Image Super-Resolution via Sparse Representation over Coupled Dictionary Learning Based on Patch Sharpness

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***Abstract*—In this paper a new algorithm for single-image super-resolution based on sparse representation over a set of coupled low and high resolution dictionary pairs is proposed. The sharpness measure is defined via the magnitude of the gradient operator and is shown to be approximately scale-invariant for low and high resolution patch pairs. It is employed for clustering low and high resolution patches in the training stage and for model selection in the reconstruction stage. A pair of low and high resolution dictionaries is learned for each cluster. The sharpness measure of a low resolution patch is used to select the appropriate cluster dictionary pair for reconstructing the high resolution counterpart. The sparse representation coefficients of low and high resolution patches are assumed to be equal. By multiplying the high resolution dictionary and the sparse coding coefficient of a low resolution patch, the corresponding high resolution patch is reconstructed. Simulation results in terms of PSNR and SSIM and visual comparison, indicate the superior performance of the proposed algorithm compared to the leading super-resolution algorithms in the literature over a set of natural images in sharp edges and corners.**

Keywords–single-image super-resolution; sparse representation; sharpness measure-based clustering;multiple dictionary pairs

I. Introduction

In recent years, sparse representation over learned dictionaries has received a great deal of attention in solving image processing problems such as denoising [?], super-resolution [?], compression [?] and pattern recognition [?]. This representation is based on using an overcomplete dictionary matrix $D \in R^{n \times k}$ which contains k atoms for approximately representing a signal $x \in R^n$. In this form, the approximation is $x \approx D\alpha$, where α represents the sparse coding coefficients of x. The representation is sparse when most of the coefficients of α are zero. Given x and D, the problem of determining α is referred to as sparse coding which can be formulated as

$$\arg\min_{\alpha} \|x - D\alpha\|_2 \;\; subject\, to \;\; \|\alpha\|_0 < S, \qquad (1)$$

where $\|\ \|_2$ and $\|\ \|_0$ are the vector Euclidean norm and the number of non-zero elements in a vector, and S denotes sparsity.

learned dictionaries are obtained by training over a set of example signals. Popular vector selection algorithms such as the Matching pursuit (MP) [?], the orthogonal matching pursuit (OMP) [?], the basis pursuit (BP) [?] and the focal underdetermined system solver (FOCUSS) [?] are used to give a good solution to the sparse coding problem.

The variability of signals in a class is less than their variability in general [?]. It is thus intuitive to consider class dependent dictionaries. According to this, K-means clustering proposed by Dong et al. [?] divides the training data into a number of clusters and learns compact cluster dictionaries. The training set is divided into subspaces using K-subspace clustering in [?] by Feng et al. Then, these subspaces are employed to extract the shared bases to construct the dictionary. Yu et al. constructed a structural dictionary as a composition of learned orthogonal bases in [?]. A corresponding structural model selection is applied over these structural dictionaries.

This paper focuses on the problem of single image super-resolution using sparse representation over multiple dictionaries. The works conducted by Yang et al. [?] and Zeyde et al. [?] employ a single pair of dictionaries. The sparse representation coefficients of the low resolution (LR) and high resolution (HR) patches are assumed to be similar with respect to their own dictionaries. Each HR patch is reconstructed by imposing the sparse coding coefficients of its LR counterpart on the HR dictionary.

Features such as sharp edges, corners and textures are difficult to represent. These features are characterized by high gradient magnitudes. An important discriminating property for image patches is the patch sharpness measurement (SM) which is defined via the gradient operator [?]. Thus, this important fact is employed to design a set of structured coupled LR and HR dictionary pairs in this paper. The training data is clustered into a number of clusters based on SM and then each cluster is used to train for a pair of coupled LR and HR dictionaries. The SM value of each LR patch is used to identify the corresponding cluster in the reconstruction stage. The optimal number of clusters is empirically determined according to the accuracy of

978-1-4799-7412-2/14 $31.00 © 2014 IEEE
DOI 10.1109/EMS.2014.67

SM-based model selection and the representation power of each pair of cluster dictionaries. Simulation results indicate that with more than seven clusters there is a decrease in the performance.

The performance of the proposed algorithm is compared to single image super-resolution algorithms [**?**], [**?**], [**?**] by testing over benchmark images. The peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are used as performance measures. The superior performance of the proposed method is shown in the images with sharp edges and corners in visual and quantitative results.

