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Literature Review of Wavelet-Based Model for Image Denoising

Vineeta Goswami[1], Prof. Nagendra Patel[2]

M-Tech Research Scholar[1], Research Guide[2]

Department of Computer Science Engineering, Rewa Institute of Technology

Abstract: A signal is the function of one or several variables that carries useful information. A signal is said to be biological if it is recorded from a living system and conveys information about the state or behaviour of that system. For example, the temperature record of a patient, the voltage record by an electrode placed on the scalp, and the spatial pattern of X-ray absorption obtained from a CT scan are biological signals. In a brief about the basic nature, characteristics, origin and recording of the biomedical signals like ECG, EEG and the EMG is given. This also gives a detailed description of wavelet transform with mathematical representation. Signals are Omni-present in the real world. Signals are the vehicle for delivering information such as sound and images. Signals represent a value or amplitude that varies depending on its location within a particular domain. Some signals occur in the time domain; that is the amplitude of the signal varies with time. Other signals occur in the spatial domain; that is the amplitude of the signal varies depending on its spatial location. An audio signal is an example of a time-domain signal having amplitude that varies with time. A digital image is an example of a spatial-domain signal having an amplitude, or intensity that varies depending on the spatial location within the image.

Keywords: Birothogonal wavelet, heavy noise, nonlocal similarity, split Bregman, total variation (TV).

I. INTRODUCTION

The digital multimedia revolution is upon us. The exchange of information is rapidly moving away from the traditional analog realm and into the digital arena fostered by the increasing availability of the internet in homes and at work. The speed and ease of which digital media is transferred and manipulated makes it an attractive alternative to conventional analog media such as audio and video. An example of digital media that has received a lot of attention in recent years is digital images. Digital image processing techniques can be used to compress, reduce noise, or even understand information present in digital images making this format even more desirable.

The Discrete Wavelet Transform (DWT) is a signal processing technique that is beginning to show promise in the field of digital image processing. The new JPEG2000 and MPEG4 still image and video compression standards are based upon the DWT and are shown to produce superior results over their previous incarnations that do not use the DWT. The DWT has potential for many other applications to digital images other than compression such as noise reduction. A hardware DWT core could be integrated into digital camera or scanners to perform image processing inside the device such as image compression to increase the amount of images that can be stored internally. Despite the benefits a hardware DWT core could provide to these applications there are very few hardware implementations of the DWT commercially available

Origin of Biomedical Signals

Human body is made up of a number of systems e.g- respiratory, cardiovascular, nervous system, etc. Each of these systems is made up of several subsystems that carry on many physiological processes. Each physiological process is associated with certain types of signals referred as Biomedical signals that reflect their nature and activities. Different types of biomedical signals are:

- Biochemical signals e.g. hormones, neurotransmitters
- Bioelectrical signals e.g. potentials, currents
- Biomechanical signals e.g. pressure, temperature

Bioelectric signals are specific types of biomedical signals which are obtained by electrodes that record the variations in electrical potential generated by physiological processes. Examples of bioelectric signals are:

- Electrocardiogram (ECG)
- Electroencephalogram (EEG)
- Electromyogram (EMG)
- Electrooculogram (EOG) among others.

Commonly Used Biomedical Signals

The signals which are commonly used are:

The electromyogram (EMG): It is the electrical activity of the muscle cells.

- The electrocardiogram (ECG): It is the electrical activity of the heart /cardiac cells.

- The electroencephalogram (EEG): It is the electrical activity of the brain
- The electrogastogram (EGG): It is the electrical activity of the stomach
- The phonocardiogram (PCG): It is the audio recording of the heart's mechanical activity.
- The carotid pulse (CP): It is the pressure of the carotid artery.
- The electoretinogram (ERG): It is the electrical activity of the retinal cells
- The electrooculogram (EOG): It is the electrical activity of the eye muscles.

