VOL. 5, NO. 1, JANUARY 2010 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

BIOMEDICAL IMAGE ANALYSIS USING WAVELET TOOLS FOR EMERGENCY MEDICAL APPLICATIONS

A. K. M Fazlul Haque[1], Md. Hanif Ali[1] and M Adnan Kiber[2]
[1]Department of Computer Science and Engineering, Jahangirnagar University, Dhaka, Bangladesh
[2]Department of Applied Physics, Electronics and Communication Engineering, University of Dhaka, Dhaka, Bangladesh
E-Mail: akm_haque@yahoo.com

ABSTRACT
In this paper, the analysis of 2D signals, especially emergency biomedical images are performed using the wavelet tools of MATLAB, has been presented for medical application. In terms of 2D signal analysis, an image is taken and added with different four types of noise (Salt and Peeper, Speckle, Gaussian and Poisson). After that all of the noisy images are de-noised for further comparison with the statistical data of the original image. Later the decision is taken based on the impact of the noises, which noise is less harmful and from which noise the signal can be reconstructed mostly. The applications of wavelet in different sectors along with some practical usage are also discussed.

Keywords: biomedical images, noise, de-noise, 2d signal analysis, statistical parameters.

1. INTRODUCTION
Everywhere around us are signals that can be analyzed. For example, there are seismic tremors, human speech, engine vibrations, medical images, financial data, music, and many other types of signals. Wavelet analysis is a new and promising set of tools and techniques for analyzing these signals from which we can find out the most overwhelming noise and less harmful noise as well as their reconstruction properties. Recently wavelets have been used in a large number of biomedical applications. The wavelet packet method is a generalization of wavelet decomposition that offers a rich range of possibilities for signal analysis. The multi-resolution framework makes wavelets into a very powerful compression [1] and filter tool [2], and the time and frequency localization of wavelets makes it into a powerful tool for feature extraction [3]. There are some works on 2D signal analysis using wavelet [4-9].

Most of the works focused on the signals with respect to extreme noisy channel and large abnormalities using conventional FFT and wavelet method. In this paper, wavelet methods are developed for the extraction of small variations of 2D signal. Wavelet method of signal processing found the small abnormalities in signals and they are de-noised and checked out the statistical data for getting the result of analysis.

2. BACKGROUND DATA AND MATERIALS
Between 1924 and today, the US Federal Bureau of Investigation has collected about 30 million sets of fingerprints [4]. The archive consists mainly of inked impressions on paper cards. Facsimile scans of the impressions are distributed among law enforcement agencies, but the digitization quality is often low. Because a number of jurisdictions are experimenting with digital storage of the prints, incompatibilities between data formats have recently become a problem. This problem led to a demand in the criminal justice community for a digitization and a compression standard. In 1993, the FBI's Criminal Justice Information Services Division developed standards for fingerprint digitization and compression in cooperation with the National Institute of Standards and Technology, Los Alamos National Laboratory, commercial vendors, and criminal justice communities [5]. Let's put the data storage problem in perspective. Fingerprint images are digitized at a resolution of 500 pixels per inch with 256 levels of gray-scale information per pixel.

Figure-1. An FBI digitized left thumb fingerprint.

A single fingerprint is about 700,000 pixels and needs about 0.6 Megabytes to store. A pair of hands, then, requires about 6 Megabytes of storage. So digitizing the FBI's current archive would result in about 200 Terabytes of data. (Notice that at today's prices of about $900 per Gigabyte for hard-disk storage, the cost of storing these uncompressed images would be about 200 million dollars). Obviously, data compression is important to bring these numbers down.

The image on the left is the original; the one on the right is reconstructed from a 26:1 compression (Courtesy Chris Brislawn, Los Alamos National Laboratory).

Biomedical Images are analyzed by the wavelet method (Matlab wavelet Tool). Continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt$$

The results of the CWT are many wavelet coefficients C, which are a function of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal.

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. To gain a better appreciation of this process, it is performed a one-stage discrete wavelet transform of a signal. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree.

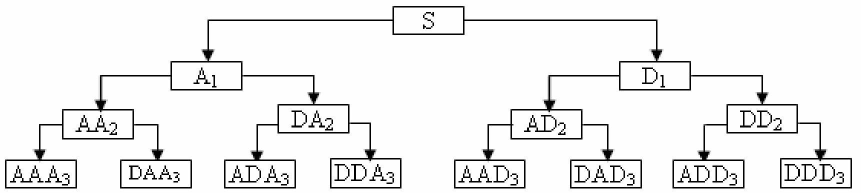

Figure-2. Wavelet packet decomposition tree.

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. In wavelet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level approximation and detail, and the process is repeated. The wavelet packet decomposition tree has been shown in Figure-2.

