The Hybrid Framework for Image Reconstruction Using Matched Wavelet Estimation

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Abstract*- Constructing an Image reconstruction algorithm which includes an additive component –Reconstruction Error and has an inverse problem in compressive sensing makes the overall process a tedious work. In this paper, the proposed methodology gives a new hybrid approach to solve a former problem. The Newly constructed hybrid approach is the combination of four salient features. 1. Second Level Wavelet Decomposition is done prior to the image processing of a give image to get the sparse value of the samples in the beginning stage. 2. Image Denoising is done after the energy quantization to elevate the levels of samples latter the decomposition of wavelets. 3. Reconstruction error value is reduced drastically by taking the sub sample value using a simple matrix. 4. Shrinkage Image reconstruction is carried out to combine the entire tasks to build the image to with low Reconstruction error and high fidelity. In comparison with the existing methodology the newly proposed work gives excellent results in image reconstruction.*

Keywords- Matched wavelets; Compressed Sensing; Wavelet Decomposition; Shrinkage Image Reconstruction

I. INTRODUCTION

Image Reconstruction, as the core technology of the image processing where the process includes iterative algorithms to reconstruct the images using certain image techniques. At the same time, image reconstruction is an indispensable technology in information retrieval. This paper beholds the concepts with image reconstruction in compressed sensing applications. A Compressed sensing [3] is a technique which involves signal processing for gathering and reconstructing a signal to get solutions related to linear systems which is underdetermined. CS technique is based on the principle that with optimization the signal sparse value can be exploited into fewer samples than required by the traditional theorems. The two basic process [6] involves in the sparse value gathering are: 1.Sparsity, gathering the required value of signal to be in some required domain. 2. Incoherence, which can be applied to get the isometric property which is sufficient for the sparse signals. Restricted isometric property can be used as an analyzing tool to get the overall results of the compressive sensing work.

The Traditional approach for compressed sensing [11] the application involves hybrid of two processes which have to be done constitutively for the complete image reconstruction. The cogitative process would be sampling the analog data before getting digitizing the value with the Nyquist rate and the compression with the suitable transformation of coding process. The chaotic property for the sampling of analog data preferably involves with the value of Nyquist Rate [13] which will be gathered at the minimum rate of sampling the signal values without introducing errors which is the twice the highest rate of sampling the signal. Every Projection value which is been captured with the measurement basis in the image reconstruction involves only few sparse value which in turn produces better probability value for the source. For the better value of the sparse pointed image, matched wavelet are used to compress the decomposed value and doesn't need to produce a unique value for the wavelet decomposition.

For the better image reconstruction, Lifting Technique is used to build the sparse value either by using the existing wavelets or the newly constructed wavelets [14]. This lifting technique involves non linear filters than the linear filter for the image reconstruction. It widely involves split, predicate and update stage.

This paper is been structured as follows: In Section-II, a brief note regarding the related work with the compressive sensing applications and the evaluation of the filters for the image reconstruction process is been viewed. In Section-III, the proposed methodology of the hybrid framework with the matched wavelet estimation is been discussed. In Section-IV the experimental results for the existing and the proposed methodology is discussed. In Section –V the overall conclusion for the concept is finalized.

II. RELATED WORK

G. Quellec, M. Lamard, G. Cazuguel, B. Cochener, and C. Roux had jointly proposed the implementation of the design of filter banks [19] with a degrees of freedom, and reducing moments of the primal wavelet and of the dual wavelet moments in filter bank. The prediction and update filters, in the lifting technique as Neville filters. However, in order to introduce some degrees of freedom in the design, these filters are not defined as the simplest Neville filters. The proposed process of algorithm is used with dimensionality of Lattice rather than the dimensionality of degrees of spares value of the moments.

