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Super-Resolution Image Reconstruction based on 2D Cosparse Regularisation and Self Similarity Features

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Abstract. Many applications have benefited from powerful super- resolution (SR) imaging model, and it is challenging when the missing information in the input low resolution (LR) image. In this paper, we propose a new method to reconstruct a high resolution (HR) image from a low resolution (LR) image based on two dimensional (2D) co-sparse method. The new framework is consisted of three parts. Firstly, divide the nonlinear feature of input LR image into the feature of linear subspaces and learned the LR-HR dictionaries to reduce the artifact. Secondly, 2D co-sparse regularization and self-similarity are developed to strengthen and enhance the image structure. Finally, principal component analysis (PCA) technique is used to reduce the noise in a HR patches. The final SR image can be achieved by reconstructed all HR patches. Simulation results demonstrated a better reconstruction on real image in terms of PSNR and SSIM values, and achieves various improvements compared with other methods.

Keywords: cosparse, image enhancement, image resolution, principal component analysis (PCA)

1 Introduction

Image super-resolution (SR) is considered as an active area of research, and its offers of overcoming the limitation of low resolution image, many applications have benefited such as, biomedical imaging, and astronomical imaging model. The objective of super resolution (SR) image is to reconstruct a high resolution (HR) image from its corresponding low resolution (LR) input image. SR reconstruction is an efficient reconstruction techniques that would transform high resolution quality images from cost effective imaging systems [1]. In recent year, several SR imaging method that has been proposed, and can be categorize as interpolation based method, learning based and reconstruction based methods and each of them contains several technique to overcoming high resolution problem [1]. Interpolation based methods is very common and simple approach to super resolution (SR) image based on the adaptive kernel method to estimate the unknown pixels in HR grid [2-3], considering the fact, this method have some limitations which is limited to real time applications, and the quality of reconstructed image is degraded. By using externally trained datasets Learning based method is used to reconstruct the HR image by evaluating and mapped between the pairs of LR-HR patches, this method produce blur artifacts and leads to be unsatisfactory reconstruction because of relying on external training datasets [4].

In reconstruction based method we assume the low resolution (LR) image, which consists of several degrading factors such as blurring, white noise and Gaussian noise. In fact, the low resolution image correspondence to several HR image which result in ill posed problem. Several researcher proposes different ways to inverse the problem, to achieve the optimum solution which required prior knowledge such as redundancy which is commonly used in reconstruction based method, which leads to be good resolution image and suppress image artifacts [5-6]. Super resolution image based on 2D sparse has been proposed the method is robust and provides satisfactory reconstruction, but it needs to learn 2D dictionaries which requires large processing time and memory [7]. Based on prior knowledge of the image, HR problem occurred when recovering the original high resolution image by using less information of LR image [8]. Reconstruction of HR image is generally creating an ill-posed problem because of less sufficient detailed of an input LR images. Yang et al. [8] have proposed learning joint dictionary for sparse signal reconstruction, this method provides sampled large datasets to construct dictionary, but the optimization algorithm used which required large amount of computational time due to l1-norm regularization of image patches.

Zeyde et al. [9] proposed a new scheme using principal component analysis (PCA), which inverts the large computational time and enhance the reconstructed SR image, learning dictionary will leads to enhance the reconstruction quality but algorithm is still time consuming due to the size of dictionary. Recently, a 2D sparse model has been introduced, and was applied to enhance the structure of an image [10-11]. Dong et al. [12] introduces the robust and fast method to achieve the HR images by using dictionary learned model incorporating with NLM regularization. This method is robust, but it requires large computational time due to NLM and sparsity regularization. Recently, many method have been proposed to achieve the SR image reconstruction by process several frames of LR images of the same scene to generate a one full frame of HR image which inverse the image enhancement quality due to LR fames of the scene [13-14]. Freeman et al. [15] has been proposed that high frequency component in HR image can be learned from HR patch by using Markov random method, this method achieves satisfactory reconstruction but while dealing with lots of patches that would increases the computational cost.

Yu et al. [16] proposed a new method, instead of training datasets the dictionary are learned from the LR input image, which leads to be unsatisfactory reconstruction and may introduce artifacts. Support vector regression (SVR) model has been proposed based on kernel resolution using single and general support regression for all contents of image, considering the fact that small training sets which leads to be dissatisfactory result, but requires less computational time [17]. The new method based on cloud technology was proposed to process sensing data and applied successfully in 3D reconstruction environments and fall event. This method enhanced the effectiveness of computing and minimizes the voltage utilization of the handheld devices [18]. Huahua et al. [19] provide robust method based on co-sparse regularization, which learned sub dictionary to get the image structure, this method generally require less computational processing time, due to clustered the subspace, which result in high quality reconstructed image, but requires large memory because of learning dictionary online. In recent years, 3D falling reconstruction has been introduced to detect the existence of accidentally falling by using accelerometer and wireless modules [20]. Wei at al. [21] introduced new approach using tensor patches based on multi linear analysis and coupled residue, this algorithm mainly limited to the face, and add more detailed while introducing more artifacts. Yincheng et al. [22] have used compressed sensing with prior redundancy dictionary to reconstruct the HR image, the method was simple and provide robustness compared with several other methods but training phase requires large amount of calculations and computational time. This paper present a new method which focuses on the reconstruction of super-resolution (SR) image from a degraded low resolution (LR) input image. In this framework we divide the training space into a set of subspace, from this subspace an orthogonal LR, and HR dictionary are constructed, and incorporating with 2D co-sparse regularization to localize and strengthening image structure. Secondly self-similarity is introduced to overcome the repetitive structure, and to reduce the artifacts in the image. Finally, PCA is applied to minimize the noise in the HR patches and, SR image can be achieved by reconstructed all HR patches.

