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3D Medical Image Denoising using Efficient Interpatch and Intrapatch Correlation Technique

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***Abstract*— In bio-medical field, clear MRI or CT image is very important for analysis of the disease. To denoise the image many filtering methods are available but those produce their artifacts as adverse effect. To get the clear image we should be able to remove the noise from image we are proposing a interpatch and intrapatch correlation technique. In this technique we find the sparse solution of the given image then using SVD algorithm we update the predefined DCT dictionary. For finding sparse solution we used hard thresholding method and kept the threshold value equal to 0.9. Here we use interpatch correlation that is we find the similarity within same slice whereas we use intrapatch correlation we find similarity of the slice with surrounding slices. Then we combine these two methods to perform denoising of the image. In our paper we not only denoise the image corrupted from the Guassian noise but also Poisson noise and Rician noise which is difficult to remove from the MRI images. We also improved PSNR of the image as performance measurement parameter.**

***Index Terms*— Interpatch and interapatch technique, PSNR, Guassian noise, Poisson noise, Rician Noise, Hard threshold.**

I. INTRODUCTION

In the medical field MRI ,CT images plays important role. Due to some limitation such as capturing range of the instrument, time limitation to keep the patient in the magnetic radiation we can not get clear medical images. So to diagnose disease correctly it is important to denoise the image.

In the proposed system we used 3d medical image.3d image is nothing but the combination of series of parallel 2D slices. Using 3D model diagnosis and surgical simulation can be supported. We are using sparse presentation concept in our system. Sparse is nothing but the smallest presentation of the signal.[1]

The training data is represented by a matrix M_d .This matrix is represented by

$$M_d = \beta X \qquad (1)$$

Where β is predefined DCT dictionary and X is the sparse matrix. Sparse is efficient tool used for analysis of the signal. In the dictionary β each column represents one atom. We find sparse solution means we find the similar atoms in the dictionary and finally find the representative atom to represent the group of highly similar atoms.

In short we find the sparse solution. But just finding sparse solution with the fix dictionary β is not enough. We have to update the dictionary which we are doing with the help of SVD algorithm. The dictionary β is nothing but the set of $\beta=(\beta_1, \beta_2, \beta_3\ldots\ldots) \in V^{r \times c}$ .where c>r. Thus when the noise is present in the mage $M_d= V^{cxn}$ where n represents noise in the signal. If we use fix dictionary then it can give the sparse representation of the given signal clearly but it can not give efficient sparse solution.so we need to update the dictionary.

In this paper we first compare our proposed system with the three different denoising methods. Then we explained sparse solution algorithm first part of which consist of K-means clustering and second part of it is nothing but hard thresholding. After finding the sparsest solution we update the dictionary using singular vector decomposition method .In this, we decompose the residual signal. Then finally we use interpatch and intrapatch technique to combine the 2d patches. To denoise the image corrupted by different types of noises we use different equations. Finally we use probability function to denoise the image completely.

II. LITERATURE SURVEY

Many methods are used to denoise the image e.g. spatial filtering and transform domain filtering .In the spatial filtering the image get blurred and sharp edges may get destroyed.in case of transform domain the output depends on the cut-off frequency, also it is time consuming process, computational cost is more. The solution to this is use of sparse presentation. But the problem is about the updation of the dictionary for that greedy algorithms are available.

OMP is nothing but orthogonal matching pursuit. In the OMP[6] greedy rules are used. This algorithm works better for the dictionary where the atoms are not much similar. But in the highly similar environment this pursuit gives wrong solution.

TBP is nothing but tree based pursuit. In this algorithm tree type structure is followed. That is it start with root node of the tree and end to the leaf node. At this node the child is selected, child is nothing but atom having highest similarity with the training signal. In the TBP for each iteration one atom is chosen. So for number of atoms in the dictionary those many iterations has to be executed. So TBP [2] is quite similar to our proposed method but in case of TBP as the number of iterations are more so time for searching is more. In our proposed method we use selective searching therefore time required for execution is less.

BM3D is one of the latest method for denoising. In BM3D based on hard thresholding and wiener filtering. But our method gives more PSNR than BM3D[7] .

