FACE HALLUCINATION USING PCA IN WAVELET DOMAIN

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Abstract: The term face hallucination stands for recognition based super resolution of face images to improve the spatial resolution. In this paper, we propose two face hallucination algorithms based on principal component analysis (PCA) in the wavelet transform domain. In the spatial domain, the PCA based super resolution algorithm; a low resolution (LR) observation is represented as the linear combination of LR images in an image database. Super resolved image is obtained as the linear combination of the corresponding high resolution (HR) images in the database. In the first approach proposed in this paper, PCA based hallucination algorithm is applied to the wavelet coefficients of face image. The hallucinated face image is reconstructed from the super resolved wavelet coefficients. In second method, face image is split in to four sub images and the first method is separately applied to three textured regions. Fourth region, which is relatively smooth, is interpolated using standard interpolation techniques. We compare the performance of the two proposed algorithms with their spatial domain counter parts. The proposed method shows significant improvement over the spatial domain approaches.

1 INTRODUCTION

Image acquisition is the front end of image processing. Resolution of digital images is limited, because of the fixed dimensions of sensor elements used for image acquisition. Higher resolution requires smaller sensor elements arranged at higher density which obviously increases the cost of the device. Even if the cost is affordable, sensor dimension cannot be minimized beyond a physical limit which has already reached. HR images contain more details than the corresponding LR image. Many image processing applications need HR images for better machine interpretation. Image super resolution is the process of acquiring a HR image from one or more LR images, using signal processing means, by synthesizing the missing high frequency details (Sung et al., 2003). As it is a purely computational process, it will not increase the cost of sensor. There are mainly two techniques for image super resolution. In the first method, multiple LR observations of a scene are used to reconstruct the HR image. This method is called multi-frame super resolution. The second method called single frame super resolution uses only a single LR observation of the scene to reconstruct an HR image.

The super resolution process may also introduce some unwanted high frequency components. In the case of highly textured images like grass, leaves, etc. the errors in super resolved image due to these spurious frequencies may not be significant. But in face images, the effect due to spurious frequencies may be very serious. Hence it is necessary that the face super resolution process should not introduce many unwanted details (Liu et al., 2007). The face super resolution problem has wide applications in the areas of detection, recognition, surveillance and monitoring. Face image super resolution based on recognition is termed as face hallucination (Baker and Kanade, 1999). Algorithm proposed by Baker and Kanade(1999) uses a single LR observation to synthesize an HR face image, which makes use of a training set of HR face images. High frequency details of the HR face image is learned by identifying local features from the training set.

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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. A gradient prior is learned using gradients and second gradients of the images as features. Hallucinated face is estimated using maximum a posteriori (MAP) framework, which uses leaned prior in its cost function.

In the eigen transformation based hallucination algorithm proposed by Wang and Tang (2005), first an HR database and corresponding LR face image database is prepared. LR observation image is then represented as the linear combination of LR database images. The 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, a regularization is done with respect to eigen values.

Jiji et al.(2004) proposed a wavelet based single frame super resolution method, for general images, making use of an HR image database. Observed image as well as the data base images are decomposed using wavelet transform. Wavelet coefficients of the super resolved image is learned from the coefficients of images in the database. The problem is solved under a regularization frame work using the learned wavelet prior. An edge preserving smoothness constraint is used to maintain the continuity of edges in super resoved image. Capel and Zisserman (2001) divided the face image in to six regions or subspaces and then PCA based super resolution is applied on the respective portions independantly. The subspaces are combined and a global regularization is done to minimize artifacts at the boundaries of the regions.

In this paper, we propose two methods for face hallucination in wavelet domain. In both the methods, face hallucination based on eigen transformation is applied on the wavelet coefficients. In the first method, face image is treated as a single image and in the second method, it is split into several regions and then the super resolution techniques are applied. Eigen transformation uses PCA coefficients for implementing the super resolution. Therefore the hallucination algorithms proposed in this paper are refered as face hallucination using PCA in wavelet domain and face hallucination using subspace PCA in wavelet domain.

The remaining part of this paper is organized as below. The background for Wavelets and PCA relavant to the problem of face hallucination are discussed in subsections 2.1 and 2.2 respectively. The significance of super resolution using PCA and subspace models in spatial domain as well as in the wavelet domain are given in subsections from 2.3 to 2.6. Section 3 consists of the details of simulation work and results and the paper concludes in section 4.