In Section 2, we describes the problem formulation and modeling. Section 3 introduces the 2D co-sparse signal method analysis, self-similarity features, and learning 2D dictionaries. Principal component analysis (PCA) is introduced in Section 4. Section 5 describes the image reconstruction model. The simulation and results are presented in Section 6, and finally the work was concluded in Section 7.

2 Problem Formulation and Modeling

Fig. 1 shows the block diagram which clarifies the statement, as discussed in the introduction, the major problem correlate with SR reconstruction when transforming from LR to HR image, due to missing information in the LR image which causes an ill posed problem, considering the fact, to recover the useful information is impossible, and SR image reconstruction demonstrate robustness and provide efficient algorithm to regularize the inversion, recently several method has been proposed by implementing using training phase, which generally require complex algorithm. Specifically, our new method comprised of two main parts, the first one is convert the nonlinear subspace of LR image into linear subspace, and then constructed LR, HR dictionary to reduces the blur artifacts, and the second one 2D co-sparse, and self-similarity feature was introduces to strengthen, and enhanced the image.

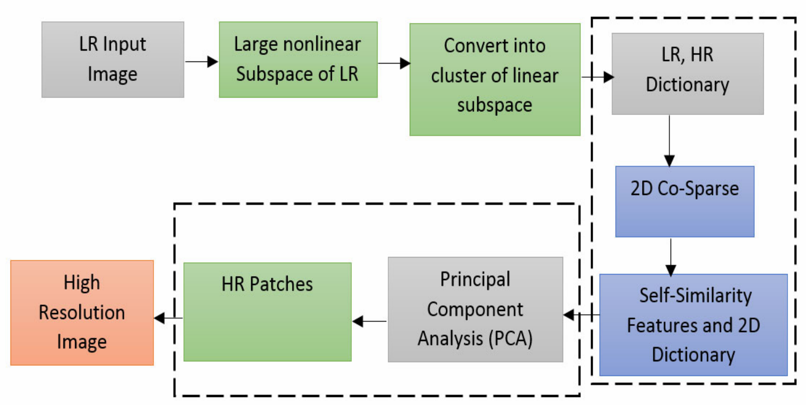


Fig. 1. Problem formulation block diagram

Reconstruction of SR image is a critical issue which associated with many problem such as visual quality, image resolution etc. Our objective is to restore and enhance the visual quality of HR image from its LR image. Traditional approaches is used to generate a SR image which generally requires several low resolution images, and the SR is categorizes under the inverse problem of recovering the high resolution images from low resolution image with respect to some prior information details, specifically the limitation of SR algorithm is to regenerate the same low resolution input image by using same algorithm. The block diagram of the proposed model shown in Fig. 1. Firstly, divide the training sample of LR feature space into sets of subspaces, and then construct the LR, HR dictionaries to achieving an efficient SR image. Secondly, the 2D co-sparse method is introduced to overcoming SR optimization problem, and enhances the image structure, and integrating self-similarity into 2D co-sparse to inverse the repetitive effect. Finally, PCA is introduces to reduce the noise in the high resolution (HR) patches, and the SR image can be constructed by reconstructed all HR patches.

2.1 Subspace Modeling

We partitioned the large nonlinear features of LR image into the cluster of linear subspace then learned the multiple LR sub dictionary. The sparse recovery techniques providing us the best optimum solution of learning the features of LR, HR image, considering the fact, it required large computational cost. We adopt a method of multiple learning from clustering of LR, HR subspace, which leads to be directly convert the LR feature subspace into the HR subspace [1].

$$Y_l = [y_{l1}, y_{l2}, \ldots, y_{lk}] \tag{1}$$

$$X_h = [x_{h1}, x_{h2}, \ldots, x_{hl}, \ldots, x_{hk}] \tag{2}$$

Let assume we have LR and HR features space $Y_l \subseteq R^M$ and $X_h \subseteq R^n$ respectively, we need to acquire the different contents of images, we assume the LR, HR image pair to construct the datasets, let $Y_l = \{y_l^1, y_l^2, \ldots\ldots, y_l^{N_s}\}$ are the training samples of LR feature space and $X_h = \{x_h^1, x_h^2, \ldots\ldots, x_h^{N_s}] = \{x_h^1\}_{i=1}^{N_s}$ is the training samples of HR feature space, where N_s is the number of LR-HR image. Let $Y_l^k = \{y_l^i\}_{i \in \omega_k}$ be the kth subset of Y_l, where ω_k represents index sets of Y_l^k. Now we need to divide the respective HR training set X_h into K subsets, now it can be represent X_h^k where k = {1, 2,…, K}, once they will into the K subsets then it coupled the subsets of LR, HR $\{Y_l^k, X_h^k\}_{k=1}^K$.

