INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH & DEVELOPMENT

ISSN 2278 – 0211 (Online)

Patch Based Image Processing

Silpa E. S.
Student Member IE, CSI, VAST, Thrissur, Kerala, India
Sreelakshmi K. N.
Student Member IE, CSI, VAST, Thrissur, Kerala India
Beena M. V.
Assistant Professor, VAST, Thrissur, Kerala India
Slipa V. M.
Student Member IE, CSI, VAST, Thrissur, Kerala India
Swapna Lazar
Student Member IE, CSI, VAST, Thrissur, Kerala India

Abstract:
Image processing using local patches has become very popular and was shown to be highly effective. We propose a novel approach based on reordering of its patches. For the given corrupted image, first, we extract all the patches with overlaps. Then we will order them in such a way that they are chained in the shortest possible path. The order which we obtained will be applied to the corrupted image, implies a permutation of the image pixels to what should be a regular signal. This will help us to achieve good recovery of the clean image by applying relatively simple one-dimensional (1D) smoothing operations to the reordered set of pixels. From this, we have shown that using a carefully designed permutation matrices and simple and intuitive 1D operations such as linear filtering and interpolation, the proposed scheme can be used for image denoising and inpainting, where it achieves high quality results.

Keywords: *Image permutation, inpainting, denoising*

1. Introduction

Image processing using local patches has become very popular and was shown to be highly effective and useful. A patch is a small area of pixels which is called as a window. Patches are powerful primitives in the area of Image Processing. The image models enable us to systematically develop algorithms for accomplishing a particular image-related application [1]. There are basically two types of patch-based image models-descriptive and generative. Descriptive models focus on the extraction of the distinctive features from the given image so that they can facilitate the task of classifying the image into one of several classes. So we can say that they are suitable for the task of classification and recognition. Generative models preserve the information in an image that is why they are more desirable for the task of compression and restoration [9] [10].

The main concept of the patch-based processing is, extract all the patches which are very small compared to the original image size, with overlaps from the given image. Then the interrelations between those patches are found out. The different ways to find the relations between patches are: a weighted average of pixels with similar surrounding patches, clustering the patches into disjoint sets and treating each set different, seeking a representative dictionary for the patches and using it to sparsely represent them, gathering groups of similar patches and applying a scarifying transform on them. The manipulated patches are then put back to form the resulting image [11] [12].

In the patch- based method, there is an expectation that every patch taken from the image may find similar ones elsewhere in the image and a joint treatment of these patches may support the reconstruction process which enables better recovery of the image . The proposed method uses a generative patch-based image model and consists of overlapped patches. The proposed method first extracts all the overlapping patches of size $\sqrt{n}\times\sqrt{n}$. After extracting these patches, it tries to organize them in such a way that they are chained in the shortest possible path, by using the interrelations between them and the travelling salesman problem. Then, depending on the quality of the image, i.e. noisy or containing missing pixels, smoothing operations such as filtering or interpolation is applied to the reordered patches to get a good recovery of the image. So in brief the main steps of the proposed method are – for a given corrupted image, it extracts all overlapping patches, then it reorders the patches, after that it operates on the reordered patches using smoothing

algorithms and finally places the resulting patches to their original location. The proposed image reconstruction method could be able to lead to better results for image denoising and inpainting [7].
The need for efficient image restoration methods has grown with the massive production of digital images of all kinds, which are taken in poor conditions. No matter how good cameras are, an improvement in the image is always desirable to extend their range of action. Additionally patch-based image processing has become popular in recent years. So the proposed method is an image reconstruction scheme based on reordering of its patches. It is a generative patch-based method.

2. Previous Work

2.1. Image Denoising Using NL-Means via Smooth Patch Ordering

Here, introducing a new image denoising algorithm that overcomes the limitations of previous denoising algorithms. The limitations of previous algorithm were : 1) It did not take advantage of the distances between the noisy image patches, which were used in the reordering process; and 2) the smoothing filters required a separate training set to be learned from. In this work, they propose an image denoising algorithm, which applies similar permutations to the noisy image, but overcomes the above two shortcomings. They eliminate the need for learning filters by employing the nonlocal means (NL-means) algorithm and estimate each pixel as a weighted average of noisy pixels in a union of neighborhoods obtained from different global pixel permutations. In this the weights are determined by distances between the patches.
They have proposed a new image denoising scheme which is based on the NL-means algorithm and smooth 1D ordering of the pixels in the noisy image. They replaced the square neighborhoods employed by each pixel in the NL-means algorithm with a union of neighborhoods obtained from different global pixel permutations. They have shown that combined with patch classification and sub image averaging schemes, applying two iterations of proposed scheme produces results which are close to the state-of-the-art. In the future work, they wish to improve state-of-the-art algorithms like the BM3D and the algorithm proposed in by employing proposed patch neighborhoods in their block matching procedure. Additionally, the proposed image denoising scheme may be further improved by dividing the patches to more than two types, and then treating each type differently [1].