The bio-signals of electric origin are made up from integration of many action potentials. The action potential itself is the electric potential which is generated by a single cell when it is mechanically, electrically or chemically stimulated.

Fourier Transform

In 1882 the French mathematician J. Fourier showed that any periodic function can be decomposed into an infinite sum of periodic complex exponential functions, or sinusoids. After many years Fourier's ideas were generalized to non-periodic functions and finally to periodic or non-periodic discrete time signals resulting in the Fourier Transform (FT). The FT converts a time-domain signal into the frequency domain thus providing information as to which frequency components are present in a signal. The FT provides perfect resolution in the frequency domain; in other words the exact frequencies present in the signal are determined. The FT also provides perfect time resolution in the time domain as the value of the signal at every instant of time is known. The shortcomings of the FT are that while the frequencies present in a signal can be determined with perfect resolution, there is zero resolution in the time domain as the time location of these frequencies are unknown. Hence the FT is sufficient for stationary signals where frequency does not vary with time, but for non-stationary signals whose frequency does vary with time, simply knowing which frequency components exists may not be sufficient. A possible solution to finding both the frequency component and where it occurs in time is the Short Term Fourier Transform.

Biorthogonal Wavelets

A transform is described as being orthonormal if both its forward and inverse transforms are identical, therefore an orthonormal wavelet is one that is used in both analysis and synthesis of a signal. A filter having linear phase is one whose impulse response is either symmetric or anti symmetric. Linear phase is important for a variety of reasons in applications where the signal is of finite duration, such as image compression. As mentioned earlier, two-channel subband transforms are used to perform the DWT on a signal. Unfortunately, there are no two-channel linear-phase subband filters with finite support that are also orthonormal. The solution is to use two symmetric wavelets for analysis and synthesis that are orthogonal to each other, or biorthogonal. These biorthogonal wavelets exhibit linear phase and therefore are now useful. A family of biorthogonal wavelets that has proved useful in applications such as image compression is the Cohen-Daubechies-Feauveau (CDF) wavelet family. The CDF 5/3 and CDF 9/7 are two specific wavelets that will be used as continuing examples throughout this study as they provide an interesting comparison.

Heavy Noise

Any unwanted signal that interferes with the communication or measurement of an information carrying signal is termed as heavy noise. Heavy noise is present in various form or percentage in almost all environments. For example, in a digital cellular mobile telephone system, there may be several varieties of noise that could degrade the quality of communication, such as acoustic background noise, electromagnetic radio-frequency noise, co-channel radio interference, radio-channel distortion, outage and signal processing noise. Noise can cause various transmission errors and may even disrupt a communication process and hence noise processing is an important and integral part of modern signal processing systems. On the basis of the range of frequency present, noise can be broadly categorised into Broadband Noise and Narrowband Noise:

Classification Of Noise

- *Broadband Noise*

Broadband noise is caused by turbulence and is random in nature. Turbulent noise distributes its energy evenly across the frequency bands. The examples are the low frequency sounds of jet planes and the impulse noise

- *Narrowband Noise*

In narrowband noise most of its energy is concentrated at specific frequencies. This type of noise is related to rotating or repetitive machines, so it is periodic or nearly periodic in nature. Examples of narrowband noise include the noise of internal combustion engines in transportation, compressors as auxiliary power sources and in refrigerators, and vacuum pumps used to transfer bulk materials in many industries. The transformer noise which is the hum noise due to the magneto-strict ion consists of higher harmonics of the power-line frequency. In another way the noise can be classified into two types: linear noise and nonlinear noise. The broadband noise is mostly linear. But there are situations where noise coming from a dynamic system may be nonlinear and deterministic. Such nonlinear but deterministic noise is referred to as chaotic noise. Some examples of chaotic noise are Logistic chaotic noise, Lorenz chaotic noise and doffing chaotic noise. One practical example of chaotic noise is the fan noise which often shows chaotic behaviour.