2.2 LR-HR Dictionary

Learning the multiple LR, HR dictionary are constructed, by using the method vectors of LR, HR features and can represent the linear combination of atoms in their respective subspaces. Let suppose the given low resolution (LR) image Y_l and the high resolution image (HR) X_h, the LR imaging model can be form as,

$$Y_l = LBX_h + n \tag{3}$$

where L and B are the down sampling and the blurring operator, and n is the Gaussian noise. Inspired from the idea of 2D sparse [1].

$$D_l = \arg\min_{D_l} \sum_{i\in\omega k} \left\| y_l^i - D_l^k c_i^k \right\|_2^2 \tag{4}$$

$$D_h = \arg\min_{D_h} \sum_{i\in\omega k} \left\| x_h^i - D_h^k c_i^k \right\|_2^2 \tag{5}$$

where $D_l \subseteq R^{d_l \times n_l}$ is the K^{th} sub dictionary of LR which represent the features of $\{Y_l^k\}$ and $D_h \in R^n$ is the K^{th} sub dictionary of HR which represent the feature of $\{X_h^k\}$

Eq. 4 and Eq. 5 is the joint optimization problem which can be solved by learning the LR sub dictionary and then convert into the HR sub dictionary. Where $\{c_i^k\}$ represent the shared coefficient of LR and HR sub dictionary respectively.

$$c_i^k = (D_l^{KT} D_l^K)^{-1} D_l^{KT} y_l^i \tag{6}$$

$$D_l = \arg\min_{D_l} \sum_{i\in\omega k} \left\| y_l^i - D_l^k (D_l^{KT} D_l^K)^{-1} D_l^{kT} y_l^i \right\|_2^2 \tag{7}$$

Similarly,

$$D_h = \arg\min_{D_h} \sum_{i\in\omega k} \left\| x_h^i - D_h^k (D_h^{KT} D_h^K)^{-1} D_h^{kT} x_h^i \right\|_2^2 \tag{8}$$

Eq. 8 represent the optimization problem, we need to provide optimum solution by using the LR dictionary features. As we know that component y_l^i representing the same features of $\{Y_l^k\}$, so we can replace to solve the problem accurately and by defining the Frobenius norm.

$$D_l = \arg\min_{D_l} \sum_{i\in\omega k} \left\| y_l^i - D_l^k D_l^{KT} y_l^i \right\|_2^2 \tag{9}$$

$$D_l = \arg\min_{D_l} \left\| Y_l^k - D_l^k D_l^{kT} Y_l^k \right\|_F^2 \tag{10}$$

In Eq. 10 the Y_l^k is a matrix, and each column in the matrix is the vector from subspace $\{y_l^i\}_{i\in\omega k}$ and, $\|\cdot\|_F$ is represent the Forbenius norm used for matrices, similarly the HR dictionary can be formed as below,

$$D_h = \arg\min_{D_h} \left\| X_h^k - D_h^k D_h^{kT} X_h^k \right\|_F^2 \tag{11}$$

3 2D Cosparse Model

Signal recovery is a critical issue, which mean how to recover the accurate signal with the presence of noise, and receive great deal of attention of researcher to deal with such problem, 2D co-sparse method is an alternative to the sparse which yielding and provide unique solution of the linear problem in image processing model. Inspiring from the idea of 2D sparse model [7], can be denoted as below,

$$X = D_l B^T D_h^T \quad \text{s.t}\|B\|_1 = k \tag{12}$$

where $D_l \subseteq R^{d_1 \times n_1}$ and $D_h \subseteq R^{d_1 \times n_2}$ are the LR and HR dictionaries respectively, and B is the sparse coefficient with $B \in R^{n_1 \times n_2}$.

$$X = \arg\min_{X,B} \|Y_1 - BL\, X_h\|_2^2 + \left\|D_l^h B^T D_h^{H^T} - RX_h\right\|_0 + \lambda\|B\|_1 \tag{13}$$

where λ is the coefficient which balancing the co-sparsity term against fidelity $\|\,.\,\|_0$ are the l0 norm which counts the number of non-zero's elements, and $\|\,.\,\|_2$ are the second norm.

$$X = \arg\min_{X,B_i} \|Y_l - BL\, X_h\|_2^2 + \sum_{i=1}^{N}\left\|D_{li}^h B_i^T D_{hi}^{H^T} - RX_h\right\|_0 + \lambda\|B\|_1 \tag{14}$$

Equation 14 is the super resolution joint optimization problem with 2D co-sparse method which represented on both direction horizontal and vertical respectively, and ensuring the every image patch is the sparse represent of both dictionaries D_{li} and D_{hi} respectively and B_i^T is the sparse matrix.