In 2000, J. O. Chapa and R. M. Rao, “The Algorithms for designing wavelets to match a specified signal,” [5] had proposed the algorithms to find a solution for the scaling function spectrum from the wavelet spectrum. Signal Representation for the applications involves adaptive coding and recognition of pattern requires wavelets that are similar to the signal. Depending on the wavelet design, Composite wavelet design from the previous wavelets will be used. Two sets of equations are developed that allows designing the wavelet directly.

In 2005, G. Piella, B. Pesquet-Popescu, and H. J. Heijmans, “Gradient-driven update lifting for adaptive wavelets,” [18] had proposed the construction of adaptive wavelets by means of an extension of the lifting scheme. Based on the local characteristics the input sample to the update stage is gathered. The process yields lower entropies than process with the fixed update filters which are highly adaptive for the compressed sensing applications.

In 2006, X. Zhang, W. Wang, T. Yoshikawa, and Y. Takei, “Design of iir orthogonal filter banks using lifting scheme,” [23] proposed the concept lifting scheme which is the efficient tool for constructing second level wavelet Decomposition. It includes the concept of how iir filter can be designed using lifting scheme. Proactively, the lifting framework concept includes filters following various techniques and concludes those filters can considerably reduce the reconstruction error of the image.

In 2008, Y.Liuand, K.N.Ngan had proposed a concept in “Weighted adaptive lifting-based wavelet transform for image coding,” [14] where new weighted adaptive lifting(WAL)-based wavelet transform is presented. The previous countermeasures for adaptive directional lifting (ADL) approach, such as mismatch between the predict and update steps, interpolation favoring only horizontal or vertical direction, and invariant interpolation filter coefficients for all images are derived. Widely working on adaptive lifting based wavelet transform the process derives two major contributions, one is the improved weighted lifting, which maintains the consistency between the predict and update steps as far as possible and preserves the perfect reconstruction at the same time; another is the directional adaptive interpolation, which improves the orientation property of the interpolated image and adapts to statistical property of each image. The Experimental Results shows the value of the process in the following derivatives, WAL-based wavelet transform for image coding outperforms the conventional lifting-based wavelet transform up to 3.06 dB in PSNR.

In 2009, J.Blackman and M. N. Do, “Two-dimensional geometric lifting,” [4] had proposed a Regularized iterative algorithms have emerged the standard approach which focus on the inverse problem with the images which is been emerging for the past decades. Results where amazing with the parameters as computational cost of the forward and adjoin operators and the difficulty of hyper parameter selection. The input derivative for the process is the normal operator used for the convolution operation with the forward modelies. The inverse problem is solved by using the CNN followed by the direct convolution which conjoined with the physical model of the system being used. The simple and the sophisticated task concerned with the image reconstruction is done with the usage of the matrix. The Result produced is well processed with the projections of two dimensional lifting process of the images.

In 2015, N. Ansari and A. Gupta [2] had proposed the concept of Signal-matched wavelet design via lifting using optimization techniques. Modulating to the framework involved, the predicate stage polynomials are obtained by least square creation and the update stage polynomials are obtained by the total variation minimization of the given signals. The efficacy of matched-wavelets is illustrated on transform coding gain and signal Denoising. The same couplet in 2016 [1] has came up with the suggestion as, The image reconstruction for the matched wavelet estimation can be built up with the partial canonical identity matrix For the better results, the standard wavelet measures which is been compared on the sparse basis will be used up with partial values of the matrix. The three major part of contribution involved here is, 1. Lifting mechanism used to aggregate the value for the sparse value process. 2. The simple partial canonical matrix which reduces the reconstruction time for the images used. 3. To improve the reconstruction performance the L-pyramid wavelet decomposition is followed. The Performance reconstructed value for the image with the Gaussian sensing matrix is improved drastically with the PCI matrix used for the CS based applications.

On conclusion with the related work, three salient features are taken into consideration, 1. With compressed sensing applications, large sample values from the Nyquist rate for the wavelets are not required, hence the sparse values are derived which in turn increase the construction parameter for the process to a greater extent. 2. With matched wavelets, sampling the entire image is not ad joint hence the sparse measurement values can be taken. 3. With Lifting technique, by using the predict and the update stage filters delivers the reconstruction error. By predicting the usage of these filters the results are not shown as expected. To solve this proposed methodology is correlated with the new series of steps in image reconstruction.