2.2. Image Restoration Using Reordering of Its Patches

The need for efficient image restoration methods has grown with the massive production of digital images of all kinds, which are taken in poor conditions. No matter how good cameras are, an improvement in the image is always desirable to extend their range of action. Additionally patch-based image processing has become popular in recent years. So the proposed method is an image reconstruction scheme based on reordering of its patches. It is a generative patch-based Method. If the given image is corrupted, it extracts all patches with overlaps, and organizes them to have the shortest possible path, using approximate travelling salesman problem. Then it operates on the reordered patches using smoothing operations like median filtering and cubic spline interpolation to get the recovered image.
The proposed method could be used for image denoising and inpainting, and could show good results in both cases. The proposed method uses a generative patch-based image model and consists of overlapped patches. The proposed method first extracts all the overlapping patches of size nn. After extracting these patches, it tries to organize them in such a way that they are chained in the shortest possible path, by using the interrelations between them and the travelling salesman problem. Then, depending on the quality of the image, i.e. noisy or containing missing pixels, smoothing operations such as filtering or interpolation are applied to the reordered patches to get a good recovery of the image [3].

2.3. Variable Patch Size, Sparse Representation over Learned Dictionaries

This paper addresses the patch size issue in sparse representation over learned dictionaries. A strategy for selecting the best patch size is proposed. It is empirically shown that the representation quality of natural image patches depends on the patch size considered. The proposed strategy selectively chooses the most appropriate patch size based on the resulting sparse representation error. The sparse representation of each small sized image region is taken by selecting the most suitable patch size for the patch containing this region. The proposed strategy is shown able to improve the sparse representation quality as seen in numerical experiments both quantitatively and qualitatively
The proposed strategy requires dividing an image into patches with different patch sizes. Each patch size requires a corresponding dictionary for sparse coding. Then, each patch at each size is sparsely coded over its corresponding dictionary. To this end, the sparse representation of each of the smallest size patches can be obtained by directly coding this patch over the corresponding smallest-size dictionary. Alternatively, this representation can be obtained by extracting it out of the sparse approximation of each of the larger patches that contain this patch of interest. Since patches are one-dimensional, linear extraction operators can be conveniently designed for such an extraction. Small-size patch extraction is carried out by pre-multiplying a larger patch with the suitable extraction operator. At this stage, the mean-square-error (MSE) measure between the true patch value and its several representations is calculated. In this work, the MSE measure is used to decide on the most appropriate representation of a patch. This means that the most appropriate patch size is selected in terms of the representation MSE measure.

2.4. Patch-Based Methods for Variational Image Processing Problems

Blocks taken inside images, or patches, are at the very heart of many Image Processing applications. Examples include compression standards such as JPEG decompose images into small blocks of pixels, movie compression algorithms add a step of block motion estimation to this, and block matching is still a competitive approach to motion estimation and structure-from- motion tasks. Patches are indeed handy because they allow us to assume local properties of images that have little chance to be true when looking at the big picture: locally, colours are almost constant, textures almost periodic, or 3D transforms become affine. Hence, considering only small image parts does greatly help to simplify and justify the assumptions about the nature of the said data.

In this paper, we explore alternative approaches to non-locality, with the goals of i) developing universal approaches that can handle local and non-local constraints and ii) leveraging the qualities of both non-locality and sparsity. For the first point, we will see that embedding the patches of an image into a graph-based framework can yield a simple algorithm that can switch from local to nonlocal diffusion, which we will apply to the problem of large area image in painting. For the second point, we will first study a fast patch preselection process that is able to group patches according to their visual content. Their main goal is to explore the use of patches as the principal primitives of interest. By exploiting their redundancy and imposing different forms of sparsity, we will revisit some classical Image Processing problems with a patch-centric viewpoint in a mathematical framework that allows leveraging of both local patchwise and global constraints. Finally, we will take our reflection even further by considering a case where only some binarized measures, and not pixel data, is available.