3.1 Self- Similarity Features

We proposed the new approach integrating the non-local self-similarity features, which can be used to enhance and improve the quality of high resolution reconstructed image. Let assume that a similar patch or patterns can be present in an image, for patch x_i searching for a similar patches with in the image x, we can select patch x_i^l, which is similar patch of x_i and the error can be $e_i = \left\|x_i - x_i^l\right\|_2^2 \le t$, where t is the preset threshold. Inspired with the reference [12], considering the fact that each patch x_i has similar patches with in the full image x, let assume $\boldsymbol{x_i}$ be the mid pixel value of the patch x_i, and $\boldsymbol{x_i^l}$ is the mid pixel value of the patch x_i^l. We can predict the patch x_i by using weighted average of $\boldsymbol{x_i^l}$, which can be written below,

$$x_i = \sum_{i=1}^{l} b_i^l \boldsymbol{x_i^l} \tag{15}$$

where b_i^l is weight assigned to the $\boldsymbol{x_i^l}$, considering the fact there is large scale of non-local redundancy in images, so the error has been updated.

$$e_i = \left\|x_i - \sum_{l=1}^{l} b_i^l \boldsymbol{x_i^l}\right\|_2^2 \tag{16}$$

From Equation 14 we integrating the nonlocal similarity feature term into 2D co-sparse based representation method to enhance the performance of the sparse signal.

$$X = \arg\min_{X,B_i} \|Y_l - BL\, X_h\|_2^2 + \sum_{i=1}^{N}\left\|D_{li}^h B_i^T D_{hi}^{H^T} - RX_h\right\|_0 + \lambda\|B_i\|_1 + z.\left\|x_i - \sum_{l=1}^{l} b_i^l \boldsymbol{x_i^l}\right\|_2^2 \tag{17}$$

where z is the constant parameter which balancing the nonlocal similarity term, which improves and enhance the resolution of reconstructed image in the presence of similar patches present in an image. Now simplified the above Equation 17.

3.2 Learning 2D Dictionary

We have learned a 2D dictionaries earlier D_l and D_h respectively, the optimization problem can be written as below,

$$B_i = \arg\min_{B_i} \left\|D_l B_i^T D_h^T - X_h\right\|_F^2 + \lambda\|B_i\|_1 \tag{18}$$

Equation 18 is the optimization problem of 2D dictionary, where B is the sparsing coefficient matrix, and X_h is the reconstructed HR image patch. Converting in to one 1D dictionary can be written as below,

$$(D_i, B_i) = \arg\min_{D_i, B_i} \|D_l B_i - X_h\|_F^2 + \lambda \|B_i\|_1 \tag{19}$$

where D_i is the joint optimization problem that would share the same features of LR and HR image.

4 Principal Component Analysis (PCA)

Principal component analysis (PCA) technique is used for compressing large amount of data into smaller features, and commonly used in pattern recognition and digital signal processing [23]. The PCA method is used to remove the noise and has been used in adaptive image denoising by computing the PCA transform of each image patch [24]. Using the PCA method to find out the orthonormal transformation matrix. The key objective to PCA is to solve the large amount of calculation and complexity of algorithm in [22].

We are applying PCA to each high resolution patch to reduce a noise in the patch, and to suppress the large amount of calculation, which also leads to satisfactory reconstruction of HR image. In Eq. 19 to maintain the balance between l_1 and l_0 norm, only extracting Z to form an eigenvectors to D_z, and the error $\|D_i B_i - X_h\|_2^F$ would be minimizes in Eq. 19. Let assume $D_i = [D_1, D_2, ..., D_i]$, and $B_i = D_i^T X_h$.

$$i = \arg\min_i \|D_i B_i - X_h\|_2^F + \lambda \|B_i\|_1 \tag{20}$$

Eq. 20 is the optimization problem after applied PCA, where X_h is the high resolution patch, D_i and B_i is the joint dictionary and sparsing coefficient respectively.

5 Image Reconstruction Model

Image reconstruction model has been proposed by using the following steps:
(1) Upscale the input image by using bicubic interpolation.
(2) Extracting the features of image by using bilateral filter.
(3) Adding self-similarity features to enhances the image structure, and applying PCA to suppress the noise in a HR Patch.
(4) Final image is constructed by reconstructed all high resolution patches.

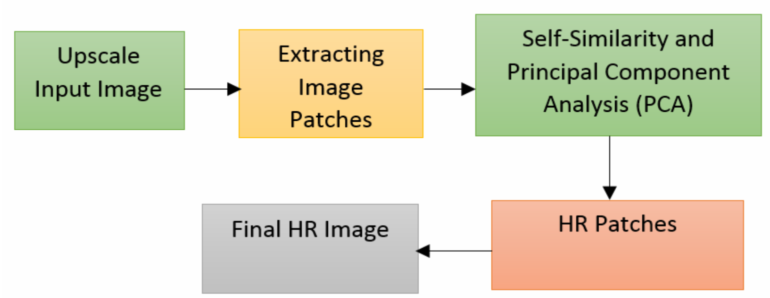


Fig. 2. Image Reconstruction Model

Reconstruction of HR image based on HR patches, firstly magnify the input image which is assumed to be generated the high resolution image X_h based on joint dictionary, and let assume the low resolution input image Y_l is used to scale up by using the bicubic method to achieve the equivalent high resolution image X_h and have the same size as X_i. Let assume the X_h be a high resolution image vector, and the low resolution image vector are Y_l so, $Y = Y_l R_{ki}$, where i is the number of patches which is I = 1, 2, 3 … N. R_{ki} is a matrix extraction feature of patch Y from Y_l, then to separate patch Y in to small patches let assume P_k, so the Equations can be formed as below.

