AN ADAPTIVE METHOD FOR IMAGE RESTORATION USING SPARSE REPRESENTATION

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ABSTRACT

Image restoration is a well explored topic in the field of image processing. In this paper, we introduce a new method for image restoration using sparse representation. The aim here is to reconstruct a high quality image from one or several of its degraded versions such as noisy, blurred or undersampled using sparse representation. To improve the performance of sparse representation based image restoration, the image nonlocal self-similarity is exploited to obtain the good estimates of the sparse coding coefficients of the original image. The sparse coding coefficients of the observed image are then centralized to those estimates. Thus the sparse coding noise which is defined as the difference between the sparse coding coefficients of the original image and the sparse coding coefficients of the observed image is suppressed to obtain the good quality image. To achieve this, a robust algorithm for image restoration is proposed which outperforms the existing algorithms in terms of improved performance.

Keywords- *Image Restoration, Sparse Representation, Sparse Coding Noise, Nonlocal Similarity.*

I. INTRODUCTION

Sparse representations of signals have drawn considerable interest in recent years. Sparse representation codes an image patch as a linear combination of few atoms chosen out from an overcomplete dictionary [9]. Sparse representation based image restoration have shown good results in applications such as remote sensing, medical imaging, surveillance, entertainment, etc. The quality of image restoration mainly depends on whether the used sparse domain can represent well the underlying image.

Image restoration aims to recover a high quality image from its degraded versions such as noisy, blurred or undersampled, which may be taken, for example, by a low-end camera and/or under limited conditions. For an observed image y, the problem of image restoration [1] can be formulated as:

$$y = \mathrm{H}x + \upsilon \qquad (1)$$

where H is a degradation matrix, x is the original image and υ is the additive noise vector. Assume that x has a sparse representation over the dictionary, i.e. $x = \Phi\alpha$, where $\Phi \in R^{nxM}$ (N < M) is an overcomplete dictionary and α is the sparse coding coefficient. Since the observed image is degraded, it is very difficult to recover the true sparse code α_x of the original image x from the observed image y.

Various image restoration methods [2] have been developed to obtain the better image quality. In the past decades, extensive studies have been conducted on developing various image restoration methods. Due to the ill-posed nature of image restoration, the regularization-based techniques have been widely used by regularizing the solution spaces. The classic regularization models, such as the quadratic Tikhonov regularization and the TV regularization are effective in removing the noise artifacts but tend to over smooth the images due to the piecewise constant assumption.

In recent years the sparsity-based regularization has led to promising results for various image restoration problems. Several algorithms were existing for image restoration using sparse representation. Some of the recently developed algorithms are Block Matching 3D Shape Adaptive Principle Component Analysis algorithm, Learned Simultaneously Sparse Coding method, Expected Patch Log Likelihood method, Adaptive Sparse Domain Selection method, etc. When the noise level is high, the above mentioned methods tend to generate many visual artifacts.

Our sparsity-based image restoration method recovers the original image x from observed image y by solving the l_1-minimization problem (counting number of nonzero coefficients). To faithfully reconstruct the original image x, the sparse code α_y of the observed image y should be as close as possible to the sparse code α_x of the original image x. In other words, the difference $\upsilon_\alpha = \alpha_y - \alpha_x$ which is called as sparse coding noise [6] should be reduced. To reduce the sparse coding noise, we centralize the sparse codes to some good estimation of α_x by exploiting nonlocal similarity in the observed image and centralize the sparse coding coefficients by means of K-Means PCA, block matching and iterative shrinkage algorithm.

II. METHODOLOGY

Our proposed method of image restoration can be organized into three levels, namely Level 1, Level 2 and Level 3. In Level 1, an input image is fed through the noisy channel to obtain the degraded image. This is as shown in the fig. 2.1 (a).

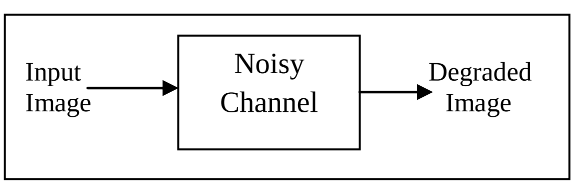

Fig. 2.1 (a) Level 1 of the Proposed Method

In Level 2, our proposed algorithm called 'Robust Algorithm for Image Restoration' is applied on the degraded image to obtain the original image. This is as shown in the fig. 2.1 (b).