III. PROPOSED METHODOLOGY

A. Energy Quantization:

The proposed methodology for the image reconstruction starts by importing the features for minimizing the reconstruction error and also to derive the solution for the inverse problem. Considering the system under observation as S, which is affected by the noise n_0, original image as *I* and its derivatives as I0,I1,I2,I3..and so on. The process needs to find the following conservative to start the process.

$$I : I_0 = SI + n_0 \qquad 1$$

(a) (b)

Fig 1:An Revised image with values [0,256] to be quantized with Energy E a)Original Lena Image b)Image Lena with quantized Energy E=32 to be summed to original image.

The summation value of conservative of image is calculated to identify the decomposition level of the image. Any image processing process like the image construction, the image Segmentation, clustering, restoration, registration, classification and many others considered with the above problems are sparse imposed. i.e.; not all the posed conditions will be true: Solution may exist or not, Solution may be unique and cluster, Solution depends on the classification of data. To solve the inverse problem adding the quadratic regularity in terms of quadratic energy E of the problem can be wait well suited.

B. Double Decomposition of wavelet:

Before decomposing the given wavelet with the system under test with time t, the scanning mechanisms is needed to overview and identifies the pattern of samples. The identification can be either row wise or column wise or can be conducted on both [1]. Two mechanism used for scanning the pattern are: 1.Raster Scanning pattern: With Raster scanning pattern, the row samples or the column samples are stacked up one after the other for reviewing the samples on the both sides. Demerits lies when the discontinuity exists from scanning the pattern for one column ends and other column starts, this case lies similar to the rows also. 2. Serpentine Scanning Pattern: To overcome the discontinuity in the raster scanning pattern, scanning of all the rows and the column in reverse direction is done. Serpentine scanning pattern is effective to sudden agitations at the row and column findings and its better for the proposed methodology.

On experimental basis, the first level decomposition of images can be applied along rows and the columns, which contains the four elements as low pass and high pass filters for subdivisions termed as LL, LH, HL, HH respectively. If the procedure is repeated on the first sub component it's termed as regular pyramid wavelet decomposition. At the high cost of computational performance the regular pyramid decomposition is carried out. To avoid this demerit the low pass filter on row side and the high pass filter on the column side is applied gradually. In Second level of decomposition both sides the process is carried out. For Example the sub bands are further subdivided into L_2L_2, L_2H_2, H_2L_2, H_2H_2 respectively. The same pattern is carried out for the higher level of decompositions.

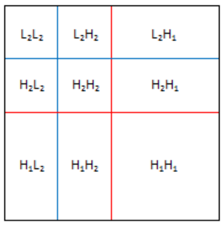


Fig 2: Second Level L-Pyramid Wavelet Decomposition

When the double decomposition in the second level is applied directly to the image, the sampling ratio acquired is not enough or it doesn't produce proper sampling values for the image reconstructions. It shows the lesser improvement at lower sampling ratios of 20% and 10%, to avoid it the energy quantization is increased to 90% to 30%. The lower bands used for the image reconstruction will be richer in the lower frequencies. While following the image reconstruction with double decomposition, results will be amicably sustainable for both lower and the higher frequencies resolution. The Algorithm defines the process below:

Algorithm 1: Second Level Wavelet Decomposition

Initialize $I= I_0$, $\Phi=n_0$

LL, LH, HL, HH=Level 1 subcomponent element

Repeat

$I^{k+1} = (1-EI_0n) + r(con\Phi^{k+1} + \alpha I_0)$

Out image= partial construction (image (I^{k+1})

Until convergence

End of Algorithm

The Experimental double decomposition and the efficacy of Lena image is shown as below:

(a) (b)

Fig 3: (a) Second level decomposition of the image Lena with in image. (b) Decomposed image with the out space after quantization of required energy.

