Volume 5, Issue 6, June 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Super Resolution Image Reconstruction Based on Sparse Representation with Joint Dictionary Training and Compression

Unnati J. Patel[*]
CSE Department
Parul Institute of Engineering & Technology
Gujarat, India

Shashwat Kumar
IT Department,
Parul Institute of Engineering & Technology
Gujarat, India

Abstract— Recently, sparse representation has emerged as a powerful technique for solving various image restoration applications. In this paper, we investigate the application of sparse representation on single-image super-resolution problems. Super Resolution Image Reconstruction produces High Resolution images from one or more Low Resolution images. Sparse Representation technique obtain sparse coefficient of low resolution images and use these sparse coefficient in low resolution space to construct the high resolution image. For effectiveness, two dictionaries for low resolution & high resolution can be constructed and used to reconstruct the high resolution image. Hence Larger Dictionary increases execution time and decreases PSNR value. The Time complexity is increased due to searching for image patches and processing dictionary. Proposed work uses K-SVD for creating precise dictionary and Matching Pursuit algorithm for searching best image patches from dictionary. The Lloyd's algorithm is used to compress the Dictionary to reduce Time Complexity. The Arithmetic coding is used to encode mean value, index value and atom number of image patches. The Proposed system improves the image quality and reduces time and PSNR.

Keywords — Super Resolution, Image Reconstruction, Sparse Representation, Dictionary Learning, Compression, K-SVD, PSNR, MSE.

I. INTRODUCTION

SUPER-RESOLUTION (SR) image reconstruction is currently a very active area of research, as it overcomes some of the inherent resolution limitations of low-cost imaging sensors (e.g., cell phone or surveillance cameras) allowing better utilization of the growing capability of high-resolution displays (e.g., high-definition LCDs). Super-resolution (SR) image reconstruction is the process of recovering a high-resolution (HR) image from a single or a set of LR images. Such resolution- enhancing technology may also prove to be essential in medical imaging and satellite imaging where diagnosis or analysis from low-quality images can be extremely difficult. The essential difference between single-frame and multi-frame SR image reconstruction is that new high frequency information can also be recovered from different frames. Though multi-frame SR image reconstruction is theoretically more promising than single frame SR image reconstruction, it suffers many difficulties in real applications, such as sub-pixel image registration and the increase of computational complexity as frame number increases. On the other hand, many researchers have shown that for some real SR applications (e.g., face SR reconstruction), single-frame SR image reconstruction is as effective as multi-frame SR image reconstruction when proper image prior is incorporated. However, the performance of these reconstruction-based SR algorithms degrades rapidly when the desired magnification factor is large or the number of available input images is small. In this paper, we focus on single image SR image reconstruction.

In SR image reconstruction, the LR image can be modeled as a noisy, uniformly down-sampled version of the HR image which has been shifted and blurred, or more formally

$$\mathbf{Y} = \mathbf{WZ} + \mathbf{n} \qquad (1)$$

Where **Y** is the observed LR image, **Z** is the original HR image, **n** is the additive noise**,** and **W** is a degradation matrix representing the geometric shift, blur, and down-sampling operator which operates on **Z** to yield **Y**.

The recently emerged idea of compressive sensing theory provides a different approach in solving single-frame SR problems, exploiting sparsity as a prior. [11] Proposes to train two dictionaries for the LR and HR image patches jointly and use the coefficients of sparse representation of LR image patch to generate the corresponding HR image patch. [11] utilizes the contextual information of local patches to enhance the performance of single-frame SR image reconstruction. Nevertheless, these methods [11] try to learn a universal and over-complete dictionary to represent various image structures and the resulting highly redundant dictionary tends to cause unstable sparse decomposition of image patches or visual artifacts in image patch reconstruction. In [11], proposed to learn different sets of dictionaries from a precollected image database and chose the best set of bases for each HR image patch. However, coding the HR image patch before reconstruction is unreliable. On the other hand, their methods use only a single dictionary for both LR and HR image patches, and it is quite impossible to acquire a dictionary that trained from the original HR image patches to be the best one for LR image patches or vice-versa when the magnification factor is relatively large.

The Sparse Representation technique requires the formation of dictionaries for better SR Reconstruction. Hence the precise dictionaries for LR & HR image patches should be constructed for better results. For precise dictionaries importance is embodied into two aspects. On one hand, the dictionary should correctly reflect the content of the images; on the other hand, the dictionary is large enough that the given image can be represented sparsely. The content of the general images are so rich that there is no proper dictionary under which the given image can be represented sparsely; even if there is one, the size of the dictionary may be too large to be computed effectively. For example, the deformation, rotation, translation and the noise all can make the dictionary become too large. Therefore, sparse representation should be employed in special image compression field in which there are no above shortcomings.

In this paper, we propose novel approach for compressing the representation to overcome the existing limitations.