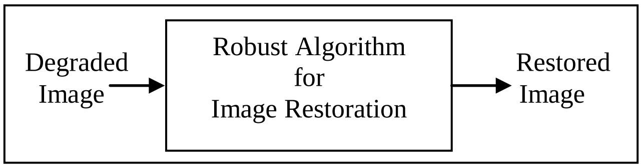

Fig. 2.1 (b) Level 2 of the Proposed Method

In Level 3, the proposed robust algorithm consists of K-Means PCA, Block Matching and Iterative Shrinkage Algorithm. This is as shown in the fig. 2.1 I.

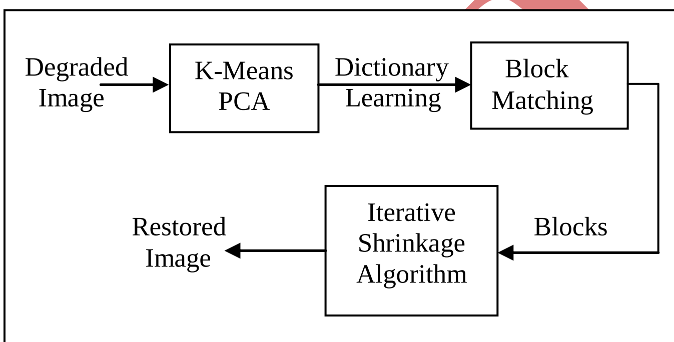

Fig. 2.1 (c) Level 3 of the Proposed Method

The K-Means PCA is used to create the dictionary of the degraded image and block matching is used to obtain the blocks and then iterative shrinkage algorithm is applied to solve the l_1-minimization problem. To this end, we obtain the restored image of improved quality.

III. K-MEANS CLUSTERING VIA PRINCIPAL COMPONENT ANALYSIS ALGORITHM

Data analysis methods are essential for analysing the ever-growing massive quantity of high dimensional data. On one end, cluster analysis attempts to pass through data quickly to gain first order knowledge by partitioning data points into disjoint groups such that the data points belonging to the same cluster are similar while data points belonging to the different clusters are dissimilar. One of the most popular and efficient clustering methods is the K-Means method [3] which uses prototypes to represent clusters by optimizing squared error function. On the other hand, higher dimensional data are often transformed into lower dimensional data via Principal Component Analysis (PCA) where coherent patterns can be detected more clearly. The main basis of PCA-based dimension reduction is that PCA picks up the dimensions with the largest variances. Mathematically, this is equivalent to finding the best low rank approximation of the data via Singular Value Decomposition (SVD). The PCA automatically performs the data clustering according to the K-Means clustering objective function.

In K-Means clustering algorithm, 'clustering' refers to a set of such clusters, usually containing all objects in the data set. Additionally, it may specify the relationship of the clusters to each other, for example a hierarchy of clusters embedded in each other. The dataset is partitioned into K clusters and the data points are randomly assigned to the clusters resulting in clustering that have roughly the same number of data points. For each data point, Euclidean distance is calculated to each cluster. If the data point is closest to its own cluster, it remains in the cluster where it is. If the data point is not closest to its own cluster, then it moves to the nearest cluster. The above step is repeated until a complete pass through all the data points results in no data point moving from one cluster to another. The mean is found and is subtracted from each of the data dimensions. The covariance matrix is calculated. The Eigen vectors and Eigen values are then calculated from the covariance matrix to obtain the principal components.

IV. BLOCK MATCHING ALGORITHM

The purpose of block matching algorithm is to find a matching block from a frame *I* in some other frame *j*, which may appear before or after *i*. This is used to discover temporal redundancy in the image sequence, increasing the effectiveness of interframe image compression. Block matching technique [4] includes three main components: block determination, search method and matching criteria. Block determination specifies the position and size of blocks in the current frame, the start location of the search in the reference frame, and the scale of the blocks. The search method looks for candidate blocks in the reference frame. The matching criterion is to determine the best match among the candidate blocks.

