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Semi-Coupled Dictionary Learning Based on Sharpness Measure for Single Image Super Resolution

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Abstract
In this research work, a new algorithm is simulated based on semi coupled dictionary learning (SCDL) for single image super resolution (SISR) problem. Semi coupled dictionaries were planned for set of clustered information. The clustered information classified in three clusters by sharpness measure based and included only those patches whose sharpness measure value is same. For task of super resolution SR, invariance of sparse representation assumed. Formerly mapping function with a pair of dictionaries were initialized for each cluster, Afterword the dictionaries, mapping function and sparse coefficients were updated. During the reconstruction phase the dictionary pair and mapping function of respectively cluster are used to recover HR image. The LR and HR dictionary pair with mapping function are selected which give the slightest sparse representation error. For high resolution patch approximation, dictionaries pair with mapping function of that cluster are utilized. In addition, it's also tried modifying the results, by observing power spectral density (PSD) of distinct images through computing sharpness-based scale-invariance ratio for patches that categorized in three clusters. The proposed work is compared with the previous research of image SR algorithms. By proposed procedure the recovery of HR image feature becomes prominent.

Keywords: - Super resolution, Semi coupled dictionary learning, Sharpness Measure, Single image super resolution, Mapping function, Sparce representations, super resolution, PSD.

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1. Introduction

Image SR is an active research topic from few decades among researches due to the increased interest of HR images in new technology system[1]–[6]. There is no reservation, that high resolution images can be taken with (HD) camera. But still, it's not yet practical for some applications to achieve that kind of high-resolution images due the limitations of cameras. Specially cost efficient in medical imaging, computer vision, satellite imaging.

In the new era of image super resolution, different kind of new techniques used for single image super resolution[7]–[12]. High resolution image could be reconstructed from single image[13][14]. The concept of author[13] on sharpness measure based and have aimed to super resolve the image over a pair of coupled dictionaries by using selective sparse representation. For achieving SR image representation sparsity is used as a regularization technique by imposing the idea that LR projection are well-preserved in linear relation of their high-resolution matching parts [15]. A directionally coupled dictionary and a mapping function for the problem of SISR, where the dictionaries are planned for a set of clusters [14]. The previous dictionary learning techniques for image SR were focused on separate high-resolution and low-resolution dictionaries. In [16] researcher proposed joint dictionary algorithm for high-resolution and low-resolution dictionaries in joint feature space, Comparing the similarity of high-resolution and low-resolution sparse coefficients. By reconstruction phase the author proposed invariance property for LR and HR patches. In [17][18] the author proposed methods for SISR based on patch wise sparse recovery, via sparse representation the learned coupled dictionaries have LR and HR images patches. The sparse representation of LR image patch in terms of LR dictionary can reconstruct its fundamental HR image patch with dictionary in HR image patch space. The learning problem is a bilevel optimization problem, whereas optimization contain an ℓ^1 -norm minimization problem in its constraints.

A cross style images synthesis is proposed by semi coupled dictionaries learning [19], where a mapping function and pair of dictionaries are learned instantaneously under semi coupled dictionary learning, and the structural domain of two style images are well characterize by the pair of dictionaries, While the intrinsic relation of two styles image domains keeps by the mapping function. The dictionaries will not be fully coupled, while more flexibility is given to mapping function for precise conversion of two style images, where to enhance the robustness of SDCL, image nonlocal redundancy and clustering are introduced. In [20] the author proposed a new algorithm for SISR utilizing coupled-wavelet and a spatial domain dictionary pair, for clustering purpose scale invariant property is used for HR and LR resolution patch pair. Then pair of coupled dictionaries are learned online for cluster utilizing LR image, where the coupled dictionary which are based on sparse framework the standard deviation calculates the patches of low resolution to move in appropriate cluster have high standard deviation, patch collaging and little complexity methods attempts to resolve these patches and reconstruct high-resolution image. In [21] the author proposed a new image super resolution reconstruction method which based on single hybrid dictionary, where the hybrid dictionary has both LR and HR image patch samples. Over same hybrid dictionary, a linear model is applied that’s keep the relationship of sparse representation between high-resolution and low-resolution patches and provide more flexible framework to similar sparse characteristic. The planned linear model amid sparse representations of both high-resolution patch and the corresponding low-resolution patch by same hybrid dictionary suggests us a new technique to interpret the image degeneration characteristics in sparse domain. In the early decades the concept of super resolution through dictionary learning were amid on separate dictionaries for low resolution and high-resolution image patches. In [22] the author proposed a new technique for the task of SISR where multi scale dictionary learning presenting local and non-local priors. Super resolved images are recovered with the help of these priors while suppressing artifacts and estimate required high-resolution image pixels. A coupled dictionary learning algorithms is proposed by[23] for training of high-resolution and low-resolution dictionaries. In this configuration, a substitution procedure is functionated to the sparse coefficients of the low-resolution and high-resolution patches to every iteration, a sparseness factor is preferred as high-resolution or low-resolution which is used to update LR and HR dictionary. By doing this, the author attained a minor improvement by imposing sparse coefficients of high-resolution and low resolution to be similar and therefore producing results comparable to published up-to-date algorithm in[16]. In [24] the author proposed SCDL technique which provide a more flexible mapping relation among the sparse representation of LR and HR pair. For SISR, a novel methodology is proposed by a unique scale invariant image feature [25], the scale invariant used to categorize image patches into unique classes. For every class separate joint dictionaries and separate mapping matrix are learned, by creating separate dictionaries and mapping matrix helps to approximate invariant HR and LR sparse coefficients similar. In [26] the author proposed new image SR-based facial emotion recognition model is introduced. The suggested work has two main parts image SR and facial emotion recognition. Facial images have LR and HR faces which are processed by two-dimensional canonical correlation analysis model. In this model the correlation of HR and LR images are maximized. The high-resolution face images by K-nearest neighbors in high-resolution training set, based on SSIM between high-resolution and low-resolution images. The reconstruction of input low-resolution face takes place with slight error. To get super-resolved image, similar neighborhood is functionated to high-resolution training set. Then, followed comprehensive compensation stage, high-frequency components were utilized to restructure high-frequency mask. The quantity of restored facial images and detail mask is the final outcome. In [27] the author investigates the self-similarity of images and then designed low-resolution and high-resolution dictionaries where's the sparse representation and image reconstruction algorithms are compressed. Furthermore, for dictionary construction and sample training the improved K-SVD algorithms adopted, improved matching pursuit algorithms were used to get the desired single image SRSR. In [28] instead of single dictionary a multiple patches based clustered dictionaries were designed and the image patches were studied by geometric properties and the patches are clustered into different clusters. Dictionaries are gained from the training image patches from the same clusters. Learning or example-based methods used for image super resolution but both the methods require a training database, but the quality assurance totally depends on the size and type of database[16][29]. To overcome this limitation, For the prediction of high-resolution image patches, the author assumed re occurrence of similar patches within and cross image scales[30]. For the task of SISR, the author in[31] designed nine low resolution directional dictionaries, Here K-SVD algorithms [32] were used to learned the low-resolution dictionaries, while a pseudo-inverse problem used to obtain the high-resolution dictionaries. In [33] the author proposed new SR model based on deep convolutional neural network that takes image as input and result in output is a high resolution one. This method is using a mapping of low and high- resolution images which are end to end encrypted, the traditional methods of SR sparse coding handle each component separately while the CNN model jointly handle it and optimize it's all layers.