This paper is organized as follows: Section II briefly describes the single-image super-resolution via sparse representation approach. In section III, the proposed super-resolution algorithm is presented. Simulation results in section IV investigating the performance of the proposed algorithm and the representation quality of the designed dictionaries. Conclusions are presented in section V.

II. Single-image super-resolution via sparse representation

Given a LR image, obtaining a HR image of the same scene is known as single-image super-resolution which is an ill-posed inverse problem. Sparsity constraint has been effectively utilized as a regularizer to solve for this problem. This is achieved by assuming similarity between the sparse coding coefficients as proposed in [**?**], [**?**]. This idea is the basis for reconstructing patches of a HR image from their respective counterparts in the LR image of the same scene.

Sparse representation of images is carried out on the patch level. After dividing the HR image into patches, these patches are reshaped into the vector form and then combined column-wise to form an array x_H. The sparse representation of x_H over a HR dictionary D_H is as follows

$$x_H \approx D_H \alpha_H, \tag{2}$$

where α_H denotes the sparse coding coefficient vectors of x_H. These representation coefficients can be obtained using vector selection algorithms like OMP. Similar to x_H, LR vector patches x_L can be sparsely represented over a LR dictionary D_L as follows

$$x_L \approx D_L \alpha_L, \tag{3}$$

where α_L is the sparse coding coefficient vectors of x_L.

The relationship between x_L and x_H is shown as

$$x_L \approx \Psi x_H, \tag{4}$$

where Ψ is a blurring and downsampling operator.

As in [**?**] and [**?**], D_L and D_H are learned in a coupled manner, so the relationship between them will be $D_L \approx \Psi D_H$. One can see from (2) and (4) that

$$x_L \approx \Psi x_H \approx \Psi D_H \alpha_H \approx D_L \alpha_H. \tag{5}$$

It can be clearly concluded from (5) that $\alpha_H \approx \alpha_L$. This idea is the foundation for reconstructing a HR patch as in (6)

$$x_H \approx D_H \alpha_L. \tag{6}$$

This reconstruction is based on the assumption that D_L and D_H constitute as a pair of coupled dictionaries to the LR and HR training dataset as in [**?**].

To allow for local consistency of the reconstructed HR patches, a certain overlap between patches is allowed. LR patches are used for reconstructing their HR counterparts, and then these HR patches are reshaped into the two-dimensional form and merged together to obtain a HR image estimate.

III. The proposed super-resolution algorithm

In this paper, SM of image patches is employed as a clustering criterion to classify the patches in both the dictionary learning stage and the HR patch reconstruction stage. This classification is used for designing dictionary pairs that are well suited to represent image features with various sharpness levels.

TABLE I
Number of HR patches in each cluster (top) and the percentage of the corresponding LR patches correctly classified into the same cluster (bottom) via the SM criterion. The largest number of patches in a cluster with the corresponding percentage is in bold face.

Image	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Barbara	**1058** **81.6**	788 44.3	430 22.6	489 19.8	303 11.9	200 12.5	828 10.4
BSDS 198054	583 96.91	181 61.88	387 51.94	340 43.24	173 32.95	105 20.95	**631** **80.35**
Butterfly	**275** **86.9**	113 51.3	82 30.5	95 12.6	130 6.2	145 1.4	184 90.2
Input6	983 90.13	664 53.16	952 38.13	**1104** **27.72**	1049 18.21	828 14.73	1020 53.63
Lena	**1846** **90.4**	1139 52.5	469 26.9	297 12.5	187 13.4	109 9.2	49 55.1
ppt3	**3396** **98.6**	247 43.3	359 15.6	235 11.5	241 5.4	194 7.7	740 83.8
Starfish	153 67.3	**289** **45.3**	169 28.4	109 7.3	124 14.5	97 7.2	83 41.0
Text Image 1	2086 98.8	171 58.5	151 36.4	245 23.7	238 26.9	329 18.8	**3176** **70.7**
Text Image 2	516 99.2	51 52.9	89 27.0	123 26.0	130 13.8	128 32.8	**1033** **60.0**
Average	94.0	50.4	32.2	23.8	16.7	14.4	62.7

A. *Approximate scale-invariance of the image patch sharpness measure*

SM is defined from the magnitude of the gradient operator [**?**] as

$$SM = \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \sqrt{| G_i^h | + | G_j^v |}, \tag{7}$$

where G^h and G^v denote the horizontal and vertical gradients and N_1 and N_2 denote the patch horizontal and vertical dimensions, respectively.