Noise Control Techniques

- Passive Noise Control

Passive noise control techniques employ sound absorbing material, enclosures, barriers and silencers to attenuate the undesired noise. These passive techniques are effective for high attenuation over a broad frequency range; but are unable to absorb low frequency noise. For low frequency noise the passive techniques become relatively larger and heavier thus considerably increasing the cost. This often makes the passive approach to reduce low frequency noise very impractical. But the fact is people are more uncomfortable with low frequency noise rather than high frequency noise because low frequency noise is not only annoying but produces fatigue, irritation and loss of concentration, therefore affecting productivity. If low frequency noise is mixed with speech, it reduces speech intelligibility In a noise generating system the amplitude of the low frequency noise is mostly higher than other frequencies. Hence there is a growing demand for reducing low frequency noise.

- Active Noise Control

The design of an active noise controller using a microphone and an electronically driven loudspeaker to generate a cancelling sound was first proposed and patented using a purely analog electronic approach in 1930 in France by Coanda and in US by Lueg in 1936 The patent outlined the basic idea of ANC, , but at that time it could not be applied to practice because of a number of factors. Advanced and accurate electronic instruments (microphone, loudspeakers, digital personal computers) were not available, digital signal processing and the concept of adaptive systems were not started then and there was no proper knowledge on noise and various sources of noise. During the latter half of the 20th century, emergence of digital signal processing made ANC a viable technique for practical noise reduction. Latter on advances in adaptive systems and adaptive signal processing which facilitate a time varying system with the ability to adapt to changing environment, not only revolutionized ANC but also further opened up its field of applications. Development of high speed special purpose digital signal processors helped realize practical ANC. More recently fusion of the soft computing approaches like artificial neural network, fuzzy logic and hybrid techniques (neuro-fuzzy techniques) with existing ANC techniques have made ANC powerful than ever before. ANC is currently being researched for use to control noise from jet engines, helicopter, motor vehicle engines, ventilation systems, generators, transformers, industrial machinery, traffic, MRI units, torpedoes, headphones and even amplified music.

Nonlocal Similarity

Nonlocal Similarity Image Filtering In the next subsection review the method proposed by Buades et al., then SIFT, and then propose our approach to image denoising and super-resolution

The key idea of the nonlocal means filter is that a given noisy image

f : Ω ⊂ R 2 7→ R is filtered by

$$u(\mathbf{x}) = \int w_f(\mathbf{x},\mathbf{y}) f(\mathbf{y}) d\mathbf{y}\,, \qquad (1)$$

where u : Ω 7→ R is the denoised image and wf : Ω ×Ω 7→ R + is a normalized weight function written as

$$w_f(\mathbf{x},\mathbf{y}) \doteq \frac{e^{-\frac{d_f^2(\mathbf{x},\mathbf{y})}{h^2}}}{\int e^{-\frac{d_f^2(\mathbf{x},\mathbf{y})}{h^2}} d\mathbf{y}}\,, \quad \text{for} \quad d_f^2(\mathbf{x},\mathbf{y}) \doteq \|f_{\mathbf{x}} - f_{\mathbf{y}}\|^2_{G_\sigma} \qquad (2)$$

is the L2-norm of the difference of fx (i.e., f centered in x) and fy (i.e., f centered in y), weighted against a Gaussian window Gσ with standard deviation σ. The map df (x, y) measures how similar two patches of f centered in x and y are. If two patches are similar, then the corresponding weight wf (x, y) will be high. Vice versa, if the patches are dissimilar, the weight wf (x, y) will be small (but positive). While the parameter σ defines the dimension of the patch where study the similarity of two patches, the parameter h regulates how strict or relaxed in considering patches similar. The final of the nonlocal means filter is that several (similar) patches are used to reconstruct another one. Notice that the similarity of patches in df is defined up to translation. In other words, can only match patches that are simply in different locations, but otherwise unchanged – with the same orientation and scale. This motivates us to consider the larger class of similarity measures that discounts scale and rotation changes, i.e., a similarity-invariant measure. In theory, defining this measure is just a matter of introducing two more integrals in df and an inverse similarity-transformation in eq. (1) to align the patches being averaged. In practice, however, because this similarity has to be computed multiple times for each patch, this introduces considerable computational burden that makes the ensuing algorithm all but impractical. One way to address this problem is to find a function that estimates a rotation and a scale at each patch with respect to a common reference system, so that each patch can be transformed into a "canonical" patch. Once this is done, one can apply the original nonlocal means filter.