Table 1: 2nd level Decomposition's SNR values with Energy.

Sr.no	Sample images	Energy E	SNR Values
1	Lena	52	25.574
2	Beads	55	23.531
3	Peppers	59	23.728
4	Balloons	63	23.090
5	Flower Set 1	67	22.803
6	Peppers2	69	26.174
7	Mandrill	70	28.659

C. Noise Acidity in Image Reconstruction:

Traditionally every sensed signal that is used for the compressive sensing follows both the activities of compression and sensing separately. While carrying the process, the signal at least has quantized noise owing to the infinite precision of the sensing wavelet. The non-local algorithms uses soothing filters to evaluate the original image from the samples punched and blowed up with the image used for the reconstruction. With the predefined filters the proposed process is summed as follows. The Maximum and Minimum convolution is been identified samples for the images used for the rotation. This particular methodology exploit the scenario that curves moving under their image curvature will be smooth out and the value gets disappear after the rotation.

The method of noises can also be additive to the interpretation depends of the suitable choices of the wavelet basis quantized with the energy in earlier stage. The image method noise of the convolution with a Gaussian kernel G_h is

$$u - G_h * u = -h^2 \Delta u + o(h^2), \qquad 2$$

for h small enough.

The values can be either viewed in topographic map, intensity (with black and white pixel values) with the height from the surface of the image. The motion of the curvatures will undergo replication of the sharpness of the image. The small values of the contours and their corresponding noise will disappear from their image quickly. To remain the sharpness, it's better to stay the values on their boundaries.

Algorithm 2: Image Denoising

Initialize θ= motion of curvature

Min and max value: F = min(K,0)&& F=max(K,0)

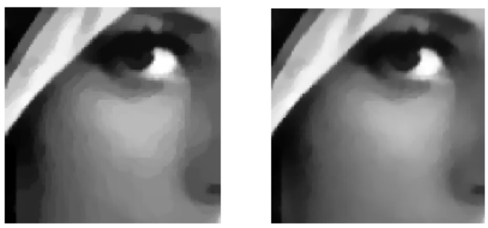
Rotation: $Y_{\theta=}$ (x*cosθ) +(y*sinθ)

X_θ=(x*sinθ)+(y*cosθ)

Respective values passed to predefined filters

End of Algorithm

While processing the substantial image Denoising produce the following results:



(a) (b)

Fig 4: (a) Normal Image Denoising Output with Lena Image.(b) Image Denoising With Motion Curvature With Lena Image.

The Noised image processed to Image Denoising and further enhanced to retain and maintain the new values of the sampled images used for the image processing. The Spectral feature selection values preserve both the local and global structured feature with the samples. With the predefined values the blowup images are shown as follows.

Fig 5: Blowed up Image shots of the Lena image After Image Denoising with Predefined Filters.

4. Construction of Partial Canonical Identity Matrix (PCI):

With the increase in demand of digital images, the cost of computation and the calibration to get the original image owing to the image reconstruction requires high process requirements. Earlier stage of computation, Single pixel cameras where used to avoid capturing the entire source rather to capture the needed as one pixel at a time which in turn produce the linear combination of values. This would relatively has problems like high computational for a large size of image, A/D quantization and coupling effects with the photons sensed.

Gaussian and Bernoulli sensing matrices are implemented lately with several new methodologies to capture the sample values. When the reconstruction of the image is processed the entire sample values are taken from the above matrices with in turn increase the computational performance parameters. Now to simply the above, Partial Canonical Identity Matrix [1] is been used. With this the reconstruction of the image requires only the position of the sampled images rather than the information of all entries in matrix.

The PCI Matrix is constructed by sensing the image at sub-Nyquist rate by capturing less number of pixels without being sensed with entire information of the images. Considering the image I with dimension MxN, Instead of capturing the entire sampling details as the product of the values (MN), the fewer M samples of the required point of the image value is been taken. The Partial value of the matrix is been narrated as 1 for the sample values which is been captured and 0 for the value which is not been. It's been denoted as Φp.