$$P_k = \sum_{i=1}^{N} R_{ki} Y_{li} \quad \textbf{(21)}$$

$$P_h = \sum_{k=1}^{K} P_k \quad \textbf{(22)}$$

$$P_h = \sum_{k=1}^{K} \sum_{i=1}^{N} P_{ki} Y_{li} \quad \textbf{(23)}$$

In Eq. 21 the term R_{ki} Y_{li}, which builds the high resolution patches. Let α_i is the column vector which contain the value of x^l_i, and a_i is the column vector contain the weight of b^l_i which can predict patch x_i, so Eq. 17 can be modified as below,

$$X = \arg\min_{X,B_i} \|P_h - BL\, X_h\|_2^2 + \sum_{i=1}^{N} \|D_i B_i - RX_h\|_0 + \lambda \|B_i\|_1 + z.\sum_{x_i = x} \|x_i - \alpha_i \alpha_i\|_0^2 \quad \textbf{(24)}$$

$$\arg\min_{X_h} \|(R_{ki} Y_{li}) - P_h\|_2^2 \quad \textbf{(25)}$$

Eq. 25 recovering the lost information in the HR patches.

$$X_h = X_i + R_{ki}^T R_{ki} P_h \quad \textbf{(26)}$$

The final image can achieve by reconstructed all HR patches P_h and adding X_i to achieves the high resolution (HR) image, where $R_{ki}^T R_{ki}$ is a diagonal matrix which weights the each pixels of high resolution image. Where X_i is the equivalent image which contain less information due to processing of low resolution input image.

6 Simulation Results

To demonstrate the performance of proposed SR method compared with several methods, namely as Bi-cubic, Yang [8], Yincheng [22]. Several experiments has been conducted to comprehensively analyze the effectiveness of the proposed method. We have chosen 60 frames of HR images with different sizes, in learning part 500,000 LR, HR image patch are extracted [7], and train 2D dictionary which is used to represent the LR-HR image patches. Secondly, k mean algorithm is used to sectionized the training datasets into 300 clusters. In order to achieves a good reconstruction the selection of patch is very critical issue, we selects the image patch size of 7×7 to reduce the LR features and artifacts.

6.1 Visual Analysis with Different Patch Sizes

In this sub section, we are carrying out SR experiment on the Lena image to analysis the visual qulaity and effect of algorithm by using a different patch sizes of (5×5), and (7×7). Fig. 3 shows the visual comparison and detailed information of two deblurring images with different patches. Sparse representation method [8], and redundant dictionary method [22], were used the image patch size (5×5) to reconstruct an SR image, the image is blur with less contrast and brightness, and achieve less PSNR, (see Fig. 7). The proposed method used the image patch size of (7×7), our result shown better resolution with good contrast SR image.

(a) (5×5)

(b) (7×7)

Fig. 3. Visual Comparison of Lena Image

6.2 Results with Deblurred Images

In this section, several experiments has been conducted to demonstrate the effectivness of the proposed method interms of visual qulaity and resolution. In Reconnection part firstly, we down sampled the original image, to generate the input LR image Y_l by using bicubic interpolation with scaling factor of 3, and magnifying the input LR image to gain the equivalent image X_i. Secondly, extracting the features of patch information. Finally, the SR image is constructed by all HR patches.

The original SR image can be constructed, but the resolutiuon, contrast and brigthness remains the critical issue, the SR image reconstruction. Fig. 4 (a) is the original SR image, Fig. 4 (b) is the degraded LR image size of (64×64), Fig. 4 (c) and 4 (d) are the visual comparisons of bicubic method with proposed method, respectively. The bicubic interpolation algorithm itself is fast, but gives the worst reconstruction quality of SR image, which leads to be unsatisfactory results, with less contrast and blurriness. The proposed method achieves better SR reconstruction with good resolution and contrast, and also outperforms several methods, while maintaining the computational time.


(a)


(b)