Split Bregman

The "Split Bregman" framework for solving optimization problems. By applying the method to image denoising and compressed sensing problems, this method is a very efficient solver for many problems that are difficult to solve by other means. Besides its speed, this algorithm has several advantages: Because the Split Bregman algorithm makes extensive use of Gauss-Seidel and Fourier transform methods, it is easily parallelizable. Also, it has a relatively small memory footprint compared to second order methods that require explicit representations of the Hessian matrix. Both of these characteristics make Split Bregman a practical algorithm for large scale problems. Finally, the method is easy to code.

Total Variation

Rudin et al. proposed Total variation (TV). It is a constrained optimization type of numerical algorithm for denoising the noisy images. The total variation of the image is minimized subject to constraints involving the statistics of the affected noise. The constraints are imposed using Lagrange multipliers. Here are using the gradientprojection method. This amounts to solving a time dependent partial differential equation on a manifold determined by the constraints. As the solution converges to a steady state which is the denoised image.

In total variation algorithm, the gradients of noisy image, g(x,y) in four directions (East, West, North and South) are calculated. The gradients in all four directions are calculated as follows.

$$\nabla_N g(x,y) = g(x-1,y) - g(x,y)$$

$$\nabla_S g(x,y) = g(x-1,y) - g(x,y)$$

$$\nabla_W g(x,y) = g(x-1,y) - g(x,y)$$

$$\nabla_E g(x,y) = g(x-1,y) - g(x,y)$$

Where is the gradient operator. The noisy image undergoes several iterations to suppress AWGN through TV filter. The resulted output image after (n+1) iterations is expressed as:

$$\begin{aligned}
&\tilde{g}^{n+1}(x,y) \\
&= \tilde{g}^{n}(x,y) \\
&+ \frac{\Delta t}{h}\left[\nabla_N\left(\frac{\nabla_S \tilde{g}^n(x,y)}{\sqrt{\nabla_S \tilde{g}^n(x,y) + \left(m\left(\nabla_E \tilde{g}^n(x,y), \nabla_W \tilde{g}^n(x,y)\right)\right)^2}}\right)\right. \\
&\left. + \nabla_W\left(\frac{\nabla_E \tilde{g}^n(x,y)}{\sqrt{\nabla_E \tilde{g}^n(x,y) + \left(m\left(\nabla_S \tilde{g}^n(x,y), \nabla_N \tilde{g}^n(x,y)\right)\right)^2}}\right)\right] \\
&- \Delta t \lambda^n \left(\tilde{g}^n(x,y) - g(x,y)\right)
\end{aligned}$$

Where,

$$m(a,b) = \min mod\,(a,b)$$

$$= \left[\frac{sgn\ a + sgn\ b}{2}\right] \min(|a|,|b|)$$

Where

sgn x is 1 for x ≥ 0 and it is o x<0.

And λ is a controlling parameter, is the discrete time-step and is a constant.

$$\frac{\Delta t}{h^2} \leq c \qquad \text{here c is constant.}$$

A restriction, imposed for stability, is given by: here c is constant.