Algorithm 3: Construction of PCI Matrix

Initialize $I_0=M_s$

$\Phi_p=$ 1 € (minimum sampled values, i.e; 0,1,2,….M_s),
0 , Unspecified sampled values.

Repeat

$I^{k+1} \rightarrow I^k(I_x)+ r_1 con\Psi^{k+1}(I_x)\ ,I_0(I_x)$

$\Phi_p=I^{k+1}$

Until convergence of M_s

End of Algorithm

On experimental basis, the sub-sampled Lena image [0,256] is been taken. The below image is been sampled 50% by using the PCI matrix. The remaining un-captured positions in the images are being filled with zero. When the necessary image reconstruction methodology is been used, its concluded that the image with partially sampled (50%) is more than required for constructing the whole image with high feasibility. The results of the PCI matrix with other measurement matrices conclude that the image reconstruction is more durable with the partial values sampled.

Fig 6: Lena image captured with PCI Matrix with 50% sampling ratio and the zero is been used to the place where the samples is not been captured.

5. CS-Shrinkage Image Reconstruction:

Compressive sensing paradigm [18] largely asserts the fact that certain signals can be recovered from the fewer samples than the all samples that is been required in the Nyquist paradigm. It largely follows the sub-Nyquist paradigm for capturing the signals efficiently. The number of samples required for the recovery adjacently depends upon the reconstruction algorithm applied for the process. Compressive Sensing process can handle the Noises and reconstruction error associated with the process effectively. Three main properties has to be maintained in Compressive Sensing Paradigm [4]: 1. Sparsity: While compressing the original signal it stores the value in the projection basis and when it's been chosen, many coefficients value will be ignored as the values are small enough. For the non coefficient values it will be sparse. 2. Incoherence: Normally Coherence measures the highest correlated value between any two value across two different matrices. Since the CS based paradigm value follows the sparse construction, it's more likely to be concerned with the low coherence value which is required for the reconstruction process. Overall performance of the algorithm used for the recovery process can be analyzed by widely used tool, Restricted Isometric Property (RIP).

The Compressive Sensing based image reconstruction process follows three salient steps to complete the image reconstruction. Step 1: The evolution of the wavelet sparsely to attain the partially value of the sub samples with the images. Step 2: Attained samples are being divided into the odd samples and the even samples by using the Predict and the update stage filters following backward and forward interpolation assigned respective to steps. Step 3: On the gained values from the above two steps use the reconstruction algorithm to gain back the image.

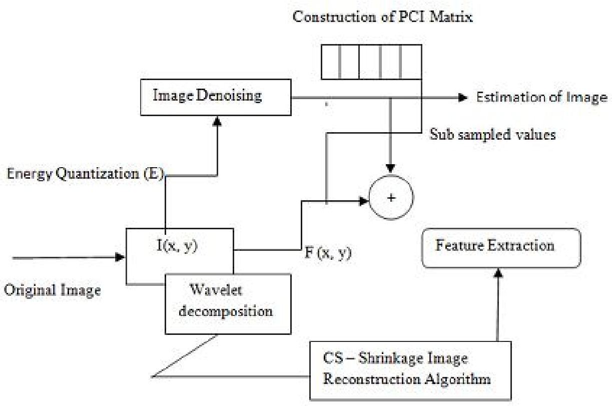


Fig 7: System Architecture

The Compressive Sensing has seen major applications in diverse fields used in images captured in camera, medical imaging, seismic imaging in biological applications, capturing image values with RADAR. It's widely used in Sparse Channel Estimation, Analog AD/DC Signal Converters, Capturing vivid information in the spectrum sensing of the analog information, ultra band wide systems. In a greater scene, Compressive sensing eliminates the need to acquire and large number of sampled data only to most of them because of their minimal sparse value. Identifying the need of the reconstruction algorithm will be widely used with the tomography applications. Tomography application with the predict filter and the update filter stage design enhance the content of the sampled ratio. The Signal acquisition and the Reconstruction model for the process differ according the requirement design. Shrinkage Image Reconstruction algorithm discussed below includes variation of both higher and lower frequencies of images and values are trained.