III SYSTEM OUTLINE

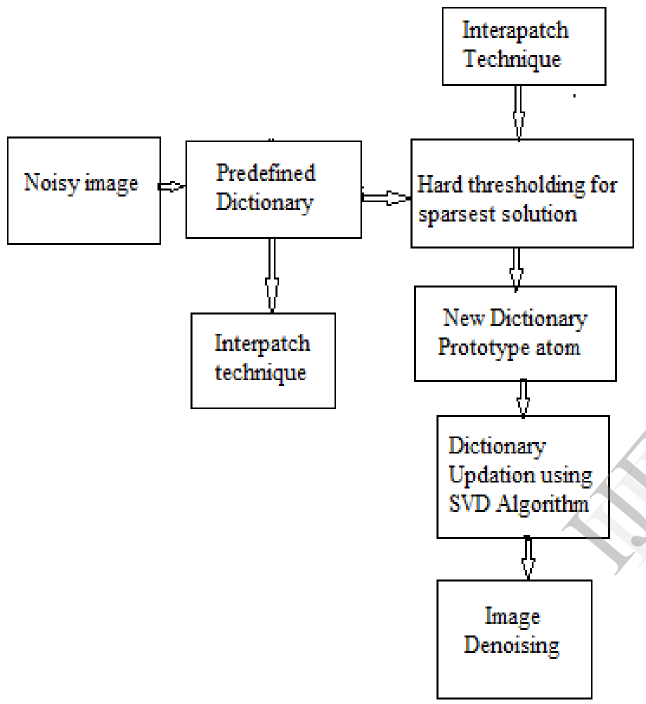

Fig. 1. Proposed System outline

Fig.1 shows block diagram our system. In the proposed system we first take noisy image which is corrupted by Guassian noise, Poisson Noise , Rician Noise. Then we take predefined dictionary and find the correlation of the atom in the same patch. This is our interpatch technique. Then we compare the same patch with surrounding patches and find the similarity between them. We choose those atom which possess highest similarity. This is nothing but intrapatch technique. After finding the sparse solution we update the dictionary using singular vector decomposition method. In SVD we decompose the residual matrix. Then using probability function we denoise the image. We denoise the image from Guassian niose, Poisson noise, Rician noise. We used PSNR parameter for measuring the denoising quality of the image. Also we calculate MSR (Mean to signal ratio) and CNR (contrast to noise ratio) as measure of the visual quality of the image.

IV IMPLEMENTATION DETAILS

4.1Sparse Presentation:

We divide our work of finding sparse solution into to parts [4]:

1) K means clustering algorithm
2) Hard thresholding Technique

4.1.1 K means clustering algorithm.

K-means clustering is a partitioning method. The function k means partitions data into k mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, k-means clustering operates on actual observations (rather than the larger set of dissimilarity measures), and creates a single level of clusters. The distinctions mean that k-means clustering is often more suitable than hierarchical clustering for large amounts of data.

Suppose we have predefined dictionary D. The dictionary D consist of N number of atoms i. e. N_1, N_2…., Nn. Then in K means clustering these atom are randomly get divided into K clusters with K* as representative atom of that cluster.

$$J^*(Ni)= \operatorname{argmax}|<K^*_j,N_i>|^2 \quad (2)$$

Then, we again compute new cluster W_j as follows

$$W_j=\{i:j^*(d_j)=j\} \quad (3)$$

Then we update the representative atom K^*_i to K^*_k by using dominant left singular vectors of the new clusters $N_{ui,\ldots..,NUj}$.

4.1.2 Hard thresholding Technique.

In the K-means clustering we divided the dictionary in sub dictionaries and calculated prototype atom. In the hard thresholding technique we calculate inner product of the i/p signal and representative atom. Then we compare it with threshold λ = 0.9.

$$F_s = \{ j:|P_f| > \lambda_s \} \quad (4)$$

Where P_f is the inner product. F_s is the cluster in which searching is done and λ is the hard threshold value which is having standard range from 0.4 to 0.9.In oor system we found good results with λ = 0.9.