3. Proposed system

3.1. Image Smoothening

3.1.1. Basic Image Model

To design a matrix P, that would produce a smooth signal when it is applied to the target image y is as follows.. When the image Y is known, the solution is to reorder it as a vector, and then apply a simple sort operation on the obtained vector. Let Y be an image of size $N = R \times C$, and let Z be a noisy or corrupted version of Y. Also, let y and z be the column stacked versions of Y and Z, respectively. A column stacked version of a matrix is a column vector, which is created by concatenating the columns of the matrix one by one. Then the corrupted image satisfies

$$z = My + v$$

Where the $N \times N$ matrix M denotes a linear operator which corrupts the image. To reconstruct y from z the proposed method employs a permutation matrix P of size $N \times N$. It is assumed that when P is applied to the target signal, it produces a smooth signal.

3.1.2. Building the Permutation Matrix P

In order to design the permutation matrix P for the corrupted image that may be noisy or containing missing pixels, any permutation defined by simply reordering the corrupted pixels into a regular signal does not necessarily smooth. Since the pixels in the corrupted image are not helpful at suboptimal ordering operation i.e. patches from the corrupted image are used. Let y_i and z_i denote the i th samples in the vectors y and z, respectively. Let x_i denotes the column stacked version of the $\sqrt{n}\times\sqrt{n}$ patch around the location of z_i in Z. It is assumed that under a distance measure $w(x_i, x_j)$, proximity between the two patches x_i and x_j suggests proximity between the uncorrupted versions of their centre pixels y_i and y_j, so the points x_i should be reordered so that they form a smooth path, hoping that the corresponding reordered 1D signal y_p will also become smooth[5].