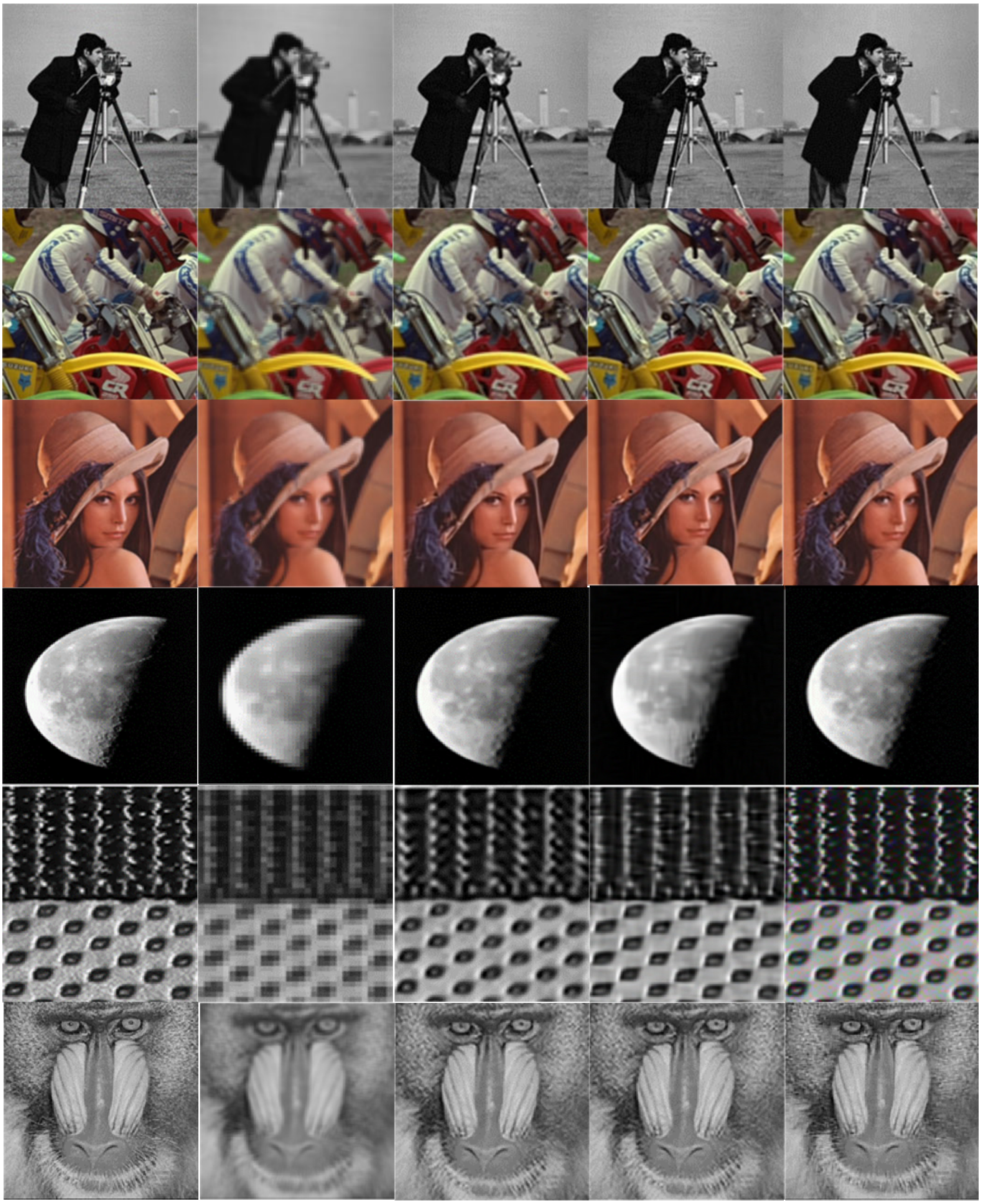

(c)


(d)

Fig. 4. Simulation of image (a) Original SR image, (b) LR degraded image, (c) Bicubic Interpolation and (d) Proposed method

6.3 Results with Different Images

To validate the efficiency of the presented method compared with other scheme namely as, Yang [8], and Yincheng [22], we conducts experiments on six different images (cameraman, lena, bike, moon, bag, baboon). Fig. 5 (a) shows the original HR image, Fig. 5(b) is the bicubic interpolation method, and Fig. 5(c)-(e) are the results of various algorithm Yang [8], Yincheng method [22], and our proposed method respectively. The result of bicubic interpolation generates low resolution image and blurred artifacts, which exacerbating the SR performance and leads to be unsatisfactory reconstruction. Yang [8] enhances the SR image quality, and outperformed the bicubic interpolation method, in terms of visual quality and good resolution image with little blurriness, this method also required large computational time because of memory allocation and dictionary size. Yincheng [22] achieves good SR reconstruction by using the training phase, which requires huge amount of calculation to learn the redundant dictionary, and required more computational time to process dictionary, to inverse the effect of [22]. Our proposed method achieves better SR reconstruction and good resolution image with rich texture details while maintaining the computational time as compared to other competent methods.



(a)Original method (b) Bicubic method (c) Yang [8] (d) Yincheng [22] (e) Proposed method

Fig. 5. Visual analysis and Comparison of proposed method with different methods (cameraman, bike, Lena, moon, bag and baboon)

6.4 Results with PSNR

We are now comparing the SR effectiveness of the proposed method with different methods. Qunatitatively and qulitatively the peak to signal noise ratio (PSNR), and structural similarity (SSIM) are used to anaylse the qulaity of reconstructed SR image, in this sub section we are discuss the experiments results interms of PSNR by using six test images see (Table 1) Bi-cubic interpolation has lower PSNR in all of test images, the method is fast itself because of inexact and less sufficient detailed, which leads to be displeasing blurred and low resolution SR image. Yang [8] proposed SR approch based on sparse representation, this method can generate good SR image with better resolution, and good PSNR values than bi-cubic method, but requires large amount of calculations due to processing of millions of patches. Yincheng [22] has better PSNR and achieves good reonstruction in all of the test images comparitvely with bi-cubic, and Yang [8] method. The proposed method demonstrate the good PSNR values in all of the test images, and achieves better SR reconstructed image with better resolution and outperforms several other methods.

6.5 Results with RMSE

In this subsection, the comprehensive comparsion between proposed method and different state of art method named as Bi-cubic interpolation, Yang [8], and Yincheng [22] interms of root mean square error (RMSE) by implementing of six images (see Table 2). The error of bi-cubic interpolation is quite high of every image compared with all of the methods. Yang [8] provides good inversion, which are the limtation of bicubic interpolation method and achieved less error. Yincheng [22] method have less error than bicubic, and Yang [8] methods, this method is fast but require large amount of calculation because of using train redundant dictionary to reconstruct SR image. The proposed method is robust method yields less error in all of the test images compared with Bicubic method, Yang [8], and Yincheng [22].