In [34]–[36] different kind of new convolutional neural networks are introduced for purpose of single image super resolution. A new novel algorithm for SISR is based on nonnegative neighbor embedding, this novel algorithm relates to example based super resolution which use dictionary for low-resolution and high-resolution trained patches which gather the unknow HR details [37]. Here a dictionary of the LR image is trained by k nearest neighbor and the high-resolution features are reconstructed under the assumption that low resolution embedding is preserved.

In the proposed work, for the task of single image super resolution, the basic idea of [17] [23] were used. The training data are divided into three clusters on the sharpness measured based, after that for each cluster the dictionary pair and mapping function were initialized. Fixing the dictionary and mapping function updated the sparse coefficients while fix the mapping function and sparse coefficients updated the dictionary pair for LR and HR, and keeping fix the sparse coefficients and dictionary pair the mapping unction were updated. The high-resolution patches are reconstructed while taking sparse coefficient and semi coupled dictionary pair along with LR image patches, taking that dictionary which has the sharpness measure value to convert the low-resolution image patches into LR image patches to reconstruct the high- resolution image.

2. Image super- resolution

The idea of SISR is an ill posed problem. Many researchers have tried distinctive kind of algorithms and techniques to the achieve an SR image. Here a special property of sparse representation is used to regularize the model process. In accordance with this model the sparse land, a vector X_H is represented over dictionary D_H and sparse representation -vector a_H. Let X_H D_H, a_H are the HR image patches correlate with dictionary D_H, and sparse coefficient a_H vector. In similar way X_L be the LR image patch, D_L and a_L be the equivalent low-resolution dictionary and sparse representations vector.

$$X_H \approx D_H \, a_H \tag{1}$$

$$X_L \approx D_L \, a_L \tag{2}$$

Here, the X_L patches are created by the help of blurring and down sampling HR images then take out low-resolution patches from these images. Due to resolution blur effect invariance property of sparse representation is considered. Given trained low-resolution and high-resolution dictionaries one can assess high-resolution patches from low-resolution patches utilizing the high-resolution dictionary and compute the low-resolution coefficients**.**

$$a_H \approx a_L \tag{3}$$

$$X_H \cong D_H \tag{4}$$

For super resolution this is a very basic idea. In [16] [19] the author planned a coupled dictionary learning mechanism in which they used coupled space instead of single one.

2.1 The proposed dictionary learning approach

Beforehand conversing attributes of proposed dictionary learning method, the clustering measure and data arrangements for SCDL is provided. The sharpness conditions utilized for the arrangement of patches into distinct clusters was as stated.

$$S(x, y) = \|I(x, y) - \mu_A(x, y)\|1 \tag{5}$$

Equation (5) declares the sharpness in pixel position (x, y), which equal to L_1 distance among $I(x, y)$ and mean $\mu_A(x, y)$ its eight adjacent neighbour's. For a particular patch the sharpness is calculated, and supposing invariance of these measures because of blur resolution, we took those patches that fulfils invariance. Upon this measure 3 clusters were made and 3 diverse class dependent high-resolution and low-resolution dictionaries were accomplished. Then patches were extracted from the same spatial scenes for both high-resolution and low-resolution data.

2.2. Training phase of SCDL

Let's X be training images for high-resolution. Now to create the low-resolution image training set from HR image set. By bi-cubic interpolation the high-resolution images were down sampled and blurred to obtained LR training image set as Y. Now from both training image sets, sampled the patches for individual image from the same spatial location. Concerning to clustering of information whereas sampling patches from low-resolution and high-resolution training information. we examine SM value of high-resolution and low-resolution if the value is same, then cluster it all in similar cluster. 2D patches of high-resolution and low-resolution were transformed in column vector, then stacked column wise in cluster matrix. Before concatenating the patches into cluster matrix, the gradient feature of patches are calculated as done by many super resolution algorithms. Let Uy be HR patches matrix and y represents cluster number. In similar mode Vy be LR matrix for patches. Joint coupled dictionary learning procedure could be specified as

$$\min\{D_u^y\ D_v^y, f(.)\} \|U^y - D_u^y \wedge_u^y\|_F^2 + \|V^y - D_v^y\ \wedge_v^y\|_F^2 + \beta\|\wedge_v^y - T^y \wedge_u^y\|_F^2 + \varphi_\mu\|\wedge_u^y\|_1 + \varphi_m\|T\|_F^2 \quad (6)$$

$$S.t.\ \|D_u^y, i\|l_2 \leq 1, \|D_v^y, i\|l_2 \leq 1.$$

The regularization terms are $\beta, \varphi\mu, \varphi v, \varphi m$ and dy_{u1}, dy_{v1} are the corresponding cluster dictionaries. Here equation (6) is resolved in 3 steps, initially explained for sparse representation coefficients while keeping mapping function and dictionaries constant. After that resolved it for dictionaries while keeps mapping functions and sparse representation constant. Lastly, explained mapping function and keeps constant dictionaries and sparse representation. The high-resolution and low-resolution cluster training data is given to every cluster, then initialized dictionaries and mapping matrix. Giving the entire dictionaries for sparse representation problem and could expressed as

$$\min\{\wedge_u^y\} \|U^y - D_u^y \wedge_u^y\|_F^2 + \beta\|\wedge_v^y - T_u \wedge_u^y\|_F^2 + \varphi_u\|\wedge_u^y\|1 \quad (7)$$

$$\min\{\wedge_v^y\} \|V^y - D_v^y \wedge_v^y\|_F^2 + \beta\|\wedge_u - T_v\ \wedge_v^y\|_F^2 + \varphi_v\|\wedge_v^y\|1 \quad (8)$$

The above problem in eq, (7), (8) is Lasso problem or vector selection problem. Various methods in literature that could resolve this problem as LARS[38]. Dictionaries are updated while finding sparse coefficients of high-resolution and low-resolution training data.

$$Min\{D_u^y D_v^y\|U^y - D_u^y \wedge_v^y\|_F^2 + \|V^y - D_v^y \wedge_v^y\|_F^2 \quad (9)$$

$$S.t.\ \|D_u^y, i\|l_2 \leq 1, \|D_v^y, i\|l_2 \leq 1.$$

The above problem in (9) is QCQP problem that could be explained as done by[16] . Last stage is updating mapping matrix in dictionary learning process.

$$Min\{T^y\}\|\wedge_u^y - T^y \wedge_v^y\|_F^2 + (\varphi_m/\beta)\|T^y\|_F^2 \quad (10)$$

Equation (10) express ridge regression problem and computed analytically. Mapping function T^y will be equivalent to:

$$T^y = \wedge_u^y \wedge_v^{yT} \left(\wedge_u^y \wedge_v^{yT} + (\varphi_m/\beta)\mathrm{I}\right)^{-1} \quad (11)$$

where, I denote the identity matrix.