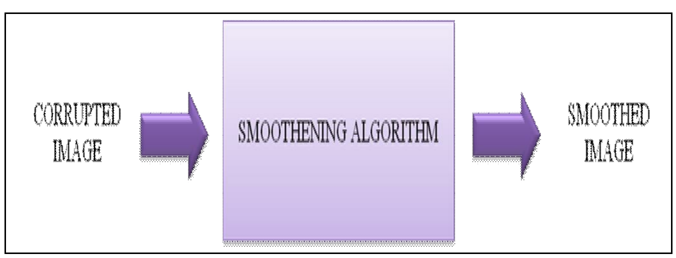

Figure 1: The Image Smoothening

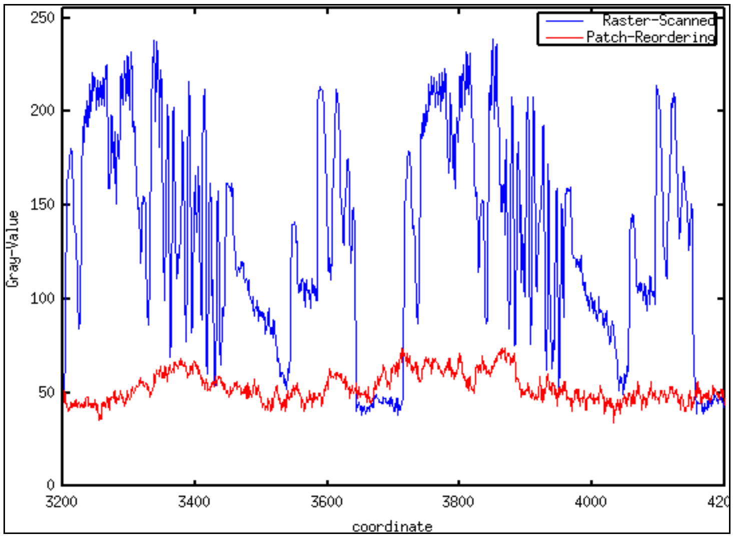

Figure 2: Raster scan Vs Patch ordering

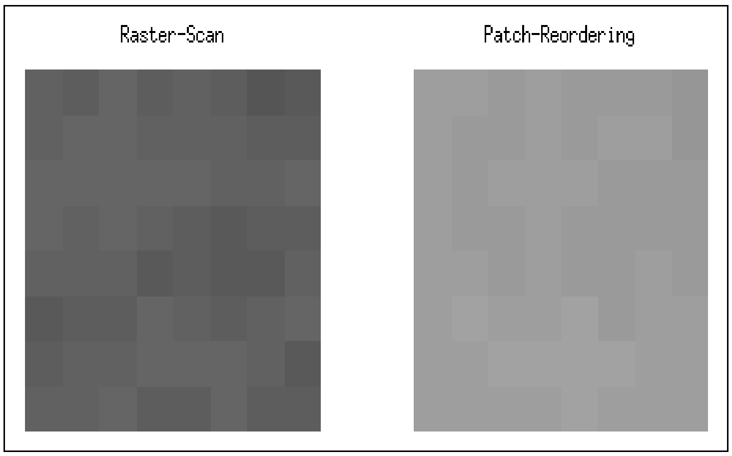

Figure 3: Output of Raster scan and Patch ordering

3.2. Image Denoising

In image denoising, the recovery of an image from its noisy version is carried out. In that case M = I and the corrupted image satisfies z = y + v. The patches xi may contain noise, and we choose the distance measure between xi and x j to be the squared Euclidean distance divided by n [4] [5]. A 1D linear shift invariant filter, is used for this purpose. There are two filters to switch between based on the patch content. The smooth areas in the image are treated differently than areas with edges or texture. First patches are partitioned into those smooth Ss and those with edges and texture Se. Next, divide the sub images also into two signals. A vector of length |Ss| that contain the smooth patches and a vector of length |Se| .Now make use of the nearest neighbour search method and extract the sub images from both divisions. Now find the filters hs, he each of length NH. Now define a filter h of length 2Nh.The vector h stores the filter taps to be designed. We substitute and obtain the reconstructed image.