If the inner product is greater than 0.9 then that particular cluster is selected for the searching of the i/p signal for best possible correlation. Then we update i/p signal which is nothing but the residual signal. We keep on repeating the same sequence until and unless we reach to stopping condition. For stopping condition we set error goal function. When the stopping condition reaches we get the final sparse solution.

Thus we can observe that due to selective searching our system takes less time to execute whereas in TBP the searching is not selective for every atom searching is done in each cluster. Thus the execution time is more in TBP

4.2 Dictionary updation using svd

$$\min_{\beta} \| M_d - \beta X \|_F^2 \quad (5)$$

To update the dictionary we have to solve the above mentioned problem] The above equation can be simplified as

$$\{u_h, r_h\} = \text{Avg} \min_{u_h, r_h} \|D_h - u_h r_h^T\|_F^2 \quad \text{subject to } \|u_h\|_2 = 1 \quad (6)$$

Here u_h is updated atom and r_h^T is coefficients in the rows of X, D_h is residual matrix. The problem is to solve the matrix D_h.To solve this problem we are using singular vector decomposition. In SVD we factorize the matrix into three matrices i.e. unitary matrix, diagonal matrix conjugate transpose of unitary matrix. Using SVD we solve the matrix D_h and update the dictionary.

4.3 Denoising of the medical image and finding PSNR.

Instead of denoising each a patch of the image we are denoising the patch using its correlation with surrounding patches and itself. We have introduced guassian , rician , poisson noise in our image with different noise levels. Then using above mentioned techniques we removed noise from the image and calculated PSNR using following formula.

$$PSNR = 20 \cdot \log_{10}(\text{Max } I) - 10 \log_{10}(MSE) \quad (7)$$

Where Max I is 255 as we are using black and white image & MSE is mean square error. We have used the parameter R which is nothing but the ratio of number of clusters(K) to the number of atoms(k) in the dictionary i.e. in short

$$R = K/k \quad (8)$$

Using this parameter we decided average recovery success rate. In our system we found best result for R=4.

V. RESULTS

5.1 output sequence of proposed system

In this section we have evaluated K-means clustering algorithm and hard thresholding. Then we updated the dictionary and calculated PSNR of the image.

We used brain image of size (264 x 241). We add the guassian noise with variance 0.01 and mean 0.Then we converted it to grey image though it is black and white still to remove hue and saturation present, if any, in the image. Then we apply our algorithms for finding sparse solution and to update dictionary.Finally we calculate PSNR to decide the quality of the denoised image. Fig. 2 to fig . 9 shows the sequence of the output of our system .