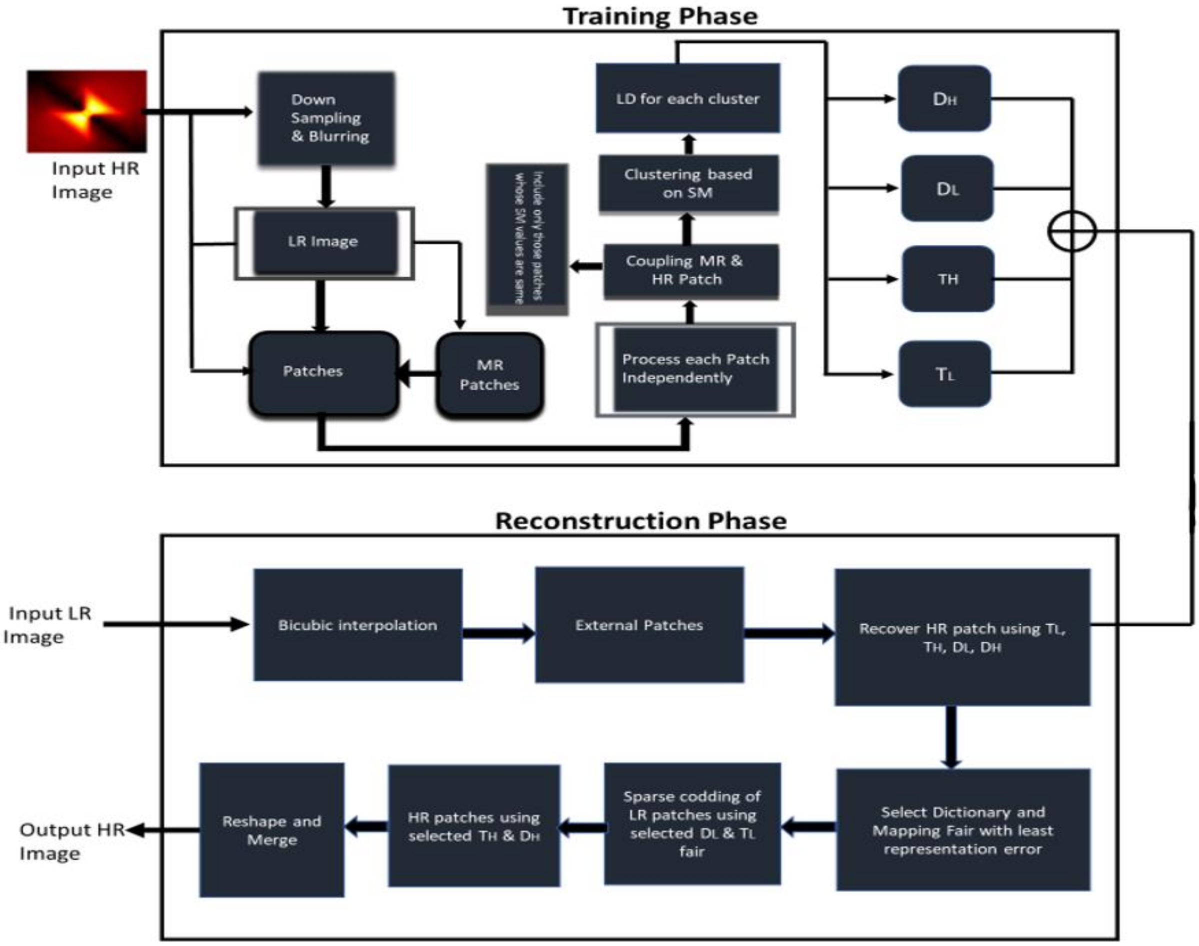


Figure 1. Training and Reconstruction phase of proposed Method

2.3 Proposed Reconstruction of super -resolution image using SCDL

For the reconstruction stage of image, an LR image is given to the input with dictionaries $D_{H,}$ D_L and mapping function T_H and T_L. First 2D image transformed in column matrix for high-resolution image enhancement. A full overlap is applied and individually low-resolution patch are first verified by SM value to adopt dictionaries pair for its reconstruction. By patch-wise sparse recovery procedure, sharpness value is calculated of low-resolution patch at hand. From sharpness value it is found that the indicated patch belongs to which cluster. Giving clustered dictionaries and mapping matrix, we compute sparse coefficients of low-resolution patch utilizing low-resolution dictionaries then mapping matrix by identical equation used in training stage. Afterward locating matrix of sparse coefficients, initially multiply sparse coefficients through training matrix and utilize dictionary of high-resolution along multiplied sparse coefficients to calculate a high-resolution patch. After calculating entire high-resolution patches, we left vector domain to 2D image space utilizing merged technique of [17]. A high-resolution image is estimated at the end.

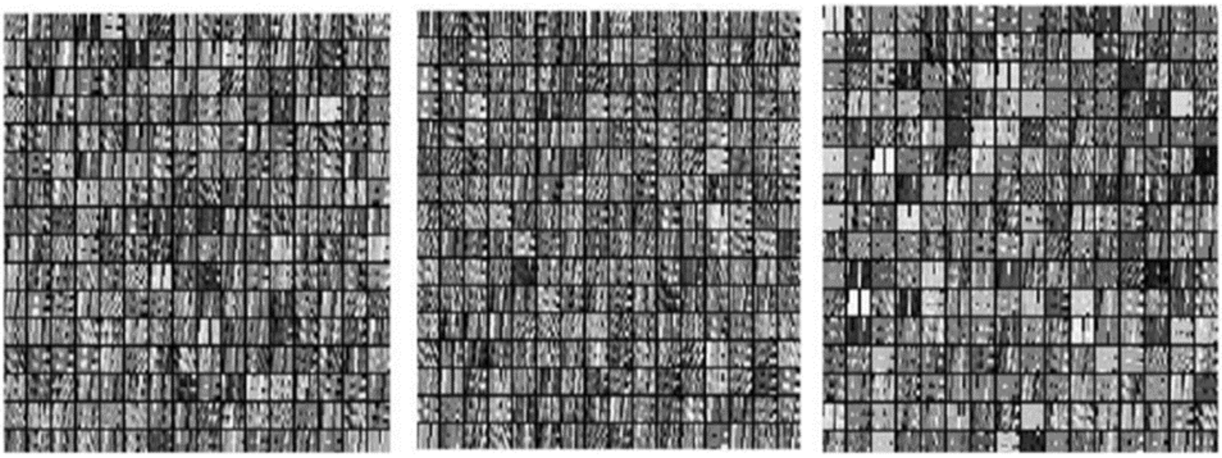


Figure 2. Atoms for LR Dictionaries

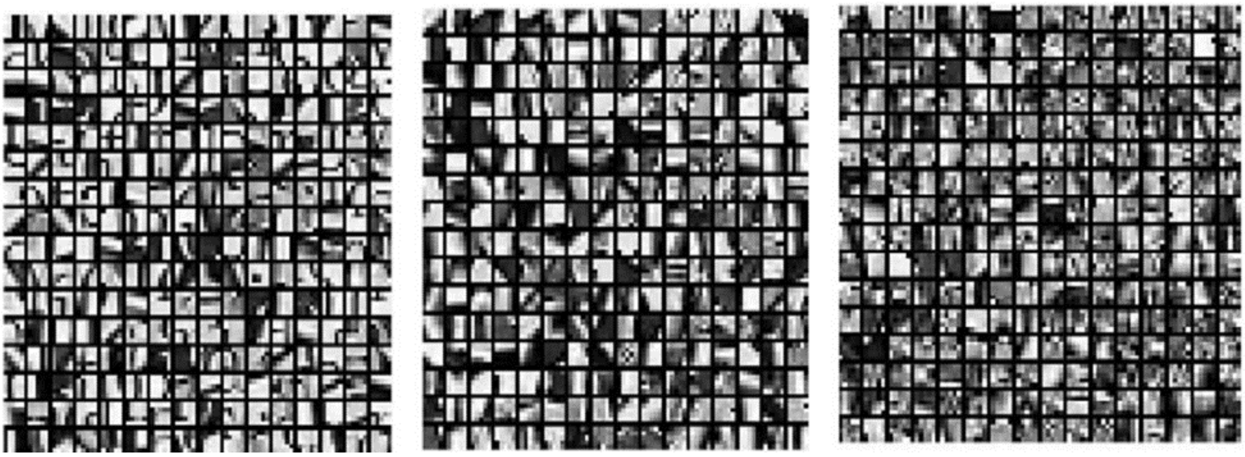


Figure 3. Atoms for HR dictionaries

3. Simulation and Results

The proposed SISR algorithm based on SCDL and SM-based has been estimated and results were measured opposed to performance of classical bi-cubic, Yang[17] and Xu et al [23], which are the state-of-the-art algorithms. Here, to every algorithm a same set of simulations parameter were applied to each algorithm.