The filtered image is then .

$$\hat{f}(x,y) = \tilde{g}^{n+1}(x,y)\ .$$

Wavelet Applications

- Typical Application Fields
  - Astronomy, acoustics, nuclear engineering, sub-band coding, signal and image processing, neurophysiology, music, magnetic resonance imaging, speech discrimination, optics, fractals, turbulence, earthquake-prediction, radar, human vision, and pure mathematics applications
- Sample Applications
  - Identifying pure frequencies
  - De-noising signals
  - Detecting discontinuities and breakdown points
  - Detecting self-similarity
  - Compressing images

II. LITERATURE SURVEY

Table 1: Summary of Literature Review

SR. NO.	TITLE	AUTHORS	YEAR	APPROACH
1	"Wavelet-Based Total Variation and Nonlocal Similarity Model for Image Denoising"	Yan Shen, Qing Liu, Shuqin Lou, and Ya-Li Hou	2017	The combination of total variation (TV) and nonlocal similarity in the wavelet domain have been prposed.
2	"Soft, Hard and Block Thresholding Techniques for Denoising of Mammogram Images"	Manas Saha, Mrinal Kanti Naskar and B. N. Chatterji	2015	The "embedded" thresholding algorithm
3	"Wavelet transform-based methods for removal of ground clutter and denoising the radar wind profiler data"	ShaikAllabakash, Polisetti Yasodha, Sakirevupalli Venkatramana Reddy, Parvatala Srinivasulu	2015	Validated with collocated global positioning system radiosonde data
4.	"A wavelet-based denoising method for color image of mobile phone,"	Xuehui Wu, X. Lu, Xue Han and Chunxue Liu,	2015	Image denoising method based on bivariate shrinkage function
5.	"Wavelet based image denoising using weighted highpass filtering coefficients and adaptive wiener filter,"	R. Saluja and A. Boyat	2015	Denoised the noisy image by adding weighted highpass filtering coefficients in wavelet domain
6	"Local Sparse Structure Denoising for Low-Light-Level Image,"	J. Han, J. Yue, Y. Zhang and L. Bai,	2015	Sparse and redundant representations
7	"K-means clustering for adaptive wavelet based image denoising,"	U. Agrawal, U. S. Tiwary, S. K. Roy and D. S. Prashanth	2015	Denoising of images corrupted with variable Gaussian noise spread across the images (dataset)
8	" Patch Ordering as a Regularization for Inverse Problems in Image Processing"	Gregory Vaksman, Michael Zibulevsky, and Michael Elad	2016	The multilevel two dimensional wavelet transform and multilevel soft threshold

Yan Shen, Qing Liu, [1] presented to suppress the heavy noise and keep the distinct edges of the images in the low light condition, authors propose a denoising model based on the combination of total variation (TV) and nonlocal similarity in the wavelet domain. The TV regularization in the wavelet domain effectively suppresses the heavy noise with the biorthogonal wavelet function; the nonlocal similarity regularization improves the fine image details. Denoising experiments on artificially degraded and low light images show that in the heavy noise condition, the proposed denoising model can suppress the heavy noise effectively and preserve the detail of images than several state-of-the-art methods.

Manas Saha1, Mrinal Kanti Naskar and B. N. Chatterji [2] Mammogram is an easy and affordable means of diagnosis of breast cancer. Like other medical data, it is also affected by noise during acquisition. Therefore, it is a challenge for the researchers to denoise the mammograms for clear data extraction. This paper aims at denoising the mammogram by the wavelet and the curvelet transform with a motive to investigate the role of the "embedded" thresholding algorithm. As the thresholding technique is a key factor for the noise reduction, a comprehensive study on the employment of the different types of the thresholding techniques with the transforms have been presented methodically. A standard mammogram from the Mammographic Image Analysis Society database is supplemented with different types of noise and then denoised by the wavelet and the curvelet transforms using the three commonly used thresholding techniques to compare the denoising performance of the thresholding algorithms along with the transforms. This investigation renders a clear insight to the selection of the thresholding technique while denoising the mammogram with the transform.