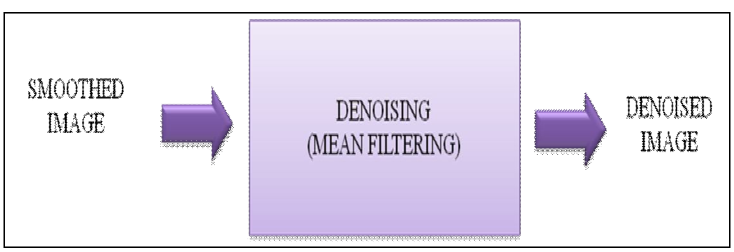

Figure 4: Image Denoising

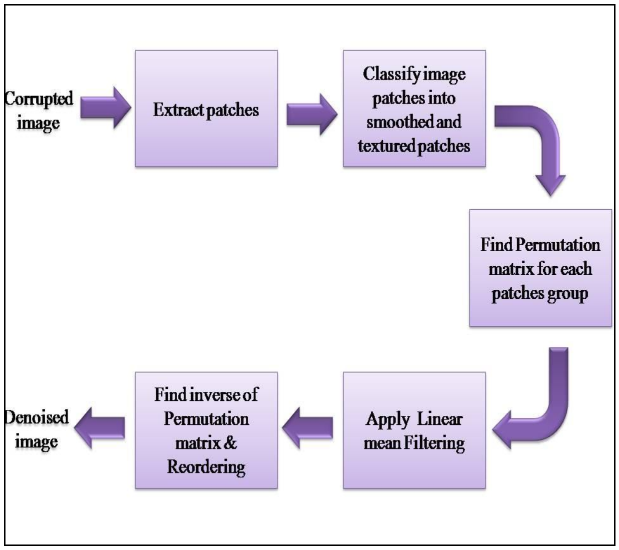

Figure 5: Image Denoising Mechanism

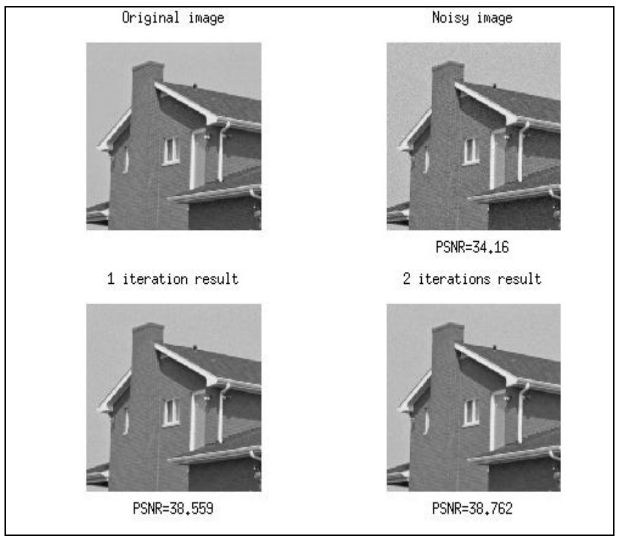

Figure 6: Image Denoising Results

3.3. Image Inpainting

The problem of image inpainting is about the recovery of missing pixels in the given image. . Here v = 0, and M is a diagonal matrix of size N X N which contains ones and zeroes in its main diagonal corresponding to existing and missing pixels, correspondingly. Each patch may contain missing pixels, and we denote by Si the set of indices of non-missing pixels in the patch xi . We choose the distance measure between patches xi and x j to be the average of squared differences between existing pixels that share the same location in both patches. First the matrix P is calculated, when a patch does not share pixels with any of the unvisited patches, the next patch in the path is chosen to be its nearest spatial neighbour. An operator H is used, which recovers the missing values using cubic spline interpolation. We apply the matrix P 1 on the resulting vectors and obtain the estimated sub-images y j . The final estimate is obtained from these sub-images. We improve our results by applying two additional iterations of a modified version of this inpainting scheme.