The evaluations are made with Yang et al. [17] and Xu et al. [23]. The algorithm of Yang is considered the baseline algorithms for the proposed method, also Xu et al.[23] which use comparable kind of dictionary learning SR technique, while the dictionary updating stage is done by means of K-SVD technique. Set-A and Set-B images were used to carried out comparison. Set-A is composed of 14 test images, which are taken from kodak set [39] while Set-B has 10 test images in which 6 images are taken from flicker image set, whereas 4 are taken from the web source. Set-B has 10 test images in which 8 are text images.

Individually and average peak to signal noise ratio PSNR and structure similarity index SSIM values for Set-A are given in table (1). From Set-A, it is clear that the bi-cubic interpolation has lowest mean PSNR performance. Yang et al.[17] technique is the 3rd best and Xu et al. [23] technique is 2nd best which is 0.187dB beyond average PSNR value and also had improvement over all the three methods in terms of SSIM. After investigating the individual PSNR values we observed that the proposed SCDL single image super-resolution algorithm was not improved than Xu et al. [23] method for all 14 images. Xu's algorithm gives better PSNR for the test images Kodak-08, Barbara, Peppers and Nu-Regions and for all other 10 images the proposed algorithm gives higher PSNR values than Xu's. Inquiring about this, PSD calculated for entire images in Set-A which are showed in figure 3, it is noted for images which has a large number of frequency content near the center and around lower frequency regions, proposed technique will outperform. Those images in which frequency contents are widespread then Xu's technique will outperform.

3.1 Quantitative Experiments

The HR image is reconstructed from a LR image by three methods, the PSNR[38] and SSIM for high resolution reconstructed image is calculated as follow

$$PSNR(X,\hat{X}) = 10\, log_{10} \frac{255}{MSE(X,\hat{X})} \tag{12}$$

In the above equation X is original HR image, while $\hat{X}$ is reconstructed image. Error between (X, $\hat{X}$) is MSE which is explained as:

$$MSE(X,\hat{X}) = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(X_{ij} - \hat{X}_{ij}\right)^2 . \tag{13}$$

Therefore, to know about the structural data in restored images, Here utilized a second term which is recognized as SSIM. The SSIM compare locals' pattern of pixels intensity which are normalized for the purpose of luminance and contrast is explained as

$$SSIM(X,\hat{X}) = \frac{(2\mu_X \mu_{\hat{X}} + C_1)\,(2\sigma_{X\hat{X}} + C_2)}{\left(\mu_X^2 + \mu_{\hat{X}}^2 + C_1\right)(\sigma_X^2 + \sigma_{\hat{X}}^2 + C_2)} \tag{14}$$

The original image X has the average in equation (14), are $\mu_X \mu_{\hat{X}}$ and $\hat{X}$ and σ_X^2, $\sigma_{\hat{X}}^2$ are noisy, original image variance, and covariance for X, $\hat{X}$, is $\sigma_{X\hat{X}}$ which is defined as:

$$\sigma_{x,\hat{x}} = \frac{1}{(N-1)} \sum_{i=1}^{N} (x_i - \mu_x)(\hat{x}_i - \mu_{\hat{x}}) \tag{15}$$

Table 1. Comparison of Proposed SCDL, SISR method against classic bi-cubic interpolator, Yang'salgorithm and Xu's algorithm. Top PSNR and bottom SSIM.

Images	Bic.	Yang	Xu	Proposed
AnnieYukiTim	31.424	32.853	32.800	**32.967**
	0.906404	0.936103	0.9355	0.936934
Barbara	25.346	25.773	**25.866**	25.848
	0.792961	0.832917	0.8330	0.834188
Butterfly	27.456	30.387	30.047	**30.670**
	0.898450	0.941782	0.9427	0.944089
Child	34.686	35.420	35.405	**35.476**
	0.841002	0.880024	0.8757	0.878972
Flower	30.531	32.442	32.284	**32.568**
	0.896804	0.930642	0.9316	0.939663
HowMany	27.984	29.219	29.182	**29.468**
	0.868694	0.91125	0.9115	0.91098
Kodak-08	22.126	22.827	**23.507**	22.987
	0.699514	0.767505	0.7963	0.797098
Lena	35.182	36.889	36.852	**37.208**
	0.921749	0.948312	0.9490	0.949711
MissionBay	26.679	28.012	27.929	**28.337**
	0.845938	0.880611	0.8883	0.895447
NuRegions	19.818	21.383	**22.074**	21.997
	0.846978	0.906266	0.9177	0.91168
Peppers	29.959	31.283	**31.996**	31.899
	0.904532	0.944194	0.9518	0.951413
Rocio	36.633	39.217	39.075	**39.289**
	0.961259	0.974378	0.9755	0.976202
Starfish	30.225	32.205	31.967	**32.373**
	0.892305	0.932731	0.9330	0.934364
Yan	26.962	28.022	28.003	**28.135**
	0.827686	0.873876	0.8740	0.876287
Average	28.929	30.424	30.499	**30.686**
	0.864591	0.904344	0.9082	0.909787

In Set-B 10 images were used for simulations which are texts images, two finest performing methods were compared. The results gotten are given in Table 2.

Table 2: Xu's versus Proposed Method in Set-B on test images.

Xu			**Proposed SCDL SISR method**		
Images	**PSNR**	**SSIM**	**Images**	**PSNR**	**SSIM**
10.tif	24.3158	0.9472	10.tif	**24.5297**	0.9561
2.tif	22.7973	0.8487	2.tif	**23.0514**	0.8503
5.tif	22.5205	0.907	5.tif	**23.4412**	0.9313
6.tif	25.5222	0.9478	6.tif	**25.7378**	0.9435
b82	27.3879	0.925	b82	**27.4646**	0.9202
t1	**24.3933**	0.8898	t1	22.2233	0.8345
t2	**18.7391**	0.7532	t2	16.3692	0.6655
t3	**19.717**	0.7741	t3	18.7558	0.7438
t4	21.22	0.6885	t4	19.2275	0.5746
Yxfo16	22.8599	0.8543	Yxfo16	**23.0263**	0.8482

The testing images in Set-B, except b82 and Yxfo16 all other images are text images in color or in gray tones, for images in table (2) marked in bold, the proposed algorithm will give higher PSNR values for the rest of images Xu's method performed well. The proposed method performed well over Xu's method and has an edge of 0.166dB in mean PSNR values. To notice if our aforementioned power spectral density argument will hold for Set-B images also, again PSD is plotted for set-B test images, which are given in Table (3). Here even when power spectral density has many dissimilar high frequencies component (widespread PSD plots) sometimes the proposed technique and sometimes Xu's[23] will give higher PSNR values. For test images 10.tif, 6.tif, 5.tif and 2.tif, the proposed algorithm will give higher PSNRs and for t4.jpg, t3.jpg t2.jpg, and t1.jpg, Xu's method. Evidently another factor is tipping to balance the proposed method or Xu's method. For good understanding why this happen, an idea is followed which is based on scale-invariance done by [13]. Three clusters were represented by Cluster1, C2 and C3 matching SM intervals of [0, 5], [6, 10], [11, 20] are designed. SM values of entire LR and HR patch of images are computed. Then Patches were arranged into three clusters Custer1, Cluster2 and Cluster3 based on calculated SM values particular intervals. The total number of HR patches were divided into each interval counted. The low-resolution counterparts are also properly classified into similar cluster are counted. Upon these counts, the sharpness measure invariance computed as ratio of low-resolution patches which are appropriately classified to all number of high-resolution patches in cluster. The scale invariance values are given in Table (3).