II. SPARSITY-BASED SR IMAGE RECONSTRUCTION

Classic image priors, such as total variation prior and gradient prior are effective in removing noise artifacts but tend to over smooth the image boundaries. As an alternative, the sparsity-based prior has led to encouraging results for various image restoration problems in recent years. The goal of sparse representation is to represent input vectors approximately as a weighted linear combination of a small number of (unknown) "basis vectors." These basis vectors thus capture high-level patterns in the input data. In this paper, two dictionaries, namely $\mathbf{\Psi h}$ and $\mathbf{\Psi l}$, are trained for the HR and LR image patches, respectively. Given any original HR image patch **z** and the observed LR image patch **y**, the sparse representation model assumes that

$$\mathbf{z} \approx \mathbf{\Psi}\ \boldsymbol{\alpha}\ \&\ \mathbf{y} \approx \mathbf{\Psi}\ \boldsymbol{\alpha} \tag{2}$$

where $\boldsymbol{\alpha}$ is the coefficient vector of sparse representation with most entries are zero or close to zero. In the scenario of image SR reconstruction, what we observe is the LR image patch **y** of the original HR image patch **z** via (1). To recover **z** form **y**, first **y** must be sparsely coded with respect to $\mathbf{\Psi l}$ by solving the following optimization problem

$$\widehat{\boldsymbol{\alpha}} = \mathbf{arg\,min}_{\alpha}\left\{\|\boldsymbol{y} - \mathbf{\Psi l}\boldsymbol{\alpha}\|_2^2 + \boldsymbol{\lambda}\|\boldsymbol{\alpha}\|_{\mathbf{0}}\right\} \tag{3}$$

Where is a small constant denotes the regularization parameter, and $\|\boldsymbol{\alpha}\|_0$ is a pseudo norm that counts the number of non-zero entries in $\boldsymbol{\alpha}$. Fortunately, if the sparse coding $\boldsymbol{\alpha}$ is *sparse enough*, the solution of the $l0$-minimization problem (4) is equal to the solution to the following $l1$- minimization problem.

$$\widehat{\boldsymbol{\alpha}} = \mathbf{arg\,min}_{\alpha}\left\{\|\boldsymbol{y} - \mathbf{\Psi l}\boldsymbol{\alpha}\|_2^2 + \boldsymbol{\lambda}\|\boldsymbol{\alpha}\|_{\mathbf{1}}\right\} \tag{4}$$

III. DICTIONARY TRAINING

A critical issue in sparse representation is the choice of dictionary and many techniques have been proposed so far to learn over-complete dictionary from collected image databases. Given a set of training examples $\mathbf{P}=\{\mathbf{p}1, \mathbf{p}2,\ldots\mathbf{p}s\}$, to find an over-complete dictionary $\mathbf{\Psi}$, we use the following formulation

$$\mathbf{\Psi} = \mathbf{arg\,min}_{\mathbf{\Psi},\mathbf{\Lambda}}\left\{\|\mathbf{P} - \mathbf{\Psi\Lambda}\|_2^2 + \boldsymbol{\varepsilon}\|\mathbf{\Lambda}\|_{\mathbf{1}}\right\} \tag{5}$$

Though (5) is not convex with respect to both $\mathbf{\Psi}$ and $\mathbf{\Lambda}$, but is convex with either one of them if the other one is fixed. Thus optimization can perform over $\mathbf{\Psi}$ and $\mathbf{\Lambda}$ alternatively to get the trained dictionary $\mathbf{\Psi}$. Since we need two dictionaries, namely $\mathbf{\Psi h}$ and $\mathbf{\Psi l}$, for the HR and LR image patches, respectively. The individual training formulations for these two dictionaries are

$$\mathbf{\Psi_h} = \mathbf{arg\,min}_{\mathbf{\Psi_h},\mathbf{\Lambda}}\left\{\|\mathbf{P_h} - \mathbf{\Psi_h\Lambda}\|_2^2 + \boldsymbol{\varepsilon}\|\mathbf{\Lambda}\|_{\mathbf{1}}\right\} \tag{6}$$

and

$$\mathbf{\Psi_l} = \mathbf{arg\,min}_{\mathbf{\Psi_l},\mathbf{\Lambda}}\left\{\|\mathbf{P_l} - \mathbf{\Psi_l\Lambda}\|_2^2 + \boldsymbol{\varepsilon}\|\mathbf{\Lambda}\|_{\mathbf{1}}\right\} \tag{7}$$

It is a training method called K-SVD. The dictionary is obtained by iteratively solving an optimization problem (3). **Y** is consisted of the training patches, $\mathbf{\Psi}$ is the dictionary. In the sparse solving stage, we compute the coefficients matrix X using Matching Pursuit method, which guarantees that the coefficient vector Xi has no more than T non-zero elements. The matching pursuit method is a sparse approximation technique which finds the best matching patch for SR reconstruction. After finding matching patch from dictionary the sparse coefficient is obtained to recover HR image patch. Then, update each dictionary element based on the singular value decomposition (SVD).