According to the above formula, SM is employed for classifying edges, corners and texture in images based on their sharpness.

Sun et al. defined the gradient profile prior in [**?**], and considered its behavior with respect to image scale. SM defined via the gradient operator is used as an approximately scale-invariant measure for a pair of HR and LR patches from the same scene. For images that contain strong edges, corners and texture this scale-invariance is stronger.

To investigate the impact of scale on SM, The following experiment is done on the set of images shown in Figure 1. Each HR image is divided into 8×8 non-overlapping patches then each patch is filtered by a bicubic filter and downsanpled by a scale factor of 2 to obtain a 4×4 LR counterpart. We consider the case of seven clusters defined to corresponding SM intervals of [0, 4], [4, 8], [8, 12], [12, 16], [16, 20], [20, 24] and [24, 255], respectively. These are denoted by C_1 through C_7 in Table I.

Figure 1. Test images from left to right and top to bottom: Barbara, BSDS 198054, Butterfly, Input 6, Lena, ppt3, Text Image 1 and Text Image 2.

The SM value of each LR and HR patch is calculated and each patch is classified into one of the clusters. Then the total number of HR and LR patches classified into a given cluster is counted. The ratio between the number of correctly classified LR patches and the total number of HR patches in a cluster is the scale-invariance ratio. Table I shows the total number of HR patches in each cluster (top) and the corresponding scale-invariance ratio (bottom). Considering the Butterfly image in Table I, 275 HR patches are classified into C_1 and 86.9 % of their LR counterparts are correctly classified into the same cluster. From Table I, SM invariance in the first (unsharp) and last (sharpest) clusters is noticeable rather than intermediate clusters C_2 through C_6. Considering the BSDS 198054 image, 96.91 % of its LR patches are classified in the first cluster and 80.35 % of them are classified in the last cluster C_7. Therefore, given a LR patch, one can predict what cluster the HR patch belongs to. In conclusion, SM can be used as criterion for classification and model (dictionary pair) selection.

Algorithm 1 The Proposed Cluster DL Algorithm.

INPUT: HR Training Image Set, Number of Clusters.
OUTPUT: A Set of Cluster Dictionary Pairs.
Divide each HR image into patches and subtract the mean value of each patch.
Reshape patches into vectors and combine them column-wise to form a HR training array.
Blur (bicubic kernel) and downsample each HR image to generate a LR image.
Divide each LR image into patches.
Upsample each LR image to the MR level.
Apply feature extraction filters on each MR image.
Divide the extracted features into patches and reshape them into column vectors.
Combine the features column-wise to form the LR training array.
for Each patch in the LR training array, **do**
    Calculate the SM value of the corresponding patch in the LR image, and find the cluster number.
    Add the MR patch to the LR training set of this cluster.
    Add the corresponding HR patch to the HR training set of this cluster.
end for
For each cluster, learn a pair of coupled dictionaries.

B. Clustering and sparse model selection with patch sharpness measure

The proposed algorithm is composed of two stages of training and reconstruction. In the training stage a set of coupled dictionaries is prepared and the best dictionary pair is selected to reconstruct the HR patches from the corresponding LR patches in the reconstruction stage.

Each HR image is filtered with a bicubic kernel and downsampled by a scale factor of 2 to get a LR version of it. Then, a middle resolution (MR) image is obtained by upsampling the LR image by a scale factor of 2. Feature extraction filters are employed to obtain features from MR images as in [**?**], [**?**].

Based on SM, each LR patch is classified into a specific cluster and the HR patch is placed into the same cluster also. These LR and HR patches are used for training LR and HR coupled dictionaries. The training is based on the method proposed in [**?**]. The main steps of the training stage are summarized in Algorithm 1.

In the reconstruction stage, the SM value of each LR patch is calculated and used to identify the corresponding cluster. Then the sparse representation coefficients of the corresponding MR patch over the cluster LR dictionary are calculated. The HR patch is reconstructed by right multiplying the cluster HR dictionary and the calculated sparse representation coefficients. Finally, the reconstructed HR patches are reshaped into the 2-D form and merged to obtain a HR image estimate. Algorithm 2 outlines the reconstruction stage.