Table 3: Scale Invariance of Regular Texture Images and Text images entire numbers of HR patches categorized in each interval (top) SM invariance (bottom)

Image	C1	C2	C3
10	**31,864**	936	**11,570**
	94.15328	38.3547	**97.74417**
2	**3,173**	898	**2,529**
	98.6133	50.33408	**51.16647**
5	**10,502**	672	**7,426**
	94.79147	75.44643	**94.68085**
6	**26484**	983	**11,509**
	91.69687	26.14446	**99.18325**
b82	463	700	1,438
	90.49676	77	57.30181
t1	960	**71**	**949**
	98.85417	**64.78873**	**55.00527**
t2	607	**16**	**1,402**
	99.17628	**75**	**64.47932**
t3	406	**328**	**1,255**
	92.11823	**40.54878**	**75.21912**
t4	**36**	**118**	**1,871**
	52.77778	**61.86441**	**9.353287**
yxf016	1,173	274	1,154
	97.78346	52.91971	53.37955

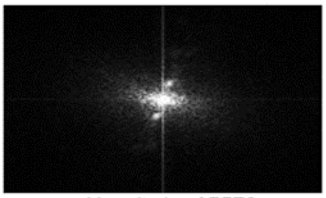
It is noted from table (3) that the images have numerous frequency components (widespread PSD). Whenever number of high-resolution patches in Cluster-2 and/or Cluster-3 is low and the sharpness measure invariance ratios were also low then Xu's [23] technique would be successful. For those images that's power spectral density had frequency components frequently at low frequencies then the proposed technique will continuously achieve best results over Xu technique.

To investigate further, eight images are taken from Kodak set [39] that has widespread power spectral densities also computed their equivalent sharpness measure invariance values which depicted in table (4). For the entire illustration outcomes are as expected, when for Cluster 2 and/or Cluster 3, numbers of high-resolution patches were arranged into intervals and corresponding sharpness measure invariance values are low, the Xu's method will give better performance than the proposed algorithm.

Table 4: Scale Invariance of Regular Texture Images and Text images entire numbers of HR patches categorized in each interval (top) SM invariance (bottom)

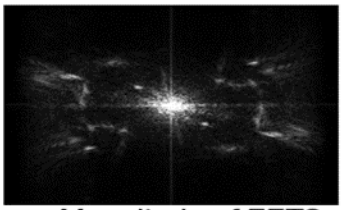
Image	Cluster-1	Cluster-2	Cluster-3
AnnieYukiTim	4985	**1092**	**859**
	99.29789	**44.87179**	**47.6135**
Barbara	5414	**2012**	**2978**
	99.64906	**41.6501**	**19.37542**
BooksCIMAT	1115	**865**	**934**
	98.74439	**60.34682**	**53.31906**
Fence	1068	598	935
	99.1573	**27.59197**	**37.75401**
ForbiddenCity	710	580	1624
	98.87324	**48.7931**	**4.248768**
Michoacan	676	**372**	**1494**
	37.57396	**36.29032**	**30.25435**
NuRegions	46	112	2384
	4.347826	**29.46429**	97.86074
Peppers	1481	**371**	**357**
	98.64956	**63.8814**	**48.7395**


AnnieYukiTim.bmp


Magnitude of FFT2

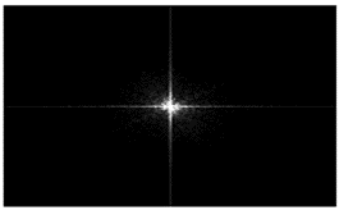

Phase of FFT2


Barbara.png


Magnitude of FFT2


Phase of FFT2


child.jpg


Magnitude of FFT2


Phase of FFT2

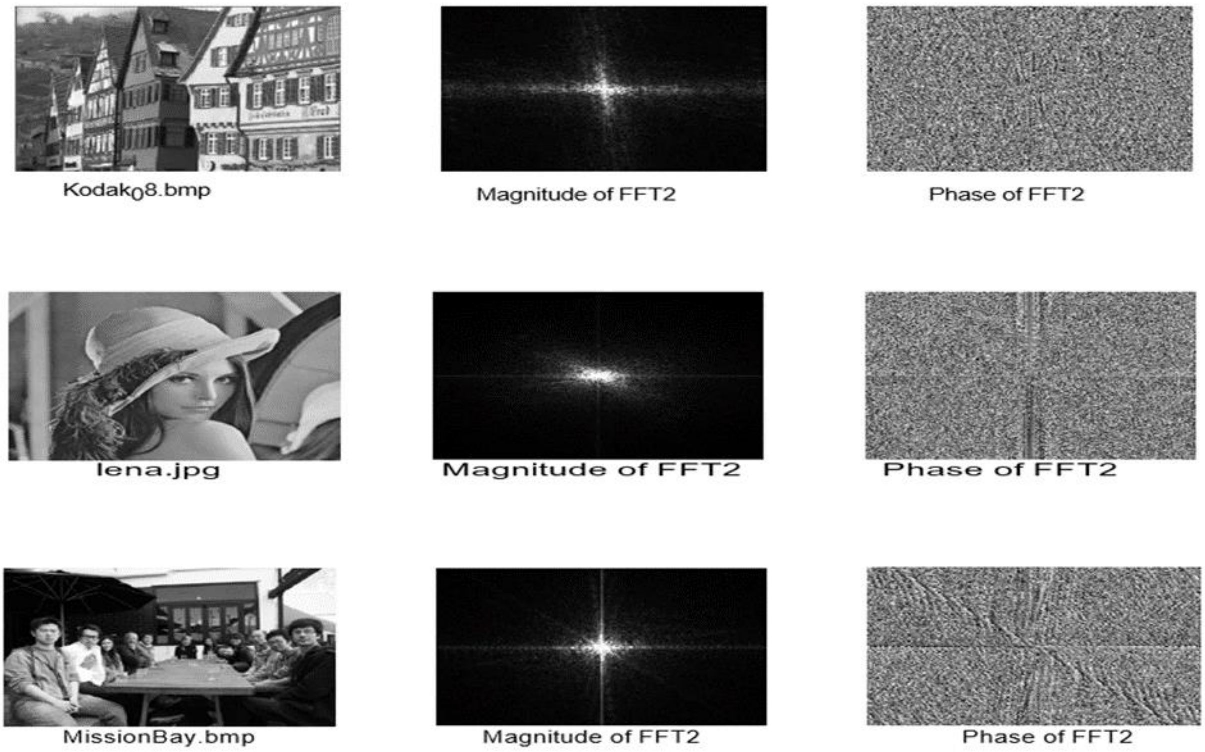
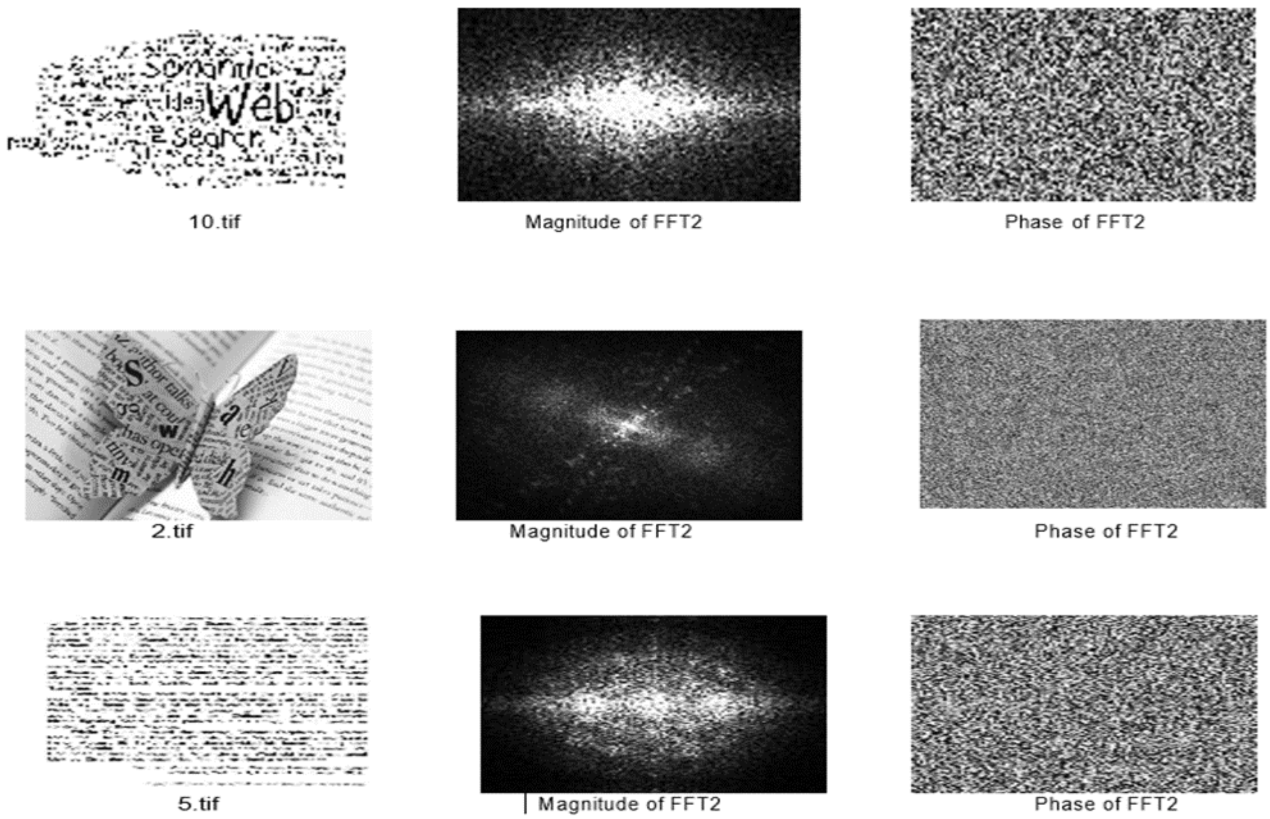