V. ITERATIVE SHRINKAGE ALGORITHM

Iterative Shrinkage is a simple technique used for restoring signals and images. When the signal is represented in terms of suitable basis (for instance a wavelet basis) smaller coefficients are set to zero and larger coefficients above some threshold are possibly shrinked. Therefore, thresholding (or shrinkage) usually produces signals that are sparse, i.e., that have only a small number of non-zero coefficients. So it works particularly well if the original noise free signal can be well-approximated by a sparse one. Iterative Shrinkage algorithm [5] is used to solve the l_1-norm minimization problem [7] by finding out the shrinkage operator as shown in the equation (3) and substituting in the equation (2) as shown below:

$$\alpha_y = \underset{\alpha}{argmin} \left\{ \|y - \mathrm{H}\Phi \cdot \alpha\|_2^2 + \Sigma_i \Sigma_j \lambda_{i,j} |\alpha_i(j) - \beta_i(j)| \right\} \tag{2}$$

which is convex and can be solved efficiently. In the (l+1) th iteration, the proposed shrinkage operator for the j^{th} element of α_i is

$$\alpha_i^{l+1}(j) = S_\tau\left(v_{i,j}^{(l)} - \beta_i(j)\right) + \beta_i(j) \tag{3}$$

where $S_\tau(\cdot)$ is the classic soft-thresholding operator and $v^{(l)} = K^T(y - K \cdot \alpha^{(l)})$ where $K = \mathrm{H}\Phi$, $K^T = \Phi^T \circ \mathrm{H}^T$ and $\tau = \lambda_{i,j}/c$ where c is a auxiliary parameter.

VI. EXPERIMENTAL RESULTS

To verify the image restoration performance of the proposed algorithm, we have conducted extensive experiments on image denoising, deblurring and super-resolution. The basic parameter setting is as follows: the patch size is 7x7 and number of clusters K = 70. The loop iterates number of times until the sparse coding noise is approximately reduced to zero. To evaluate the quality of the restored image, the PSNR (Peak Signal to Noise Ratio) and SSIM (Structural Similarity Index Module) are calculated. The PSNR and SSIM values obtained for the given image is mentioned below.

6.1 IMAGE DENOISING RESULT

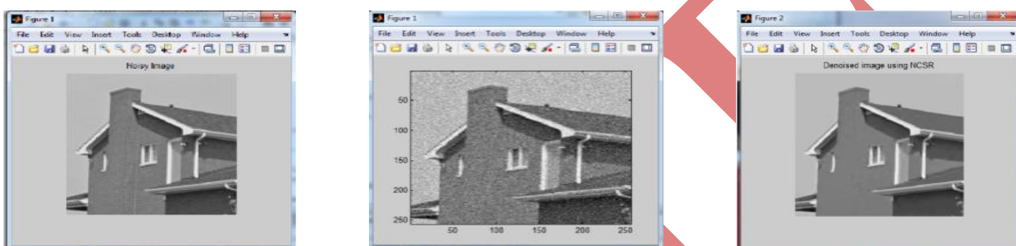

Fig. 6.1 Denoising result of the *House* image with random noise corruption.
From left to right: original image, noisy image and denoised image
PSNR of the noisy image = 22.134287, PSNR of the denoised image = 33.975243, SSIM = 0.8742.

6.2 IMAGE DEBLURRING RESULT

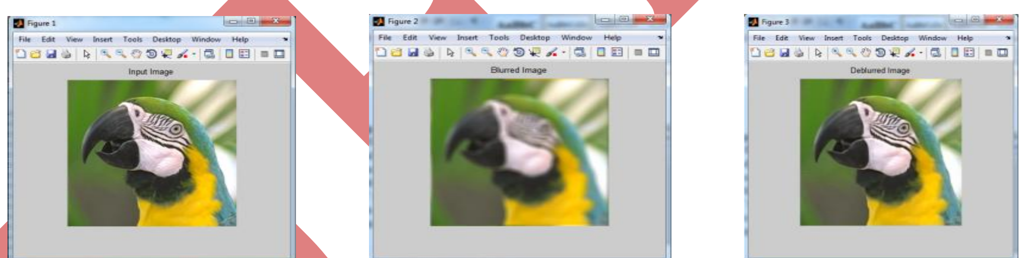

Fig. 6.2 Deblurring result of the *Parrot* image with standard deviation √2.
From left to right: original image, blurred image and deblurred image.
PSNR of the blurred image = 23.871135, PSNR of the deblurred image = 31.96, SSIM = 0.91105

