and bicubic interpolated image.

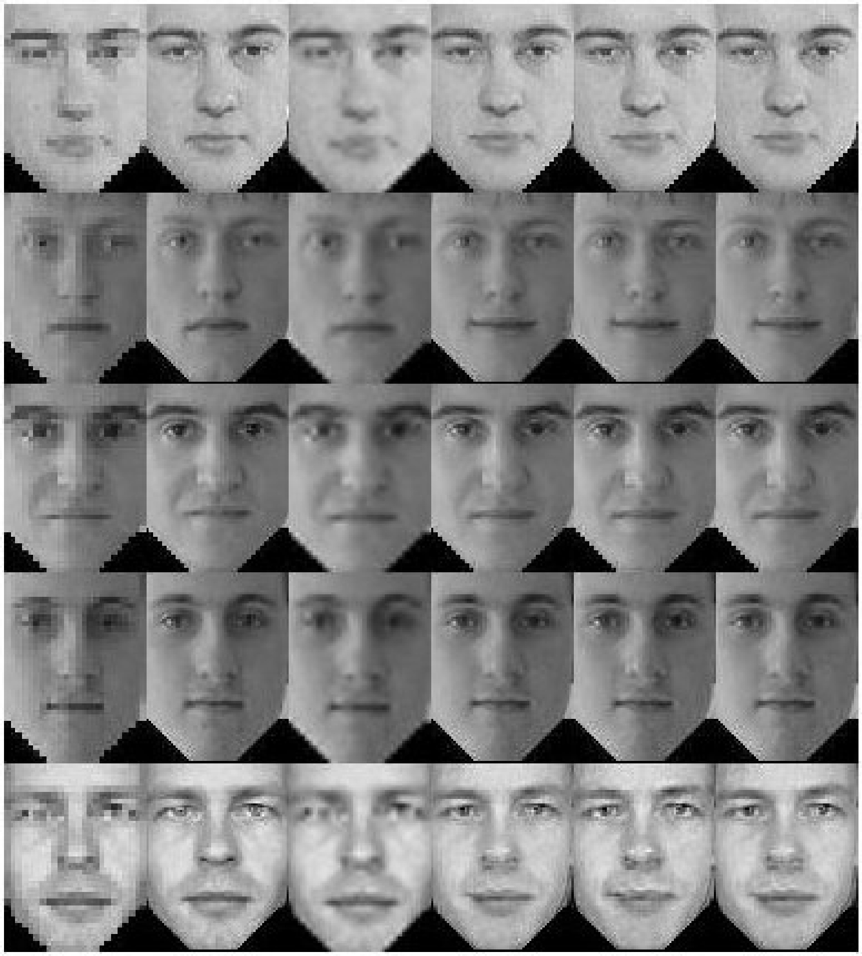

FIGURE 14: Result of hallucination experiments. Input image (first column), original image (second column), bicubic interpolated (third column), Eigen Transformation in spatial domain (fourth column), in wavelet domain (fifth column) and in DCT domain (sixth column). For ***Q****=4*.

Test Image	ET in spatial Domain (*Q=4*)	ET in Wavelet Domain (*Q=4*)	ET in DCT Domain (*Q=4*)	Bicubic Inter-polation. (*Q=4*)	ET in spatial Domain (*Q=8*)	ET in Wavelet Domain (*Q=8*)	ET in DCT Domain (*Q=8*)
a	29.803	29.514	29.585	20.157	29.780	30.021	29.328
b	31.486	31.337	31.633	23.735	30.777	29.958	29.105
c	33.424	33.114	33.290	22.501	31.601	30.705	31.050
d	32.027	31.820	32.030	22.684	31.222	28.958	31.402
e	23.623	23.106	23.737	19.179	22.404	20.755	22.456

TABLE 2: Comparison of performance of Eigen transformation based face hallucination algorithms in spatial, wavelet and DCT domains. PSNR for magnification factors Q=4 and Q=8.

7.4 Comparison of hallucination results

Figure 14 and figure 15 shows the hallucination results of Eigen transformation in spatial domain, wavelet domain and DCT domain respectively for magnification factors 4 and 8. The first three images in each set are input LR, original and bicubic interpolated images. Tables 2 and 3 compare Eigen transformations in three domains with respect to the parameters PSNR, MSSIM and CC respectively. Eigen transformation in DCT domain has the best performance followed by Eigen transformation in spatial domain and then in the wavelet domain, in terms of the above three parameters.