Algorithm 4: CS –Shrinkage Image Reconstruction

Initialize $I=I_o$, M_s=Mat, $\Phi_p=\theta$

$\Phi_p= I^k$
P_s = (Forward(x, y)) odd samples
U_s= (Backward(x, y)) even samples
Repeat

Calculate the gradient values
$I_{k+1} \rightarrow$ Con (Forward(x, y)) +Con (Backward(x, y))
$\Phi_{k+1} \rightarrow \max(|\beta, \Phi^{-k+1}|)$

Until Convergence (max of iterations)

End of Algorithm

As per with the new proposed algorithm derivation, the Original Lena image is subjected to the entire subjected process and the outcome progressively observed as follows.

(a) (b) (c)

Fig 8: CS-based Shrinkage Image Reconstruction. (a) Original Lena Image of dimension [0,256] (b) Noised image (c) Reconstructed Image.

IV. EXPERIMENTAL RESULTS

This Section is wholesomely divided into discussing the Performance Measures to evaluate the efficacy, brief about the reconstruction error obtained, and the experimental results obtained from the execution. The Performance Measure [13] on overall gives the substantial view of the behavior, activities and the improvement path for the deliverables.

A. Peak Signal-To-Noise Ratio (PSNR):

The Peak Signal-to-Noise ratio [1] is the expression for the ratio between the highest value of the image and the distorted noise that affects the quality of the reconstructed image. Since the values in the entire process carries the dynamic range, PSNR usually expressed in logarithmic decibel scale. Sometimes it's referred as the ratio between the largest and the smallest value that quite changing through the entire process. The PSNR value is expressed as follows,

$$\text{PSNR} = 10\log_{10}\left(\frac{(\max(I))^2}{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}|I(i,j)-I'(i,j)|^2}\right) \quad 3$$

Where **I** is the original image, I' is the reconstructed image, max is the operator for finding the highest value and m, n is the dimension of the image. The operation max gives the highest intensity value of the image.

B. Feature Extraction Using GLCM:

The feature extractions are computed from the observed combinations of intensity values at various positions which are relatively submitted in the statistical distribution [15]. Now, according to the highest value gathered from the combinations the statistical values are classified as first, second and higher order combinations of values. The GLCM feature extraction in this paper contains both first and second order features. The Extracted features are discussed below.

1. Inverse Difference Moment or Homogeneity:

IDM represents the local homogeneity given with high intensity of the pixels.

$$\text{IDM}= \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}Pij}{1+(i-j)^2} \quad 4$$

2. Correlation:

Correlation measure the dependency of the neighborhood pixels in the linear ad joint values.

$$\text{Correlation}= \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j)P(i,j)-\mu x\mu y}{\sigma x\sigma y} \quad 5$$

3. Angular Second Moment or Energy:

Angular Second Moment is also been called as Energy. It's the sum of the squares of the entries in the GLCM which is been derived by in build function glcmcomatrix.

$$\text{ASM}= \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}P{i^2}j \quad 6$$

4. Entropy:

In Compressive Sensing, there is a need for the amount of information need to be image compression, for this purpose entropy is been used. It identically measures the amount of information being transmitted.

$$\text{Entropy}= \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}-Pij * \log Pij \quad 7$$

C. Reconstruction Error (RE):

Any reconstructed image after the processing of image will undergoes changes according the techniques applied. It's fatal that the reconstructed image undergoes error which is to be identified. The actual image is compared with the reconstructed image and the square of the difference is been taken to calculate the original error.

$$\text{RE}= \sqrt{\frac{\sum_x\sum_y\left(I(x,y)-I'(x,y)\right)^2}{M\,X\,N}} \quad 8$$

D. Experimental Setups:

This experimentation uses windows 8 (64 bit) operating system and Intel (i5) processor with 4GB RAM. MatLab R2014b is used for implementation. The proposed methodology works on various image dataset.