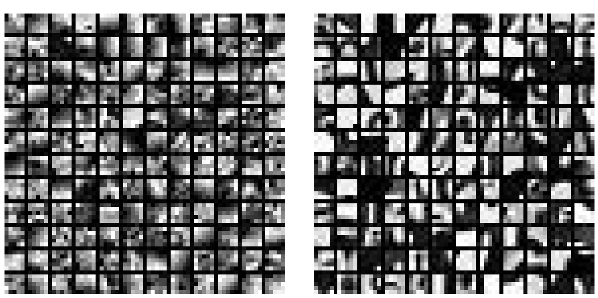
The computational complexity of the proposed reconstruction stage is similar to that of Yang et al.'s algorithm [**?**]. Most computational complexity is related to the sparse coding stage. Although multiple dictionary pairs are employed in the proposed algorithm, only one pair is selected for reconstruction. Compared to the algorithm in [?], the dictionary pair selection adds a bit more computational complexity in calculating the SM value of each LR patch in the proposed algorithm.

Algorithm 2 The Proposed Single-Image Super-resolution Algorithm.

```
INPUT: A LR Test Image, Cluster Dictionary Pairs.
OUTPUT: A HR Image Estimate
Divide the LR image into overlapping patches.
Upsample the LR image to the required resolution level (MR).
Apply feature extraction filters on the MR image.
Divide the extracted features into overlapping patches and reshape
them into vectors.
for Each LR patch do
    Calculate the SM of the LR patch.
    Determine the cluster this patch belongs to.
    Sparsely code the features of the corresponding MR patch over
    the cluster LR dictionary.
    Reconstruct the corresponding HR patch by right-multiplying the
    HR dictionary of the same cluster with the sparse codes of the
    MR features.
end for
Merge overlapping patches to obtain a HR image estimate.
```

IV. Simulation Results

This section presents the performance of the proposed algorithm as compared to the algorithms by Yang et al. [?], Zeyde et al. [?] and the state-of-art algorithm of He et al. [?]. These algorithms have different natures in the training and testing stages. Thus, for fair comparisons, the employed parameters are set as close as possible.



(a) (b)

Figure 2. Reshaped example atoms of HR dictionaries. (a) Cluster C_1 (unsharp cluster). (b) Cluster C_7 (the sharpest cluster).

A HR image is filtered by a bicubic filter and downsampled by a scale factor of 2 to obtain a LR counterpart. A LR patch size of 5×5 is used for the proposed algorithm and the algorithm of Yang et al. [?], with a 4-pixel patch overlap. Zeyde et al. [?] uses a patch size of 3×3 with a 2-pixel patch overlap and He et al. [?] uses a patch size of 7×7 with a 6-pixel overlap. In all algorithms, a scale factor of 2 is used for image super-resolution.

Similar to [?], dictionaries of the proposed algorithm are learned in a coupled manner. This learning is done over the 1000-image Flicker data set [?] and nine typical text images. 40,000 pairs of LR and HR training patches are randomly chosen and used for each cluster dictionary training.

In Yang et al. [?], a single dictionary pair with 1000 atoms is used and the training dataset is the same as the proposed algorithm. Zeyde et al. [?] employs the training data set provided by the authors for learning a pair of 1000-atom dictionaries. They used the K-SVD method [?] with 40 iterations and sparsity 3 for dictionary learning. A final-back projection stage is added to this algorithm for fair comparison as the other algorithms have this stage. The default design parameters and training dataset are used for training a pair of 771-atom dictionaries in He et al. [?].

TABLE II

PSNR and SSIM comparisons of bicubic interpolation, the algorithms of Zeyde et al. [?], Yang et al. [?], He et al. [?] and the proposed algorithm, respectively.

Image	Bicubic	Zeyde et al.	Yang et al.	He et al.	Proposed
Barbara	25.35 0.7930	**25.89** **0.8374**	25.86 0.8357	25.84 0.8372	25.82 0.8353
BSDS 198054	24.75 0.8267	26.56 0.8771	26.85 0.8816	26.98 0.8839	**27.24** **0.8847**
Butterfly	27.46 0.8985	30.59 0.9384	31.26 0.9457	31.44 0.9463	**31.84** **0.9487**
Input6	28.08 0.8523	29.93 0.8957	30.15 0.8976	30.24 0.8989	**30.37** **0.8994**
Lena	34.71 0.8507	35.68 0.8625	36.36 0.8631	**36.58** **0.8647**	36.35 0.8631
ppt3	26.85 0.9372	29.30 0.9572	29.68 0.9604	29.79 0.9621	**30.17** **0.9639**
Text Image 1	17.52 0.7246	18.47 0.7893	18.58 0.7974	18.54 0.7953	**18.92** **0.8139**
Text Image 2	18.38 0.6845	19.42 0.7630	19.46 0.7669	19.44 0.7662	**19.78** **0.7822**
Average	25.39 0.8209	26.98 0.8651	27.28 0.8685	27.36 0.8693	27.56 0.8739