ShaikAllabakash, Polisetti Yasodha, Sakirevupalli Venkatramana Reddy, Parvatala Srinivasulu [3] Various non-atmospheric signals contaminate radar wind profiler (RWP) data, which produce bias in estimation of moments and wind velocity. Especially, in ultra high frequency (UHF) RWPs, ground clutter severely degrades wind velocity estimation. Furthermore, at higher altitudes, noise dominates the clear air signal. Thus, the important tasks of signal processing in a RWP are (i) to eliminate the clutter signal, (ii) to detect the weak atmospheric signals buried inside the noise and (iii) to improve signal-to-noise ratio. Wavelet analysis is a powerful tool to differentiate the characteristics of the ground clutter and noise from the atmospheric turbulence echo at the time series level. The authors have implemented the signal processing for lower atmospheric wind profiler radar at National Atmospheric Research Laboratory, Gadanki, India, using wavelet transforms. In this study, they present the implementation approach and results. The wavelet-based algorithms use different threshold levels to identify and remove ground clutter and to denoise the data. The obtained results using this method are validated with collocated global positioning system radiosonde data.

Xuehui Wu, X. Lu, Xue Han and Chunxue Liu,[4] In modern society, people's requirement of mobile phone camera is higher and higher, its image denoising method is also becoming the focus of attention. In this paper, starting from the actual requirements of mobile phone image denoising, an adaptive mobile phone image denoising method based on bivariate shrinkage function was proposed. Firstly, the actual image noise was made similar to the Gaussian noise by down sampling process, and then a kind of adaptive noise variance of bivariate shrinkage function based on Bayesian denoising method was put forward to estimate variance of the down sampled image. Finally, the denoised image was grayed to further eliminate the noise in the flat areas. Simulation and actual experimental results showed that the method of this paper can get better denoising effect compared with the existing mainstream methods.

R. Saluja and A. Boyat, [5] An efficient method of removing noise from the image while preserving edges and other details is a great challenge for researcher. Image denoising refers to the task of recovering a good estimate of the true image from the degraded image without altering and changing useful structure in the image such as discontinuities and edges. Various algorithm has been developed in past for image denoising but still it has scope for improvement. In this paper, authors introduced an intelligent iterative noise variance estimation system which denoised the noisy image. Proposed algorithm is based on wavelet transform that denoised the noisy image by adding weighted highpass filtering coefficients in wavelet domain that is the novelty of the proposed work. Thereafter denoised algorithm further enhanced by adaptive wiener filter in order to achieve the maximum PSNR. Experimental results show that the proposed algorithm improves the denoising performance measured in terms of performance parameter and gives better visual quality. Mean Square Error (MSE), Root Mean Square Error (RmSE) and Peak Signal to Noise Ratio (PSNR) used as a performance parameters which measure the quality of an image.

J. Han, J. Yue, Y. Zhang and L. Bai, [6] Sparse and redundant representations perform well in image denoising. However, sparsity-based methods fail to denoise low-light-level (LLL) images because of heavy and complex noise. They consider sparsity on image patches independently and tend to lose the texture structures. To suppress noises and maintain textures simultaneously, it is necessary to embed noise invariant features into the sparse decomposition process. We, therefore, used a local structure preserving sparse coding (LSPSc) formulation to explore the local sparse structures (both the sparsity and local structure) in image. It was found that, with the introduction of spatial local structure constraint into the general sparse coding algorithm, LSPSc could improve the robustness of sparse representation for patches in serious noise. Authors further used a kernel LSPSc (K-LSPSc) formulation, which extends LSPSc into the kernel space to weaken the influence of linear structure constraint in nonlinear data. Based on the robust LSPSc and K-LSPSc algorithms, authors constructed a local sparse structure denoising (LSSD) model for LLL images, which was demonstrated to give high performance in the natural LLL images denoising, indicating that both the LSPSc- and K-LSPSc-based LSSD models have the stable property of noise inhibition and texture details preservation.