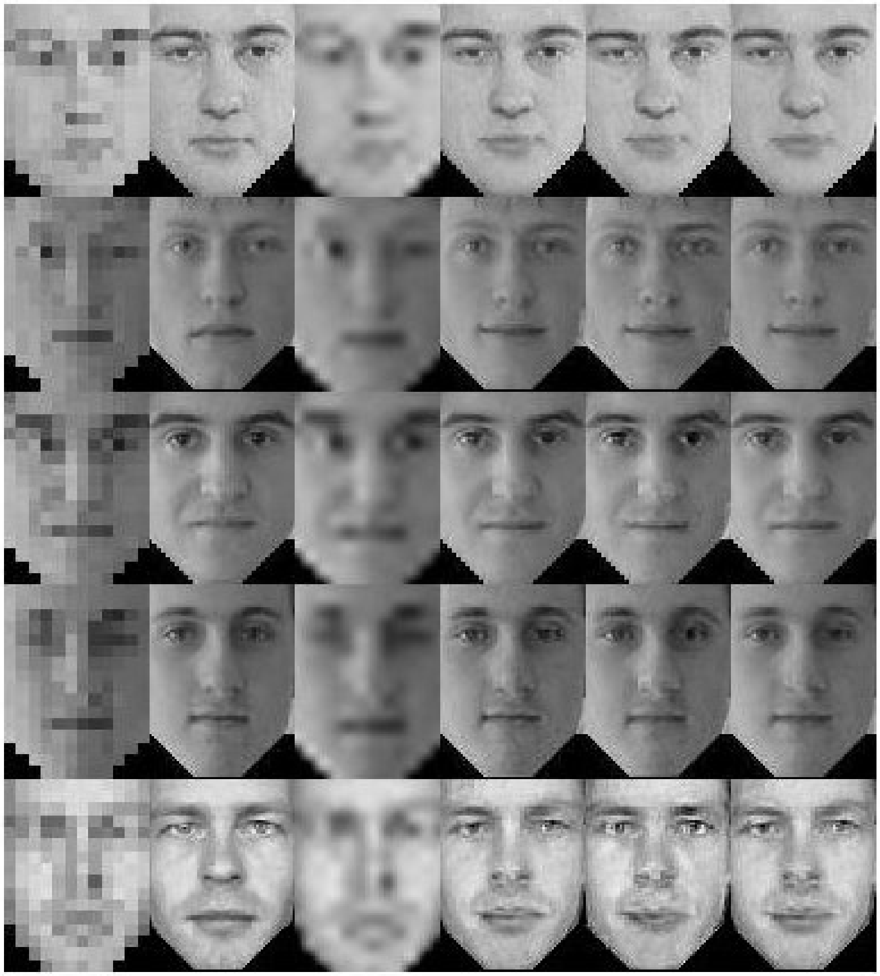

FIGURE 15: Result of hallucination experiments. Input image (first column), original image (second column), bicubic interpolated (third column), Eigen Transformation in spatial domain (fourth column), in wavelet domain (fifth column) and in DCT domain (sixth column). For ***Q***=*8*.

8. CONSLUSION & FUTURE WORK

In this work, feasibility of Eigen transformation in transform domain for face super resolution is studied. Eigen transformation is applied in wavelet and DCT domains and the performance are compared. A subspace based super resolution method is also proposed in wavelet domain. The results show that Eigen transformation is applicable in transform domain, which means that the Eigen transform can be directly applied with slight modifications on the compressed images as well as on compressed video streams. Results obtained indicate that Eigen transformation in DCT and spatial domain has the best performance followed by Eigen transformation in wavelet domain. Results of Eigen transform based method are much better and it can be used for higher magnification factor. A disadvantage with Eigen transform based method is that, it depends on the alignment of images as well as the structural similarity of images. The effect of image alignment can be reduced by using pose and illumination invariant features instead of transform coefficients. Our future work is intended on the study of the performance of Eigen transformation based hallucination on these features. Another possible extension is that study of the performance of Eigen transformation on individual DCT blocks, instead of the DCT of entire image.

Parameter	**Test Image**	**ET in spatial Domain (*Q=4*)**	**ET in Wavelet Domain (*Q=4*)**	**ET in DCT Domain (*Q=4*)**	**ET in spatial Domain (*Q=8*)**	**ET in Wavelet Domain (*Q=8*)**	**ET in DCT Domain (*Q=8*)**
MSSIM	**a**	0.84049	0.81407	0.83341	0.83905	0.84037	0.83562
	b	0.88562	0.87446	0.88476	0.88422	0.83214	0.86278
	c	0.90586	0.89278	0.90643	0.87119	0.85279	0.86685
	d	0.88597	0.87900	0.88627	0.87721	0.83214	0.87867
	e	0.67083	0.61993	0.66972	0.62173	0.54340	0.62760
Correlation Coefficient (CC)	**a**	0.98905	0.98810	0.98821	0.98869	0.98325	0.98746
	b	0.98795	0.98750	0.98785	0.98540	0.98267	0.98714
	c	0.99058	0.99168	0.99263	0.98917	0.98676	0.98913
	d	0.99261	0.99000	0.99056	0.98886	0.98151	0.98761
	e	0.96853	0.96347	0.96855	0.95821	0.94136	0.95913

TABLE 3: Comparison of performance of Eigen transformation based face hallucination algorithms in spatial, wavelet and DCT domains. Values of MSSIM and Correlation coefficient for a magnification factor Q=4 and Q=8.

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