For reconstructing a HR image, a LR gray-scale image is directly input to the super-resolution algorithm. Gray-scale and color images are employed for testing. Thus, a LR color image is first transformed to the luminance and chrominance color spaces and only the luminance component is input to the super-resolution algorithm. Similar to other super-resolution algorithms, the two chrominance channels are reconstructed by bicubic interpolation.

PSNR and SSIM [?] measures are used as quantitative performance measures. PSNR is calculated with the luminance color components of the original image and the reconstructed image, for color images. Given the true image y and its estimate $\hat{y}$, PSNR is defined as

$$PSNR(y, \widehat{y}) = 10 \log_{10} \frac{255^2}{MSE(y, \widehat{y})}, \tag{8}$$

where $MSE(y, \widehat{y})$ denotes the mean-square error between y and $\widehat{y}$. The average SSIM value of the luminance and the

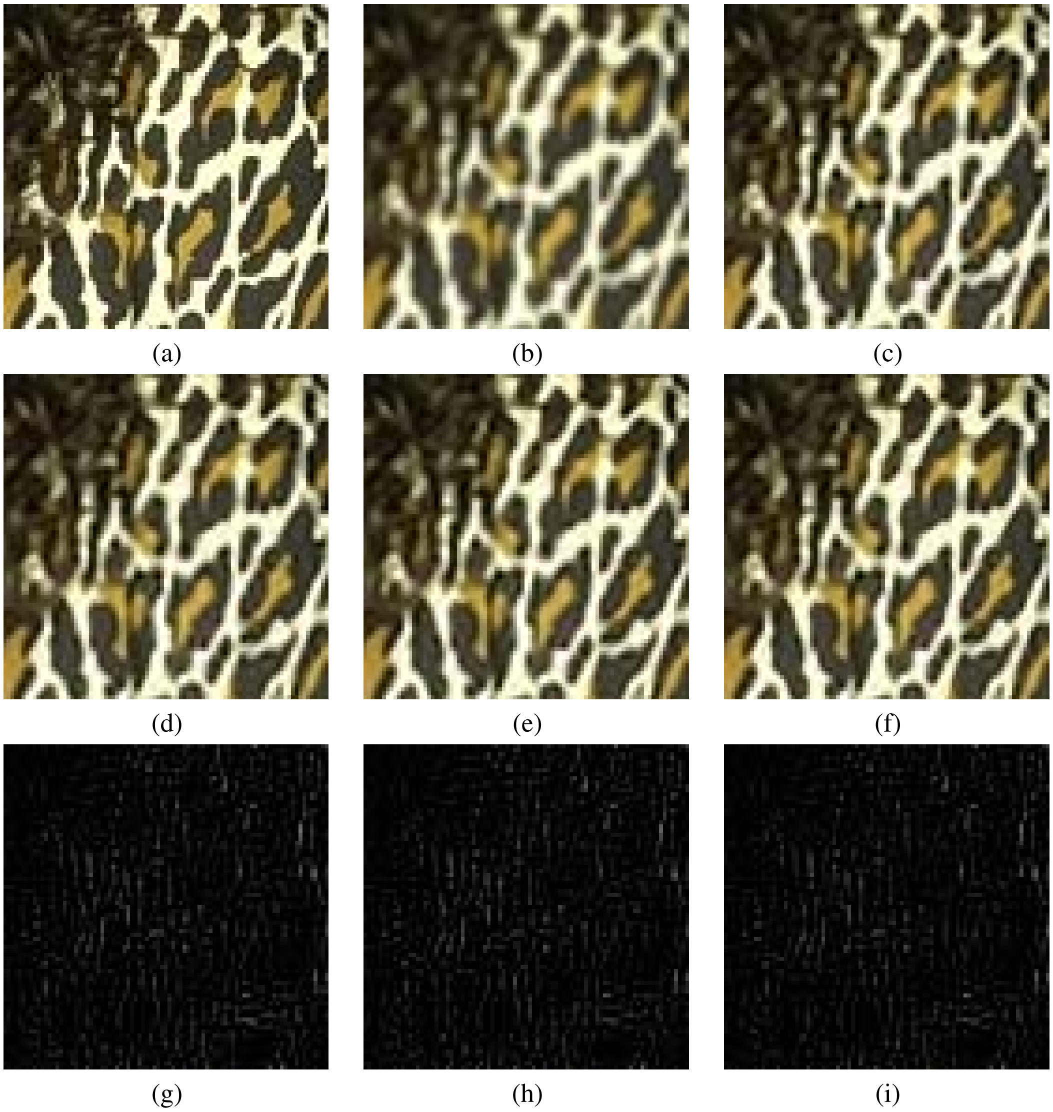


Figure 3. Results showing a portion of the BSDS 198054 image. (a) Original image. (b) Bicubic interpolation reconstruction. (c) Reconstruction of Zeyde et al. [**?**] (d) Reconstruction of Yang et al. [**?**] (e) Reconstruction of He et al. [**?**] and (f) Reconstruction of the proposed algorithm. The last row shows the difference between the original image and (g) Yang et al.'s reconstruction, (h) He et al.'s reconstruction and (i) The proposed algorithm's reconstruction.

two chrominance components of the image are calculated for color images.

For the proposed algorithm, the training data is first classified into 3, 5, 7, 9, 11 and 13 clusters. Then, a dictionary pair is learned for each cluster and SM is employed for model selection. These learned dictionaries are used for reconstructing each of the images shown in Figure 1. For each case, average PSNR and SSIM value are recorded. These averages peak at seven clusters and decreases slightly afterwards. Therefore, the number of clusters is set to seven.

Figure 2 shows reshaped atoms of the first and last cluster dictionaries designed by the proposed algorithm. The atoms in the 7-th cluster are sharper than in the first cluster. It is shown that the learned dictionaries inherit the sharpness nature of their respective clusters.