Figure 4. The Power Spectral Density Plots of Different images in Set-A



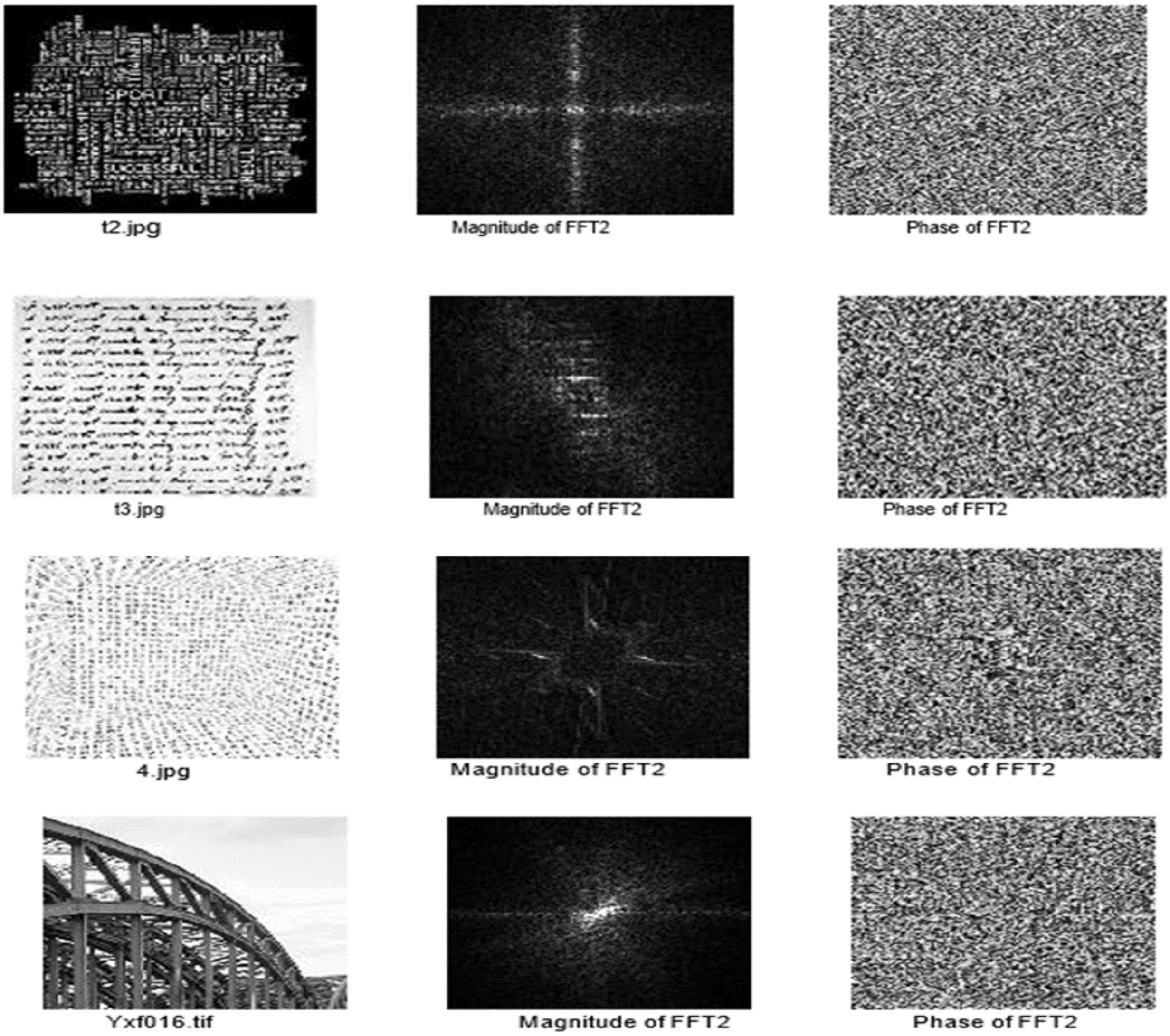


Figure 5. The Power Spectral Density Plots of Different images in Set-B

3.2Qualitative experiments of Super resolution images

The super-resolution images are reconstructed by opposing techniques for visual comparison are provided. To know about reconstruction quality, Images were zoomed out. In term of PSNR values, the proposed algorithm performed well from bi-cubic interpolation, algorithm of Yang et al. [17] and Xu et al. [23]. Bi-cubic interpolation images showed a weighty quantity of blur while other images of Yang and Xu shows moderately a smaller amount of blur. Observing at zoomed out images it could be visibly observed, the proposed method performance is better than the state-of -the art methods and has ability to reconstruct sharp patches efficiently.