$$\mathbf{min}_{A,X}\|Y - AX\|_F^2 \qquad \mathbf{s.t.}\ \forall i, \|X_i\|_{\mathbf{0}} < \mathbf{T} \tag{8}$$

IV. COMPRESSION OF A GIVEN IMAGE

Given a new image, slice it into square patches which have the same size with the training patches. The size of the patches has a direct impact on the compression efficiency. The algorithm becomes more efficient as the size increases. However, the computation complexity and the size of the dictionary also increase rapidly. The proper size should be chosen. In addition, to make the patches fit the dictionary better, the mean of each patch needs to be calculated and subtracted from the patch. After that, compute the sparse representation for each patch by solving the l_0 problem. Those coefficients whose absolute values are less than a given threshold are treated as zero. For each patch, four kinds of information need to be recorded. They are the mean value, the number about how many atoms to use, the coefficients and their locations. The tests show that many image patches require few coefficients. Consequently, compared with the use of a fixed number of coefficients, the method reduces the coding complexity and improves the compression ratio.

V. CODING AND QUANTIZATION

Entropy coding of the atom number of each patch, the mean value of each patch, the coefficients and the indexes is carried out by static arithmetic coders. The atom number of each patch is separately coded. The mean value of each patch is also separately coded. The quantization of coefficients is performed using the Lloyd algorithm, learnt off-line from the coefficients which are obtained from the training set by the MP algorithm over the dictionary. The first coefficient of each block is quantized with a larger number of bits than other coefficients and entropy-coded using a separate arithmetic coder. The model for the indexes is estimated by using the source statistics obtained off-line from the training set. The first index and other indexes are coded by the same arithmetic encoder. First coefficient is quantized with 6 bits and other coefficients are quantized with 4 bits.

VI. HR IMAGE RECONSTRUCTION

Given the optimal solution $\boldsymbol{\alpha}$ to (4), the corresponding HR image patch $\mathbf{z}$ is simply obtained by $\boldsymbol{\Psi}_{\mathbf{h}}\boldsymbol{\alpha}$.
After calculating all the HR image patches, a complete HR image $\mathbf{Z_0}$ can be constructed by concatenating all these HR image patches. Nevertheless, the produced HR image $\mathbf{Z_0}$ so far may not satisfy the SR image reconstruction model (1) exactly. In order to guarantee that the final reconstructed HR image satisfies the model (1), we simply project $\mathbf{Z_0}$ onto the solution space.

$$\hat{\mathbf{Z}} = \mathbf{arg\,min}_{\mathbf{z}}\left\{\|\mathbf{Y}-\mathbf{WZ}\|_2^2 + \boldsymbol{\varepsilon}\|\mathbf{Z}-\mathbf{Z_0}\|_2^2\right\} \quad \mathbf{(9)}$$

The optimal solution to (9) is taken as the final target HR image.

VII. ALGORITHM

Given sampled training image patch pairs {z,y} & an observed LR image Y, to get super resolution image Z, the complete scheme of SR image reconstruction based on sparse representation with joint dictionary training and compression is summarized as follows:

1. Apply K-means algorithm to partition the training patch pairs {x,y} into k clusters & calculate the centroid of each cluster.
2. For each cluster, solve the optimization problem in (3) to get subdictionaries $\boldsymbol{\Psi}_{\mathbf{h}}^{\mathbf{K}}$ and $\boldsymbol{\Psi}_{\mathbf{l}}^{\mathbf{K}}$.
3. For each LR image patch,
   - Determine the best approximation from dictionaries by applying matching pursuit using (8).
   - Fine the optimal sparse code by (4).
   - The coefficients with lower absolute value than given threshold are treated as zero. Record the remaining coefficients & their locations.
   - Encode the atom number of each patch, the mean value of each patch & indexes, quantization & encode the coefficients.
   - Reconstruct the corresponding HR patch.

4. Merge all the HR patches got in previous step to form an original estimate of the target HR image Z_0.
5. Use (9), find the closest image to Z_0 which satisfies the HR model.

VII. CONCLUSION

Super Resolution Image Reconstruction technique is used for recovering HR image from LR images. Sparse Representation technique gives best results of image reconstruction. The Sparse Representation technique employs two dictionaries of image patches for reconstruction. The existing method finds the sparse coefficient of LR images and use dictionaries of HR & LR patches for reconstructing SR image. But these dictionaries are larger in size which requires more computation and have increased time complexity. To eliminate the limitation Image Compression is employed. The image compression further comprises three algorithms as: Matching Pursuit which is sparse approximation to find best match patch from dictionaries generated using K-SVD, Lloyd's which compress the patch to reduce the size of dictionary and Arithmetic coding encodes the mean values, atom number and index value for reconstruction. The size of Dictionary reduced to [100 81] from [150 91] and hence time required for searching dictionary and computation both decreased.