U. Agrawal, U. S. Tiwary, S. K. Roy and D. S. Prashanth, [7] Clustering algorithms are used for systematic retrieval of data by organizing them into several clusters. K-Means is one such algorithm which partitions data into groups based on distance metric in an unsupervised way. Clustering is used to organize data for efficient retrieval. In this paper, authors study Denoising of images corrupted with variable Gaussian noise spread across the images (dataset). The dataset was made by applying K-Means grouping statistical parameters of the training images which are present in wavelet domain. Adaptive Soft thresholding of noisy images is done, selecting the best parameter based on the cluster. After applying inverse wavelet transform PSNR of the denoised image is calculated. Impressive results are obtained by applying this technique.

Gregory Vaksman, Michael Zibulevsky, and Michael Elad, [8]; Patch Ordering as a Regularization for Inverse Problems in Image Processing, takes an extra step forward by showing that ordering these patches to form an approximate shortest path can be leveraged for better processing. The core idea is to apply a simple filter on the resulting 1D smoothed signal obtained after the patch-permutation. This idea has been also explored in combination with a wavelet pyramid, leading eventually to a sophisticated and highly effective regularizer for inverse problems in imaging. In this work authors further studied the patch-permutation concept and harness it to propose a new simple yet effective regularization for image restoration problems. Their approach builds on the classic maximum a posteriori probability (MAP), with a penalty function consisting of a regular log-likelihood term and a novel permutation-based regularization term. Using a plain 1D Laplacian, the proposed regularization forces robust smoothness ($L1$) on the permuted pixels. Since the permutation originates from patch ordering, we propose to accumulate the smoothness terms over all of the patches' pixels. Furthermore, they take into account the found distances between adjacent patches in the ordering by weighting the Laplacian outcome. Authors demonstrated the proposed scheme on the following diverse set of problems: (i) severe Poisson image denoising, (ii) Gaussian image denoising, (iii) image deblurring, and (iv) single image super-resolution. In all of these cases, they used recent methods that handle these problems as initialization to our scheme. This is followed by an L-BFGS optimization of the above-described penalty function, leading to state-of-the-art results, especially for highly ill-posed cases.

III. PROPOSED METHODOLOGY

A strategy for digitally implementing the combination of TV and nonlocal similarity based on the wavelet technique is presented. The Wavelet transform is capable of resolving 2D singularities and represents edges more efficiently in images. Alhough best results are obtained while de-noising the test images corrupted by heavy noise, & Pepper noise in it is noticed in Bio-medical images when compared to satellite images. The Wavelet transform using thresholding techniques proves to be inferior in de-noising Bio-medical images corrupted by Random noise, heavy noise, Speckle noise and Salt and Pepper noise. A wavelet thresholding technique is removal of Poisson noise in Bio-medical images. Partial reconstruction of wavelet coefficients proves to be a failure for all types of noises tested with various images. However the visual quality of images is preserved. The characteristics of colour images and how they influence coding performance. The study from the Statistical showed that it is image gradient and spatial frequency that has a strong correlation with PSNR, CR and bpp. The magnitude of the relation between the variables, that is, image gradient and the coding performance and spatial frequency and coding performance is strong. In other words, one variable could be predicted based on the other. However, this resuit is only a Statistical association and cannot conclusively prove causality. A more detail study is needed to establish what is the cause of this association.

IV. CONCLUSION AND FUTURE SCOPE

These are the various biomedical signals which have been discussed above ECG, EEG and EMG are the most widely used biomedical signals. The nature and recording of these signals have been explained. The analysis of these signals is done so that any kind of disorder or disease could be detected. This analysis is done by various transformation methods. Any kind of change in the waveform of these signals is the indication of the disease. One of the methods is the Wavelet Transform which has been discussed here in detail. Provision of suitable work environment for the workers is essential for achieving higher production and productivity in both opencast and underground mines. Noisy working condition has negative effects on the worker’s morale and adversely affects their safety, health and performance. In order to assess the of status noise levels in mines, systematic illumination and noise surveys are needed to be conducted using appropriate statutory guidelines so that effective control measures can be taken up in mines.

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