2 HALLUCINATION WITH PCA IN WAVELET DOMAIN

In this paper two methods are proposed for face hallucination, using PCA in wavelet domain. Both the methods use, a training set of face images consisting of HR and corresponding LR images. In the first algorithm, wavelet coefficients of images in the training set are determined. Wavelet coefficients of LR observation is also determined. Eigen transformation based hallucination is applied individually on all the four wavelet coefficients, to get the super resolved wavelet coefficients. The hallucinated face is obatained by computing the inverse wavelet transform of super resolved wavelet coefficients. In the second method, face image is split in to four regions out of which three regions are textured and are more significant. The fourth region is relatively flat. Textured regions are super resolved seperately using the method described above. Flat regions are interpolated using standard interpolation techniques. In the following subsections we discuss briefly on wavelets and PCA followed by the usage of eigen vectors for super resolution.

2.1 Discrete Wavelet Transform

The Discrete Wavelet Transforms (DWT) splits the image into four spectral bands (Daubechies, 1992). Each of the subbands is one quarter in size of the original image and these coefficients (subbands) preserve the locality of spatial and spectral details in the image. This property of spectral and spatial localization is useful in problems like image analysis, especially in super resolution. Wavelet coefficients of an image are determined using filters arranged as shown in figure 1. g(n) and h(n) are the half band high pass and low pass filters respectively. Resulting wavelet coefficients are LL (low-low), LH (low-high), HL (high-low) and HH (high-high). Perfect reconstruction of the image is possible from four wavelet coefficients, using inverse DWT (IDWT). There are many types of wavelets depending on the type of filters used for g(n) and h(n). Wayo et al (2006) shows that Symlets gives better performance in PCA based face recognition techniques, over other types of wavelet. In this paper, proposed algorithms are tested with Daubechies, Symlet and Coiflet wavelets. Figure 2 shows the typical single level wavelet decomposition of a face image.

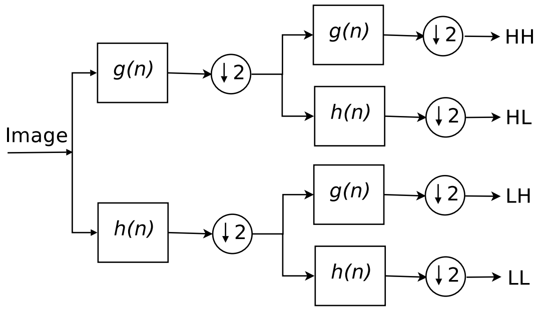

Figure 1: Filter structure for the wavelet decomposition of an image.

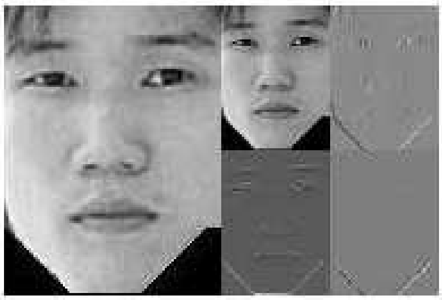

Figure 2: Single level wavelet decomposition of face image.

2.2 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, the basis function to represent these images can be found by using Eigen vectors (Moon and Stirling, 2005). Let x_i be the individual image vectors and $\overline{x}$ be the mean image vector, then the mean removed image is given by

$$l_i = x_i - \overline{x} \tag{1}$$

All images in the database are arranged in to column vectors by scanning them in raster scan order. All the mean removed images are arranged in columns to form the matrix

$$L = [l_1, l_2, ..., l_M] \tag{2}$$

Covariance matrix of L can be found as

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

Let E be the matrix of eigen vectors; $e_1, e_2, ...$be the eigen vectors and S be the eigen values of C. Then C, S and E will satisfy the following equation.

$$E = [e_1, e_2, ..., e_N] \tag{4}$$

$$C \times E = E \times S \tag{5}$$

where $S = diag(\lambda_1, \lambda_2, ..., \lambda_N)$ and $\lambda_1, \lambda_2, ..., \lambda_N$ are the eigen values. The eigen vectors are arranged in such a way that respective eigen values are in decreasing order. The images can be projected on to these eigen vectors and the coefficients w_l thus obtained are called Principal Component Analysis (PCA) coefficients.

$$w_l = E^T \times (x_i - \overline{x}) = E^T \times l_i \tag{6}$$

The mean removed image can be reconstructed using the following relation.

$$l_i = E \times w_l \tag{7}$$

Adding the mean image vector to 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 the first few coefficients alone. This feature is used in image compression and noise reduction applications.