6.3 IMAGE SUPER RESOLUTION RESULT

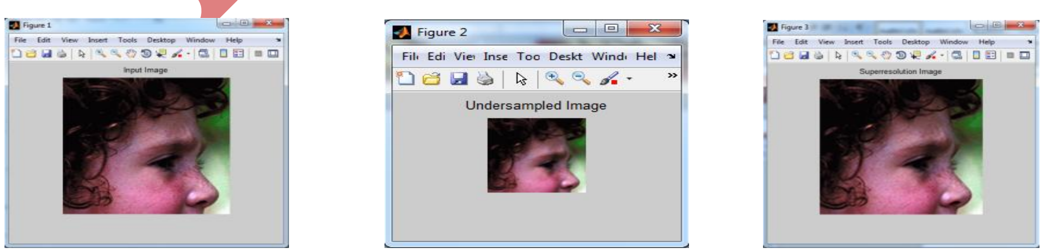

Fig. 6.3 Super Resolution result of a girl image with standard deviation 1.6.
From left to right: original, undersampled and reconstructed image.
PSNR of the undersampled image = 33.39, PSNR of the deblurred image = 33.66, SSIM = 0.8276.

VII.CONCLUSION

In this paper we presented a robust algorithm for image restoration using sparse representation. The sparse coding noise which is defined as the difference between the sparse code of the noisy image and the sparse code of the unknown original image is minimized to improve the performance of sparsity-based image restoration. The experimental results on image denoising, deblurring and super resolution demonstrated that the proposed method have achieved the highest performance and are visually more pleasant.

REFERENCES

[1] W. Dong, L. Zhang, and G. Shi, "*Centralized Sparse Representation for Image Restoration*" in Proceedings IEEE International Conference Computer Vision vis ICCV, *pp. 1259-1266, Nov. 2011*.

[2] Joel A. Tropp and Stephen J. Wright, "*Computational Methods for Sparse Solution of Linear Inverse Problems*" IEEE Transactions on Information Theory, *Vol. 98, No. 6, pp. 0018-9219, June 2010*.

[3] H.S. Behera, Abhishek Ghosh and Sipak Ku. Mishra, "*A New Improved Hybridized K-Means Clustering Algorithm with Improved PCA Optimized with PSO for High Dimensional Data Set*" International Journal of Soft Computing and Engineering, *ISSN: 2231-2307, Vol.2, Issue no. 2, May 2012.*

[4] Nicole S. Love and Chandrika Kamath flove21, "*An Empirical Study of Block Matching Techniques for the Detection of Moving Objects*" , IEEE Transactions on Image Processing, *Vol. 22, Issue no. 8, pp. 1739–1745, Jul. 2001.*

[5] I. Daubechies, M. Defriese, and C. DeMol, "*An iterative thresholding algorithm for linear inverse problems with a sparsity constraint*" Communication of Pure Applied Math., *Vol. 57, Issue no. 11, pp. 1413–1457, 2004.*

[6] M. Elad and M. Aharon, "*Image denoising via sparse and redundant representations over learned dictionaries*" IEEE Transactions on Image Processing, *Vol. 15, Issue no.12, pp. 3736– 3745, Dec. 2006.*

[7] A.N. Tikhonov, "*Solution of incorrectly formulated problems and regularization method*", Soviet Math. Dokl, *Vol. 4, Issue no.4, pp. 1035-1038, 1963.*

[8] Rafael C. Gonzalez and Richard Eugene Woods, "*Digital Image Processing*" Prentice Hall, 2008.

[9] Chris Solomon and Toby Breckon, "*Fundamentals of Digital Image Processing- A practical approach with examples in Matlab*" Wiley-Blackwell, 2010.

[10] Michal Aharon, "*Overcomplete Dictionaries for Sparse Representation of Signals*", doctoral diss., Israel Institute of Technology, Haifa, Nov 2006.

[11] http://en.wikipedia.org/wiki/Sparse_approximation

[12] http://www.see.ed.ac.uk/~tblumens/Sparse/Sparse.html