The comparison results of the proposed algorithm with the aforementioned algorithms in terms of PSNR (top) and SSIM (bottom) are shown in Table II. It can be seen in the table that the proposed algorithm performs better than Zeyde et al. [**?**], Yang et al. [**?**] and He et al. [**?**] with average PSNR improvements of 0.59 dB, 0.22 and 0.08 dB, respectively. This improvement is due to the advantage of using multiple dictionary pairs instead of single dictionary pair.

It can be clearly seen in Table II that the success of the proposed algorithm is particularly valid for images having sharp features such as text images, the Butterfly image and the ppt3 image. Considering the BSDS 198054 image, it can be seen in Table I that the majority of its patches are located in clusters C_1 and C_7. SM is highly scale-invariant in these clusters and weekly invariant in the middle clusters (C_2 through C_6). The proposed algorithm exploits the fact that SM values tend to be approximately invariant with respect to scale in sharp edges and corners.

Figure 3 compares a portion of the BSDS 198054 image with its reconstructions obtained with bicubic interpolation, Zeyde et al. [**?**], Yang et al. [**?**], He et al. [**?**] and the proposed algorithm. One can observe that edges in the proposed algorithm's reconstruction are sharper than the other algorithms. Figure 3 (g), (h) and (i) show respectively the difference between the original scene and its reconstructions from Yang et al. [**?**], He et al. [**?**] and the proposed algorithm. Clearly, the proposed algorithm produces less artifacts around sharp features.

V. Conclusion

A new super-resolution algorithm is proposed. This algorithm is based on sparse representation over multiple coupled dictionary pairs. It employs scale-invariance of SM as a data clustering for training and model selection in reconstruction. SM is used for clustering the training data and for each cluster a pair of LR and HR dictionaries is learned. In the reconstruction stage, the SM value of a LR patch is used to select the cluster it belongs to. Then, the dictionary pair of the selected cluster is used to reconstruct the unknown HR patch. The proposed algorithm is shown to be superior to the algorithms that employ a single dictionary pair. This is especially noticed for images with sharp edges and wide spread of SM values. Numerical and visual tests conducted over a set of benchmark images reveal a competitive performance of the proposed algorithm as compared to that of the state-of-the-art algorithms.

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