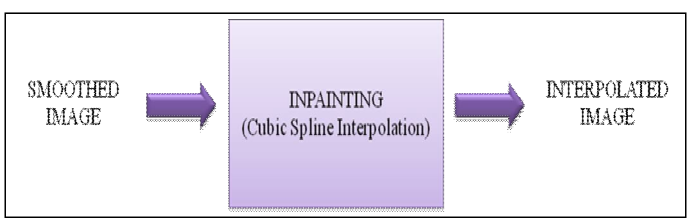

Figure 7: Image Inpainting

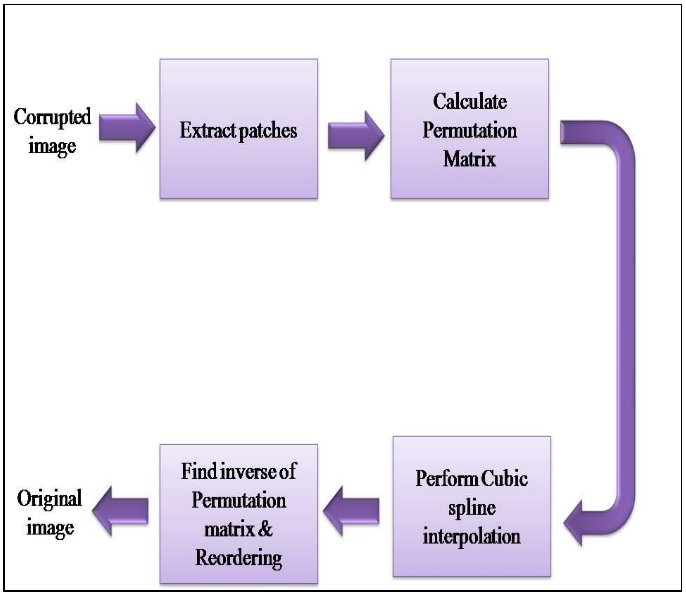

Figure 8: Image Inpainting Mechanism

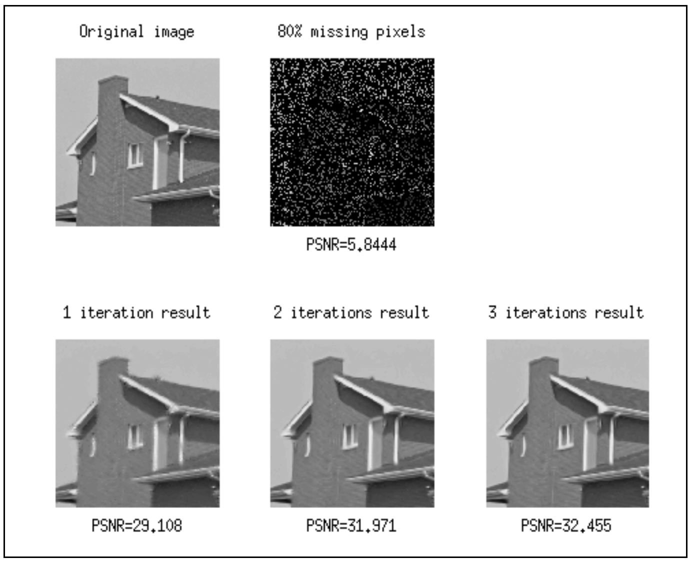

Figure 9: Image Inpainting Results

4. Conclusion and Future Work

We have proposed a new image processing scheme which is based on smooth 1D ordering of the pixels in the given image. Using a carefully designed permutation matrices and simple 1D operations such as linear filtering and interpolation, the proposed scheme can be used for image denoising and inpainting, where it achieves high quality results. For image denoising, the Mean filter which gives a good result for medium and high noise levels. For image inpainting it uses cubic spline interpolation which yields better results compared to the ones obtained with a simple interpolation scheme. The proposed method can be extended in several ways. The other distance measures can be used. The distances between the patches can also be used in the reconstruction process of the sub images. The proposed image denoising scheme may be improved by dividing the patches to more than two types, and treating each type differently.

There are several research directions to extend this work that we are currently considering. The first is to make use of the distances between the patches not only to find the ordering matrices, but also in the re-construction process of the sub-images. These distances, carry additional information which might improve the obtained results. Improvements can also be made to the patch ordering scheme itself. We have seen that this scheme performs poorly near the end of the found path, when only a small number of unvisited patches remain. A possible solution could be to develop a scheme which allows patches to be revisited more than once. A different direction is to develop new image processing algorithms which involve optimization problems in which the 1D image reordering act as regulars. These may both improve the image denoising and inpainting results, and allow to tackle other applications such as image deblurring.

5. Acknowledgment
We thank the authors of all the previous implementation methodologies, for the fruitful discussions and advices, which helped in developing the presented work. We also thank the anonymous reviewers for their helpful comments.

6. References

1. Idan Ram, Michael Elad And Israel Cohen "Image Denoising Using Nl-Means Via Smooth Patch Ordering," Acoustics, Speech And Signal Processing (Icassp), 2013 IEEE International Conference On, May 2013,Pp. 1350-1354.
2. A. Buades, B. Coll, and J. M. Morel, "A review of image denoising algorithms, with a new one," Multiscale Modeling and Simulation, vol. 4, no. 2, pp. 490–530, 2006.
3. A. H jadhav, p. N chathur, "Image restoration using reordering of its patches", proceedings of international conference on modeling and simulation in engineering & technology (ICMSET-2014), 15th - 16th february, 2014
4. P. Chatterjee and P. Milanfar, "Clustering-based denoising with locally learned dictionaries," Image Processing, IEEE Transactions on, vol. 18, no. 7, pp. 1438–1451, 2009
5. G. Yu, G. Sapiro, and S. Mallat, "Image modeling and enhancement via structured sparse model selection," in Image Processing (ICIP), 2010 17th IEEE International Conference on. IEEE, 2010, pp. 1641–1644.
6. Dong, X. Li, L. Zhang, and G. Shi, "Sparsity-based image denoising via dictionary learning and structural clustering," in Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on. IEEE, 2011, pp. 457–464.
7. D. Zoran and Y. Weiss, "From learning models of natural image patches to whole image restoration," in Computer Vision (ICCV), 2011 IEEE International Conference on. IEEE, 2011, pp. 479–486.
8. M. Elad and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries," IEEE Trans. Image Processing, vol. 15, no. 12, pp. 3736–3745, 2006.
9. J. Mairal, M. Elad, G. Sapiro et al., "Sparse representation for color image restoration," IEEE Transactions on Image Processing, vol. 17, no. 1, p. 53, 2008.
10. J. Mairal, F. Bach, J. Ponce, G. Sapiro, and A. Zisserman, "Non-local sparse models for image restoration," in Computer Vision, 2009 IEEE 12th International Conference on. IEEE, 2009, pp. 2272–2279.
11. K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-d transform-domain collaborative filtering," IEEE Trans. Image Processing, vol. 16, no. 8, pp. 2080–2095, 2007.
12. T. H. Cormen, "Introduction to algorithms.", The MIT press, 2001.
13. M. Elad, "Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing.", Springer Verlag, 2010.
14. D. Watson, "Contouring: a guide to the analysis and display of spatial data: with programs on diskette," 1992.
15. P. Chatterjee and P. Milanfar, "Clustering-based denoising with locally learned dictionaries," Image Processing, IEEE Transactions on, vol. 18, no. 7, pp. 1438–1451, 2009.
16. Mohmoud Nazzal and HuseyinOzkaramanli, "Variable Patch Size Representation over Learned Dictionaries" 2014 IEEE 22nd Signal Processing and Communications Applications Conference .VOL. XX, NO. Y, MONTH 2013.