6.6 Results with SSIM

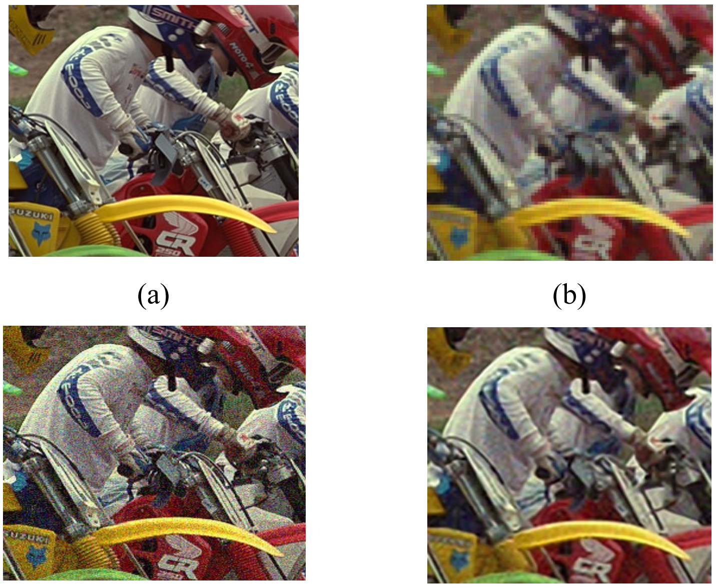
In this subsection, we are now comparing the behaviour of the proposed method interms of structural similarity (SSIM), to evaluate the SR qulaity in six test images (see Table 3). The proposed method achieves better SR reconstruction quality and SSIM values. We performed SSIM on six test images, every image is different in size, and which leads to be change in amount of similar patch. The SSIM value of each image is correlated with SR qulaity, the higher the value of SSIM, which leads to be better SR reconstructed image. The qulaity of SR image depends on SSIM, the experiment on test images is shown in Fig. 5 the visual resolution of the proposed method is better, and outperformed several other methods, named as Bicubic interpolation, Yang [8], and Yincheng [22].

6.7 Results with Noisy Image

In this section, we are now comparing the simulation results on noisy image to analysis the effectiveness of the proposed scheme. Add the guassian noise level with zero mean and 0.01 variance to low resolution input bike image. Fig. 6 shown the comparsion of our algorithm with different methods, the proposed method achieves better SR reconstruction qulaity and outperformed the bicubic interpolation and Yincheng method [22]. Fig. 6 (a) is the original image, Fig. 6 (b) is the bicubic reconstruction, the image is blurred with less resolution and also introduces artifacts. Fig. 6 (c) is withYincheng [22], the SR reconstruction qulaity is better than bicubic method, this method suppresses less noise and required large compuatational time. As shown in Fig. 6 (d), the proposed method achieves better SR reconstruction with good constrast and suppresses the noise which present in the image. Also, it reduces the large amount of calucalation, and compuatational time.

Fig. 7 shows the comparison results of PSNR with different methods by performing on six test images. Fig. 7 from Table 1. It has shown that the average PSNR value of the proposed method is better, and outperforms several other methods such as Bicubic interpolation, Yang [8] and Yincheng [22]. Also, it achieves a good PSNR value, which produces a good resolution SR image.

Fig. 8 shows the RMSE comparison of the presented method with several methods. Fig. 8 from Table 2, the error is significantly reduced by using the proposed method, due to high quality image patches of 7×7 and learning a 2D dictionary, in addition enhanced the quality of SR image and provides robustness of the proposed method compared with Bicubic interpolation, Yang [8], and Yincheng [22].



(a) (b)

(c) (d)

Fig. 6. Simulation of image (a) Original HR image, (b) Bicubic Interpolation image, (c) Yincheng [22] and (d) Proposed method