2.3 Super Resolution with Eigen Images

PCA can be used for super resolution by slightly modifying the equations to find Eigen vectors and PCA coefficients. The covariance matrix C will have large dimensions. Therefore finding eigen vectors will be difficult while the number of significant eigen vectors will be much less. Therefore an alternate scheme is used to determine the significant Eigen vectors (Turk and Pentland, 1991). Define the matrix K as

$$K = L^T \times L \tag{8}$$

Let V be the matrix containing eigen vectors of K.

$$V = [v_1, v_2, ..., v_M] \tag{9}$$

Most significant M eigen vectors of C can be determined by

$$e_i = L \times \frac{v_i}{||L \times v_i||} \text{ for } i = 1 \text{ to } M \tag{10}$$

The reconstructed image $\hat{l}$ is obtained as

$$\hat{l} = E \times w_l = L \times c \tag{11}$$

where

$$c = \frac{v_i}{||L \times v_i||} \times w_l \tag{12}$$

In 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. The LR image is represented as the linear combination of the image vectors as shown in equation (11) (Wang and Tang, 2003). Hallucinated face image can be determined by using the same coefficients but by using the HR image vectors H

$$h_{SR} = H \times c \tag{13}$$

where h_{SR} is the hallucinated face image. It simply 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. As the input resolution decreases the hallucinated image will have artefacts. These artefacts are minimised by applying a constraint based on eigen values. Let $Q \times Q$ be the resolution magnification to be done and α a positive constant. To apply the constraint, super resolved image is projected onto the HR Eigen vectors E_h, to get the coefficients w_h. Constrained PCA coefficients, $\hat{w}_h$ are obtained as

$$\hat{w}_h = \begin{cases} w_h(i) & \text{if } |w_h(i)| < \lambda_i^{1/2}\alpha/Q^2 \\ sign(w_h(i))\lambda_i^{1/2} & \text{otherwise} \end{cases} \tag{14}$$

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

$$x_h = E_h \times \hat{w}_h + \overline{x}_h \tag{15}$$

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

Figure 3: Mean face image and first few Eigen faces.

2.4 Super Resolution using Eigen 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 at the smooth regions like forehead, cheeks etc. In the second algorithm proposed in this work, face image is split in to left eye, right eye, mouth with nose and the remaining area as shown in figure 4. These regions are the subspaces of the entire face space. The dimension of such subspaces will be much less compared to the dimension of entire face space.

PCA based super resolution techniques out performs other hallucination methods if the test image is closely similar to the images in database. Otherwise, it gives better results if number of images in the database is high. If sub images are used for super resolution, the number of images required in the database is less compared to the case of whole face image for a given reconstruction error. PCA based hallucination is applied on all the subimages separately and the resulting super resolved regions are combined with the interpolated version of remaining area. The computational cost associated with this method is much less because it is easy to compute the Eigen vectors of smaller subspace images.

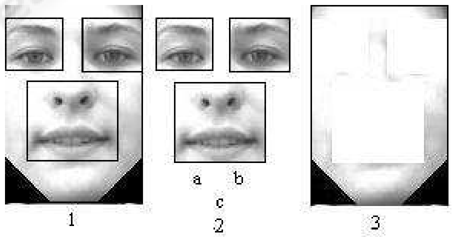

Figure 4: Face image divided into subspaces. (1) Entire face image with regions marked, (2 a, b, c) Textured regions, left eye, right eye and mouth with nose respectively. (3) Remaining smooth region.

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. 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. 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 a compressed image after properly rearranging the compressed coefficients. So there is no need for decompressing the image which will considerably reduce the computational cost.