ACKNOWLEDGMENT

I would like to acknowledge Mr. Shashwat Kumar, Assistant Professor at Parul Institute of Engineering and Technology, Vadodara for suggesting this current research topic and guiding to work upon.

REFERENCES

[1] B.R. Mohapatra, A Mishra, S.K. Rout, "A comprehensive review on Image Restoration", IJRAT (2321-9637), vol. 2, No.3, March 2014.
[2] Elham karimi, Kaveh kangarloo, shahram javadi, "A survey on super-resolution methods for Image Reconstruction", IJCA, vol. 90, No. 3, March 2014.
[3] Guangqi Shao, Yanping Wu, Yong A, Xiao Liu and Tiande Guo, "Fingerprint Compression Based on Sparse Representation", IEEE Transaction on Image Processing, Vol. 23, No. 2, February 2014.

[4] Pandya Hardeep, P. B. Swadas, M. Joshi, "A survey on Techniques and Challenges in Image Super Resolution Reconstruction", IJCSMC, Vol. 2, Issue 4,April 2013.

[5] Athira B Kaimal, S. Manimurugan, C.S.C. Devadass, "Image Compression Technique: A Survey" IJEI, vol. 2, issue 4, February 2013.

[6] Di Zhang, Minghui Du, "Super Resolution Image Reconstruction via Adaptive Sparse Representation and Joint Dictionary Training", IEEE-CSIP, 2013.

[7] A. Jegatheeswari P, B. Amudha J, C. Sudhakar R, "Sparse Representation based Image Deblurring and Super Resolution", IEEE-ICAESM, 2012.

[8] W. Dong, L. Zhang, G. Shi and X Wu, "Image Deblurring and Super Resolution by Adaptive Sparse Domain Selection and Adaptive Regularization", IEEE Transaction on Image Processing, Vol. 20, No. 7, July 2011.

[9] R. Sudheer Babu, Dr. K. E. Sreenivasa Murthy, "A Survey on the Methods of Super-Resolution Image Reconstruction", IJCA, vol. 15, No. 2, February 2011.

[10] Kathiravan srinivasan, J. Kanakraj, "A study on Super-Resolution Image Reconstruction Techniques", IISTE, vol. 2, No. 4, 2011.

[11] J Yang, J Wright, T Huang and Y Ma, "Image Super Resolution Via Sparse Representation", IEEE Transaction on Image Processing, Vol. 19, No. 11, November 2010.

[12] O. Bryt, M. Elad, "Compression of Facial Images using the K-SVD Algorithm" J. Vis. Communication Represents., vol.19, no. 4, 2008.

[13] J Yang, J Wright, T Huang, "Image Super Resolution as Sparse Representation of Row Image Patches", in Proc. IEEE conf. comput. Vis. Pattern recognit., Jun 2008.

[14] M. Aharon, M. Elad and A. M. Bruckstein, "The K-SVD: An Algorithm for designing of overcomplete dictionaries for Sparse Representation", IEEE Transaction on signal processing, vol. 54, 2006.

[15] M. Aharon, M. Elad, "Image Denoising via Sparse and Redundant Representation over Learned Dictionaries", IEEE Transaction on signal processing, vol. 15, No. 12, 2006.

[16] S. Farsiu, M. D. Robinson, M. Elad and P. Milanfar, "Fast and Robust Multiframe Super Resolution", IEEE Transaction on Image Processing, Vol. 13, No. 10, 2004.

[17] Sung Cheol Park, Min Kyu Park, Moon Gi Kang, "Super-Resolution Image Reconstruction : A technical Overview", IEEE signal Processing Magazine, May 2003.

[18] S C Park, M K Park and M G Kang, "Limits on Super Resolution and how to break them", IEEE signal Processing Magazine, September 2002.

[19] S G Mallat, Z. Zhang, "Matching Pursuit with Time Frequency Dictionaries", IEEE Transaction Processing, vol. 41, No. 12, December 1993.

Figure 1: Comparison of SR reconstruction of *Flower*. From left to right: Original image, the method in [6] (PSNR=26.9713, MSE=130.6017), and the proposed method (PSNR=34.2507, MSE=77.2696)

Figure 2 Comparison of SR reconstruction of *Grapes*. From left to right: Original image, the method in [6] (PSNR=25.8194, MSE=170.2708), and the proposed method (PSNR=31.3080, MSE=152.1512)

Figure 3 Comparison of SR reconstruction of *Tree*. From left to right: Original image, the method in [6] (PSNR=24.4876, MSE=231.3752), and the proposed method (PSNR=30.0067, MSE=205.3114)