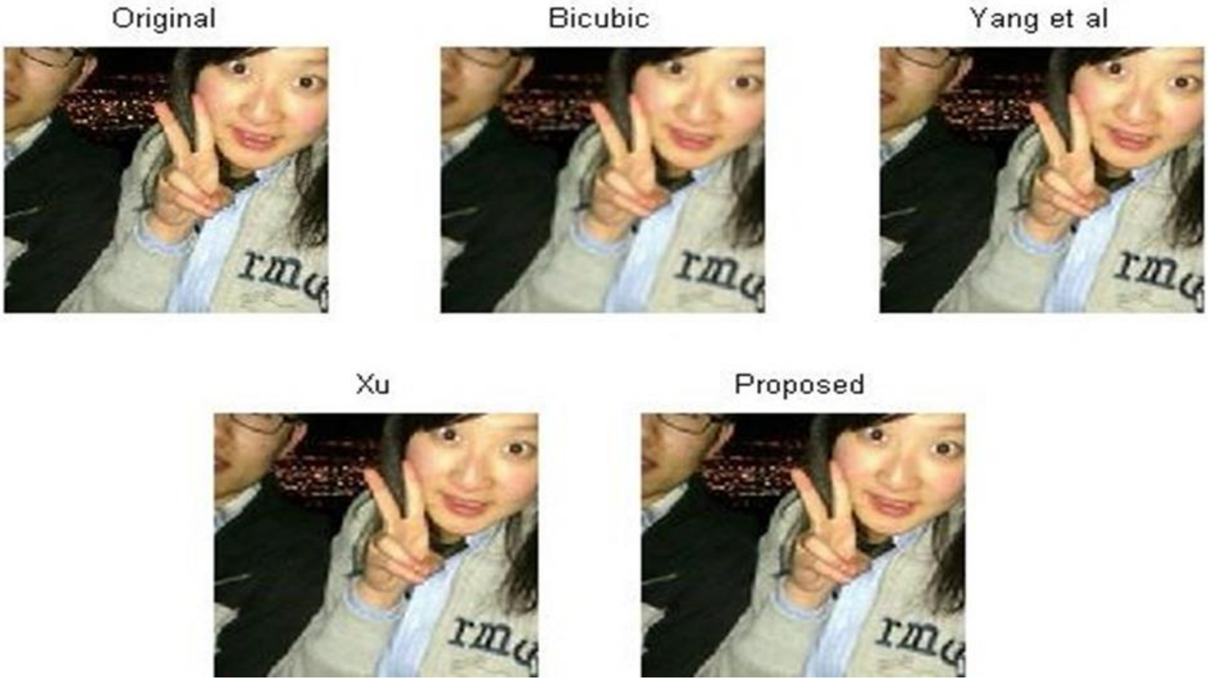


Figure 6. Visual Comparison of proposed algorithms on AnnieYukitim image with other two method of Yang and Xu

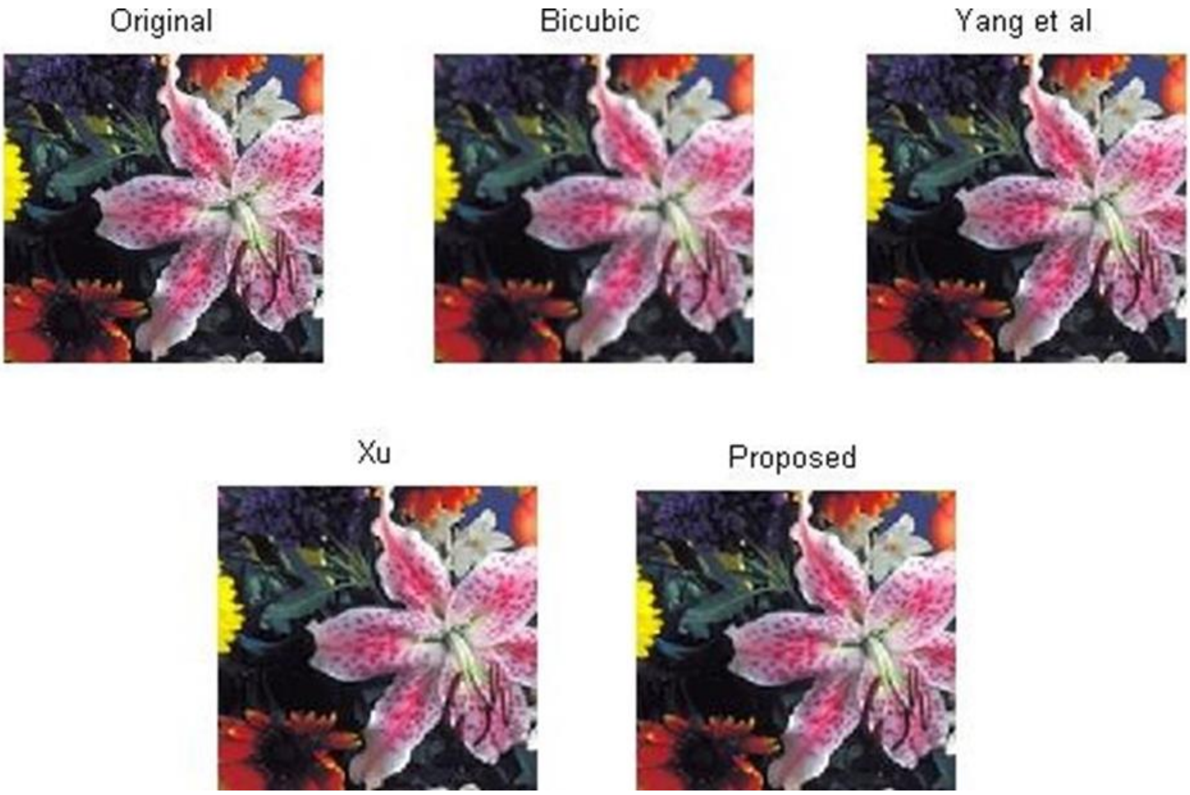


Figure 7. Visual Comparison of proposed algorithms on Flower image with other two method of Yang and Xu.

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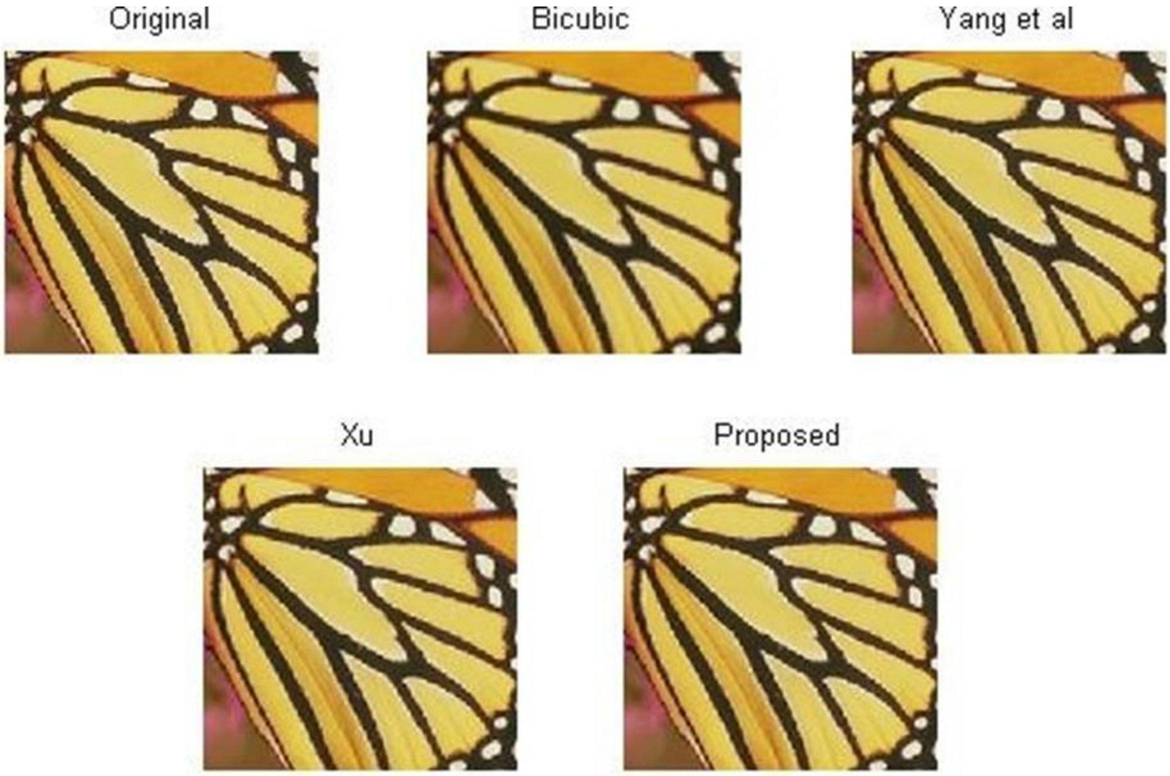