2.5 Super Resolution with Eigen Images in Wavelet Domain

In the first method proposed for face hallucination in wavelet domain, HR and LR face images in database are decomposed using DWT to form LR and HR wavelet coefficient database

$$[L_{xx}] = DWT(L) \tag{16}$$

$$[H_{xx}] = DWT(H) \tag{17}$$

where *xx* stands for LL, LH, HL and HH wavelet subbands. Test image also is decomposed with DWT and the PCA based super resolution method described in section 2.3 is applied on these wavelet coefficients separately. Resulting wavelet coefficients,h_{SR-xx}, are given by

$$h_{SR-xx} = H_{xx} \times c_{xx} \tag{18}$$

where c_{xx} is the coefficient for linear combination in different subbands, calculated using equation (12). The constraint based on eigen value, as given in equation (14), is applied individually on all the wavelet coefficients to give $\hat{h}_{SR-xx}$. Super resolved face image h_{SR} is computed by determining the IDWT of the coefficients $\hat{h}_{SR-xx}$.

$$h_{SR} = IDWT(\hat{h}_{SR-xx}) \tag{19}$$

The complete algorithm for face hallucination using PCA 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 2.3.*

Step 3: *Determine the significant eigen vectors of C using equation (10).*

Step 4: *Find the PCA coefficients w_l of the test image from equation (6).*

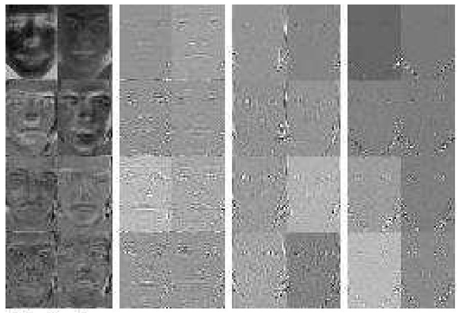

Figure 5: Eigen images of wavelet coefficients. First few Eigen images of LL, LH, HL and HH coefficients.

Step 5: *Using w_l compute the linear combination coefficients c.*

Step 6: *The super resolved coefficients are obtained from equation (13).*

Step 7: *Reconstruct the coefficients with equation (15) after applying the constraints in equation (14).*

Step 8: *Reconstruct the super resolved subimages by finding the IDWT of super resolved wavelet coefficients.*

2.6 Subspaces in Wavelet Domain

The second method proposed for face hallucination is an extension of the first algorithm. 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 4. Then the three textured regions are individually super resolved using the algorithm explained in section 2.5. The fourth region is interpolated with bicubic interpolation technique and the three super resolved regions are combined with the fourth interpolated region to form the hallucinated face image. This subspace technique in wavelet domain for super resolution, reduces computational cost considerably, because the size of regions 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. These favourable features along with the acceptable performance make it suitable for smaller systems which use input images with sufficient resolution. 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. The steps involved in the hallucination with subspace PCA in wavelet domain, 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 8 of the algorithm described in section 2.5 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.*

3 EXPERIMENTAL RESULTS

Face image database for the experiments is prepared from BioID face database, PIE database and Yale database. Front facial images are selected and manually cropped to uniform size of 128×96 after aligning with three control points, centres of left and right eyes and the centre of the lips. The distance between the control points are predefined. Distance between eye centres is fixed to 50 pixels. 103 images are prepared as described above to form the HR face image database. LR image database is prepared by down sampling the HR images. Performance of the proposed algorithms is analysed by using input images with different resolutions. To obtain a LR test image and in order to be able to quantify the improvements during super resolution, we consider a HR image which does not belong to the training set and downsample it by required magnification factor Q.

Figure 6: Hallucinated faces with the method proposed in section 2.5. Input, original, Bicubic interpolated and hallucinated images. For magnification factors of four (top), eight (middle) and eleven (bottom).

Figure 6 shows the hallucination result of the method proposed in section 2.5 with magnification factors 4, 8 and 11. The hallucinated 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 has significant components in the space orthogonal to the space spanned by Eigen vectors. As it can be observed from figure 6, 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 PCA based 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 size will be less than 11×9 pixels and the algorithm fails to produce correct result. Figure 7 show the result of the proposed algorithm, when the test image not similar to the images in the database.

Figure 7: Hallucination result with a test image not similar to the database images. Input, original, Bicubic interpolated and hallucinated face images.

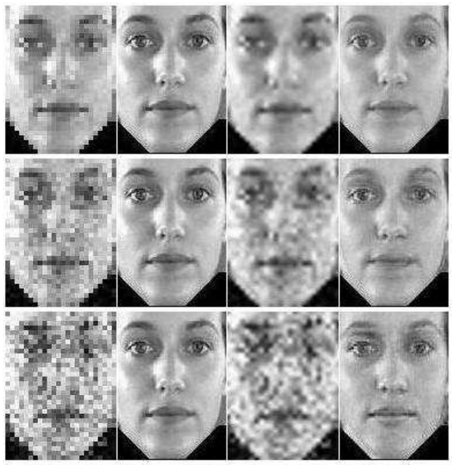

Figure 8: Hallucinated face with noisy input image. (a) Input image with Gaussian noise, (b) Original image, (c) Bicubic interpolated image and (d) hallucinated image. Noise variance $\sigma = 0.001$ (top), $\sigma = 0.01$ (middle) and $\sigma = 0.1$ (bottom).