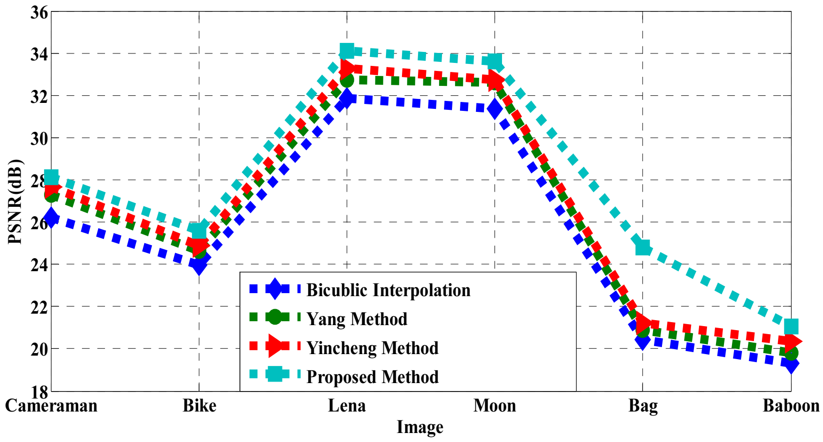


Fig. 7. PSNR comparison of proposed method

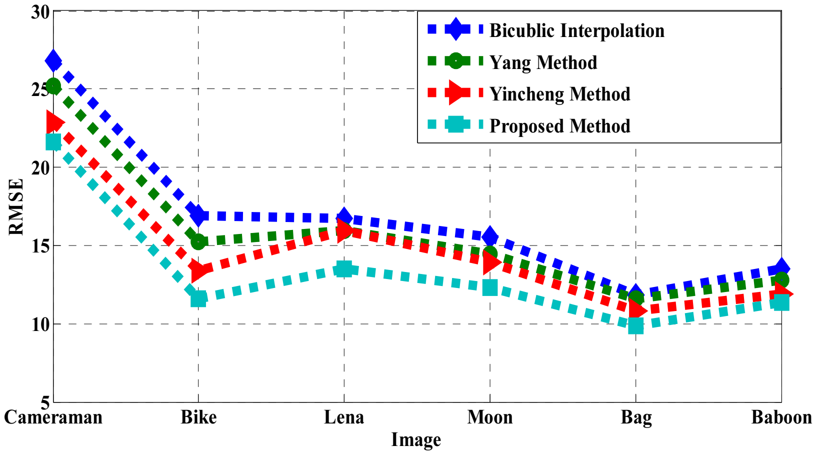


Fig. 8. RMSE comparison of proposed method

Fig. 9 shows the comparsion of the SSIM values with different methods by implementing on six test images (camerman, bike, lena, bag, moon, and baboon). The avergae SSIM value in Table 3 from Fig. 9, and the objective assement interms of SSIM values, demonstrated that the proposed method achieved good reconstruction qulaity of SR image due to selection of patch size, and learning 2D dictionary, and constantly outperforms the competing method.

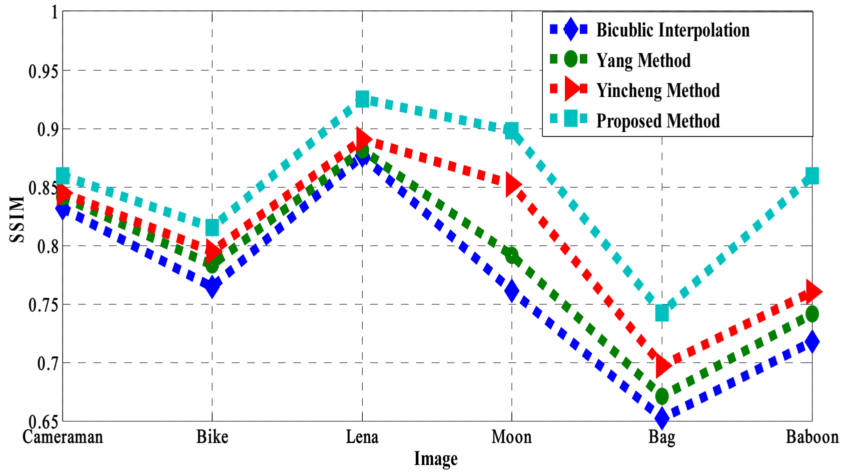


Fig. 9. SSIM comparison of proposed method

Table 1. PSNR comparison with different methods

Image	Bicubic Interpolation	Yang et al. [8]	Yincheng et al. [22]	Proposed Method
Cameraman	26.19	27.28	27.65	28.11
Bike	23.95	24.62	24.87	25.60
Lena	31.85	32.72	33.26	34.10
Moon	31.37	32.63	32.74	33.60
Bag	20.45	20.89	21.22	24.80
Baboon	19.32	19.80	20.35	21.05

Table 2. RMSE comparison with different methods

Image	Bicubic Interpolation	Yang et al. [8]	Yincheng et al. [22]	Proposed Method
Cameraman	26.81	25.22	22.85	21.60
Bike	16.91	15.23	13.37	11.62
Lena	16.75	15.95	15.92	13.53
Moon	15.56	14.48	13.93	12.32
Bag	11.68	11.59	10.82	9.85
Baboon	13.52	12.80	11.90	11.35

Table 3. SSIM Comparison with different methods

Image	Bicubic Interpolation	Yang et al. [8]	Yincheng et al. [22]	Proposed Method
Cameraman	0.832	0.842	0.845	0.860
Bike	0.765	0.784	0.795	0.816
Lena	0.877	0.882	0.891	0.925
Moon	0.762	0.792	0.852	0.898
Bag	0.653	0.672	0.698	0.743
Baboon	0.718	0.742	0.743	0.860

7 Conclusions

In this paper, we proposed an image super-resolution (SR) based on the concept of 2D co-sparse representations in terms of LR-HR dictionaries. To reduce the artifacts at reconstruction part, partitioning the LR feature into a cluster form and then learned the LR-HR dictionary respectively. The self-similarity features are incorporated to enhance the effectiveness of 2D co-sparse model, which leads to a good SR reconstructed image. The experiment conducted on six test images by using a patch size of (7 x 7), and simulation results indicates that our proposed method yields a better reconstruction, and achieved a good PSNR, and SSIM values compared with Bicubic interpolation, Yang [8], and Yincheng [22], in addition the RMSE of the proposed method is significantly reduced. At last, the presented method is a better quantitative and qualitative robust one than other SR scheme, and achieved a better resolution while maintaining the computational time which are the limitation of several methods.

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