E. Datasets:

UCI-Medical Image Datasets, MSRC, Caltech datasets are considered to evaluate the entire process. The datasets contains images of the format JPG, PNG, TIFF. MSRC dataset contains 591 images of 20 different categories. Corel dataset has 5000 images of 50 categories. Each category contains different number of images.UCI medical Image datasets contains 30608 images of 293 different categories. The below figures show the images from the dataset being used.

Fig 9: Sample Sets of images from MSRC Datasets

Various images with different spectral content starting from higher frequencies to the lower frequencies are being tested. Images such as Balloons, Peppers, Mandrill are good in lower frequencies values and Beads, Balloons are good in higher frequencies and rest of the images are varied with lower and higher frequencies.

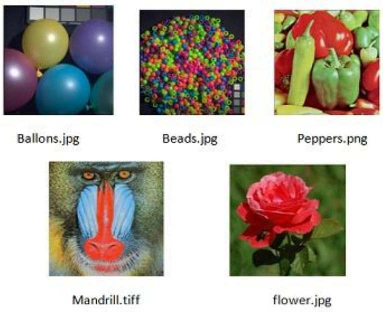


Fig 10: Sample set of images from Caltech dataset

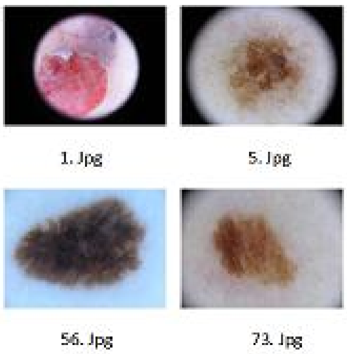
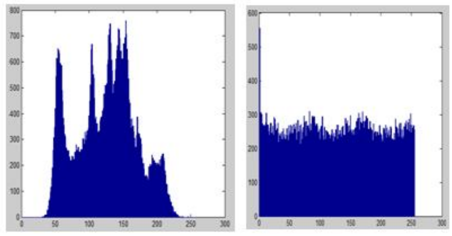


Fig 11: Sample Sets of image from UCI-Medical image Dataset

F. Results:

Different samples and different sampling ratios are treated separately with the entire proposed methodology and the sub samples are treated accordingly to identify the best values of the performance measures. The below histogram represents the featurism of the Image 'Beads' with original values and the newly reconstructed values after following the shrinkage algorithm. In Proposed Methodology, the performance Measures will be high for lower frequencies images and high for the lower frequencies images.



(a) (b)

Fig 12: Histograms for (a) Original Beads Image (b) Reconstructed image.

Comparative Analysis is done with the proposed method and the top three methods for the wavelet estimation are shown below. Double Decomposition with sub sampled PCI Matrix and the Shrinkage Image Reconstruction algorithm are used to generate the following values for the different set of images at the sampling rate of 100.

Sr.no	Image	Db$_4$	Bior 5/3	Matched	proposed
1	Beads	39.23	37.87	49.02	34.19
2	Balloons	53.00	51.38	54.41	37.63
3	Peppers	39.61	37.68	40.02	47.99
4	Mandrill	32.71	31.67	33.63	45.19
Average PSNR		39.33	37.24	38.25	41.25

Table 2: Reconstruction Efficacy Based on Shrinkage Image Reconstruction Algorithm.

V. CONCLUSION

In this paper, the proposed hybrid framework is efficiently designed for compressive a sensing application which has the real time oriented application facilities in larger sense. The Double Decomposition which is been carried out before processing the image has considerable SNR values after applying the energy quantization. The proposed shrinkage image reconstruction algorithm reduces the reconstruction value for the images which can be effectively bounded to many applications at a dynamic rate. On whole, the proposed methodology produces effective results when compared to the existing methodology.

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