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 8. This result shows the recognition performance of the algorithm with noisy observations. Figure 9 gives a comparison between the results of the proposed method with the corresponding spatial domain approach.

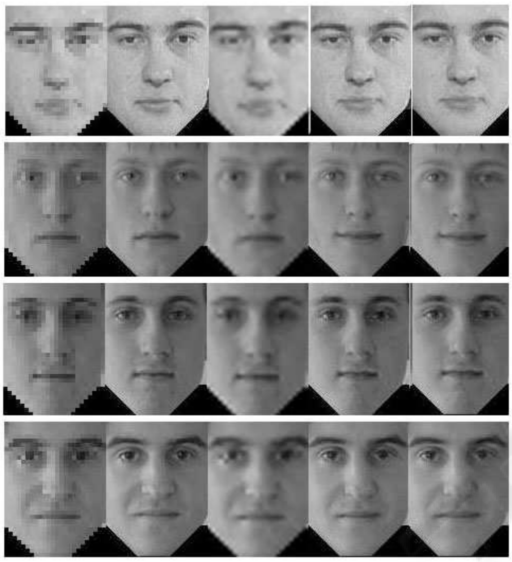

Figure 9: Hallucinated faces; Input image , Original image, Bicubic interpolated image, hallucinated image with proposed method and hallucinated result with spatial domain approach.

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 horizontally and vertically (magnification factor is two, $Q = 2$). Table 1 give the change in performance with wavelet types.

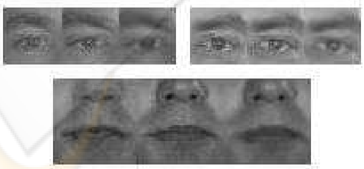

Figure 10: Textured regions reconstructed using the algorithm proposed in section 2.6. Hallucinated, original and bicubic interpolated images.

Now we show the result using the second algorithm proposed in section 2.6. Super resolved subimages are separately shown in figure 10 along with their original and bicubic interpolated versions. These results are for a magnification factor of two $(Q = 2)$. Figure 11 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.

Figure 11: Hallucinated face image with subspace PCA in wavelet domain. Hallucinated face, Original face and bicubic interpolated face image.

Table 1: Change in PSNR with different types of wavelets.

Wavelet Type	PCA in Wavelet Domain	Subspace PCA in Wavelet domain
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 2: Comparison of performance of different PCA based hallucination algorithms.

Bicubic	PCA in spatial domain	PCA in Wavelet domain	Subspace PCA in spatial domain	Subspace PCA in Wavelet domain
When test image is not included in database				
24.898	26.590	26.664	24.130	24.230
Test image within database and only 10 images in database (Recognition performance)				
29.367	32.655	44.924	30.503	30.542

The experiments are repeated with different types of wavelet function. Table 1 give the change in PSNR with different types of wavelets. Though the PSNR seems to be low, hallucinated images are sharp at eyes, nose, etc. compared to the bicubic interpolated image. In both the cases presented here, result improves considerably when the test image is accurately represented as the linear combination of images in database. Table 2 compares the PCA based hallucination algorithms in spatial domain and wavelet domain. Wavelet domain approach gives better results while providing the advantages like lower memory requirement computational efficiency.

4 CONCLUSIONS

In this paper two algorithms are proposed for face hallucination using PCA in wavelet domain. First algorithm uses the face image as a single image where as the second method splits the image into textured and flat regions. In both the cases wavelet subbands of the images are determined and PCA based hallucination technique is applied on these subbands independently. The results are compared with the eigen transformation based hallucination in spatial domain. An advantage of PCA based methods discussed here, over many other hallucination methods, is that it does not require optimization of the result. Simulation results show significant improvement in the super resolution performance of proposed algorithms. Overall performance can be improved by using multi level wavelet decomposition. Currently we are trying to apply the proposed methods in other transform domains like curvelet, contourlet etc.

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