Figure 8. Visual Comparison of proposed algorithms on Butterfly image with other two method of Yang and Xu.

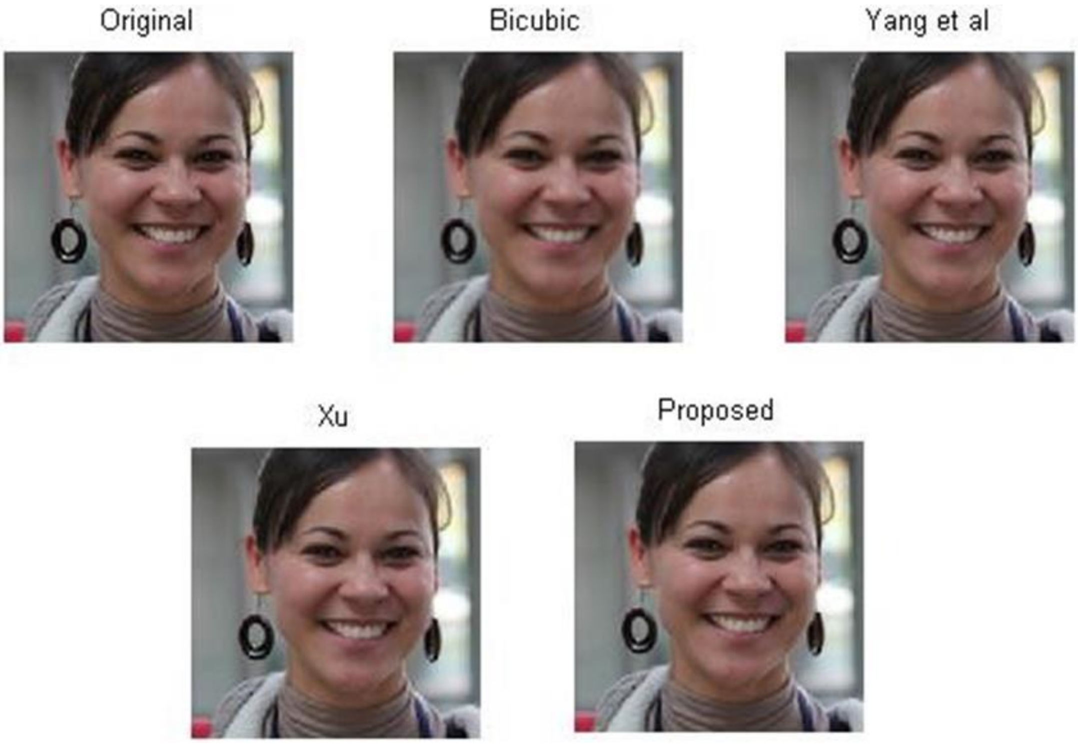

Figure 9. Visual Comparison of proposed algorithms on Rocio image with other two method of Yang and Xu.

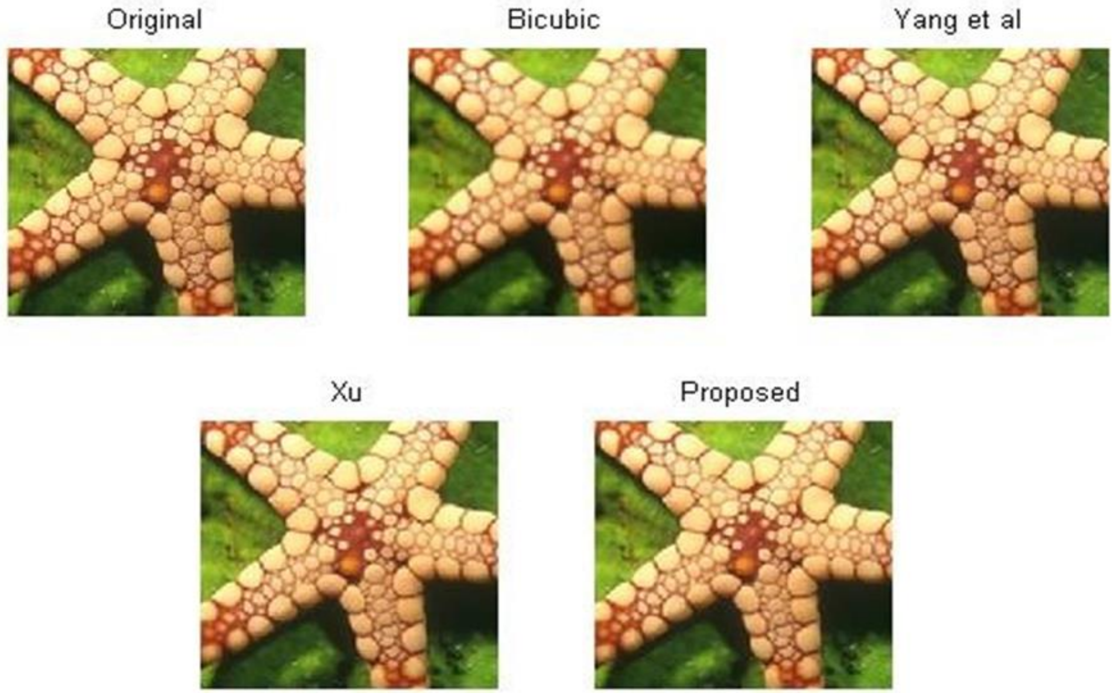

Figure 10. Visual Comparison of proposed algorithms on starfish image with other two method of Yang and Xu.

4 Conclusion

SCDL is proposed for SISR, three clusters and 3 pair of semi-coupled dictionaries are designed on sharpness measure based. For training phase 69 images set were used. The dictionaries atoms are selected 600 with patch size 5×5 are utilized. Evaluations are made with classical Bi-cubic, Yang[17] which assumed the baseline algorithms and Xu [23]. The performance of proposed method illustrates 1.757dB enrichment and SSIM 0.045 over bi-cubic and ahead also from Yang 0.262dB and Xu 0.187dB in term of PSNR and has improvement of 0.005 and 0.0015 in SSIM results. The comparison between Xu's [23] versus proposed methods the power spectral densities for both sets of images and clarify that the proposed method also ahead 1.66dB in PSNR value than Xu method.

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