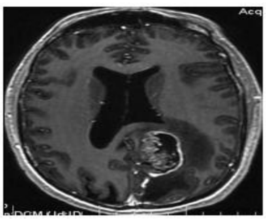

Fig. 2.Original Image R=3

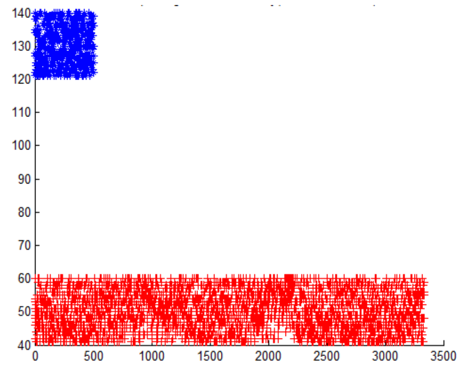

Fig. 3. Cluster plotting trained Dictionary

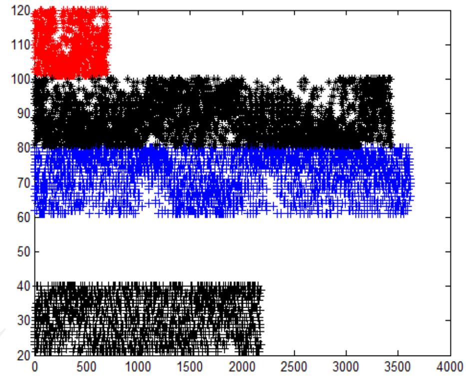

Fig. 4. Subdictionary before Updation

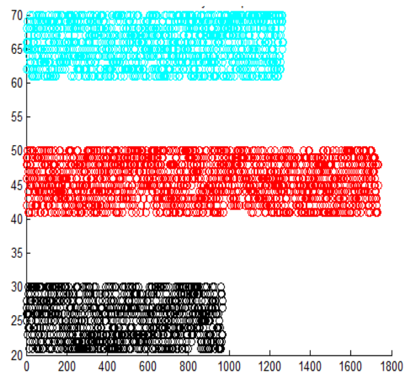

Fig. 5. Sub dictionary after updation

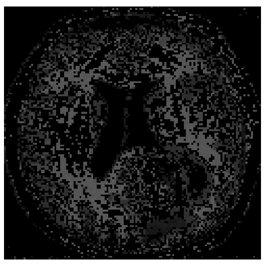

Fig. 6. Image retrieved from sub dictionary

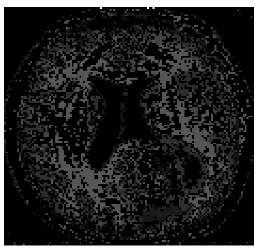

Fig. 7.Updated dictionary

Fig. 8.Noisy image, noise level=30,PSNR:20.6439dB

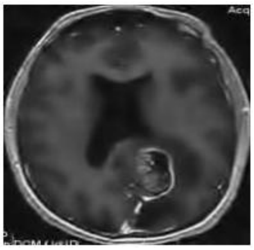

Fig. 9 Denoised image, PSNR:36.98dB

5.2 Observation Tables of PSNR and execution time for different value of R.

Table I
Results of the medical image (200x200) corrupted by Gaussian noise with different noise levels (for R =3)

Noise level	PSNR in dB	Execution Time in second
10	35.4	542.09
20	37.46	155.39
30	36.92	104.21
40	35.09	99.29
50	35.18	95.92
75	33.56	95.86
100	33.48	97.09

Table II
Results of the medical image (200x200) corrupted by Gaussian noise with different noise levels (for R =4)

Noise level	PSNR in dB	Execution Time in second
10	35.10	505.04
20	37.53	151.31
30	37.01	108.30
40	36.00	99.14
50	35.26	98.15
75	33.55	99.56
100	33.48	98.13

Table III
Results of the medical image (200x200) corrupted by Gaussian noise with different noise levels (for R =5)

Noise level	PSNR in dB	Execution Time in second
10	35.12	499.55
20	37.44	156.15
30	37.04	106.21
40	35.99	99.52
50	35.27	98.84
75	33.52	99.09
100	33.48	101.02

5.3 Observation Table of PSNR and execution time

Table IV
Results of the medical image (200x200) corrupted by Poisson noise with different noise levels

Noise level	PSNR in dB	Execution Time in second
10	40.47	166.08
20	38.10	121.73
30	36.79	100.501
40	35.96	98.09
50	35.21	96.34
75	33.57	95.39
100	33.53	96.84

5.4 Obesrvation Table of PSNR and execution time

Table V
Results of the medical image (200x200) corrupted by Rician noise with different noise levels

Noise level	PSNR in dB	Execution Time in second
10	40.05	175.53
20	37.90	106.95
30	36.63	97.50
40	35.80	94.44
50	35.03	94.07
75	33.54	94.70
100	33.50	92.97

VI. CONCLUSION

In our proposed method we have divided the image in sets of patches. Then we reconstruct image using the correlation of atoms in the same patch using k means clustering algorithm and correlation with nearby patches. We improve the execution time and accelerates image processing. Using optimization method we update the dictionary and then denoise the image.

From table I to table III we can conclude that our system gives good recovery rate for R=4. Also by observations of the table I to table V we come to conclusion that our system not only denoise the image which is corrupted from Guassian noise but also successfully denoise the image from Poisson noise and Rician noise.

Future scope of our proposed work is we can use it for other image processing application such as image deblurring , segmentation ,with some modification.

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