The wavelet decomposition tree is a part of this complete binary tree. For instance, wavelet packet analysis allows the signal S to be represented as A1 + AAD3 + DAD3 + DD2. This is an example of a representation that is not possible with ordinary wavelet analysis. Whereas the process of Fourier analysis is represented by the Fourier transform. The sum over all time of the signals is multiplied by a complex exponential. A complex exponential can be broken down into real and imaginary sinusoidal components. The results of the transform are the Fourier coefficients, which multiplied by a sinusoid of frequency yield the constituent sinusoidal components of the original signal. From the principle of FFT, it does not have possibilities to detect the little change of the signals.

2.1 De-noising noisy data

In diverse fields from planetary science to molecular spectroscopy, scientists are faced with the problem of recovering a true signal from incomplete, indirect or noisy data. Wavelet can solve this problem through a technique called wavelet shrinkage and thresholding method, David Donoho has worked on it for several years [7].

The technique works in the following way. When decomposing a data set using wavelets, filters are used that act as averaging filters and others that produce details [8]. Some of the resulting wavelet coefficients correspond to details in the data set. If the details are small, they might be omitted without substantially affecting the main features of the data set. The idea of thresholding, then, is to set to zero all coefficients that are less than a particular threshold. These coefficients are used in an inverse wavelet transformation to reconstruct the data set. Figure-3 is a pair of "before" and "after" illustrations of a nuclear magnetic resonance (NMR) signal. The signal is transformed, thresholded and inverse-transformed. The technique is a significant step forward in handling noisy data because the de-noising is carried out without smoothing out the sharp structures. The result is cleaned-up signal that still shows important details. The original signal is at the top, the de-noised signal at the bottom.

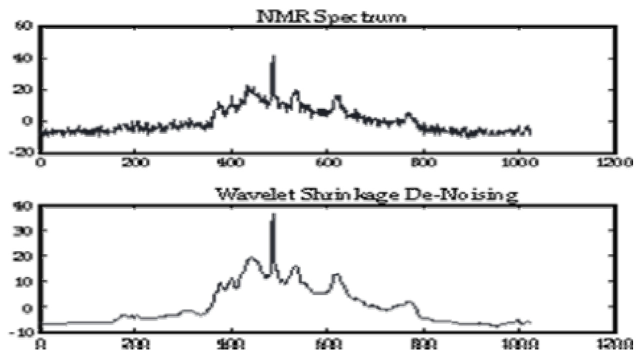

Figure-3. "Before" and "after" illustrations of a nuclear magnetic resonance signal.

2.2 Noise

In common use, the word noise means unwanted sound or noise pollution [9]. In both analog and digital electronics, noise or signal noise is an unwanted random addition to a wanted signal; it is called noise as a generalization of the audible noise heard when listening to a weak radio transmission. Signal noise is heard as acoustic noise if played through a loudspeaker; it manifests as 'snow' on a television or video image. In signal processing or computing it can be considered unwanted data without meaning; that is, data is not being used to transmit a signal, but is simply produced as an unwanted by-product of other activities. In Information

Theory, however, noise is still considered to be information (Table-1). In a broader sense, film grain or even advertisements encountered while looking for something else can be considered noise. Noise can block, distort, change or interfere with the meaning of a message in both human and electronic communication.

Table-1. Noises used in 2D wavelet analysis.

Value	Description
Gaussian	Gaussian white noise
Poisson	Poisson noise
Salt and pepper	On and off pixels
Speckle	Multiplicative noise

In communications, the additive white Gaussian noise (AWGN) channel model is one in which the only impairment is a linear addition of wideband or white noise with a constant spectral density (expressed as watts per hertz of bandwidth) and a Gaussian distribution of amplitude. The model does not account for the phenomena of fading, frequency selectivity, interference, nonlinearity or dispersion. However, it produces simple and tractable mathematical models which are useful for gaining insight into the underlying behavior of a system before these other phenomena are considered [10].

In probability theory and statistics, the Poisson distribution (pronounced [pwasõ]) (or Poisson law of large numbers) is a discrete probability distribution that expresses the probability of a number of events occurring in a fixed period of time if these events occur with a known average rate and independently of the time since the last event. The Poisson distribution can also be used for the number of events in other specified intervals such as distance, area or volume [11].

Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. An effective noise reduction method for this type of noise involves the usage of a median filter. Salt and pepper noise creeps into images in situations where a quick transient, such as faulty switching takes place [12].

Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar (SAR) images.

Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean grey level of a local area [13].

Speckle noise in SAR is generally more serious, causing difficulties for image.

It is caused by coherent processing of backscattered signals from multiple distributed targets. In SAR oceanography, for example, speckle noise is caused by signals from elementary scatterers, the gravity-capillary ripples, and manifests as a pedestal image, beneath the image of the sea waves [15,16].

3. STATISTICAL PARAMETERS

The mean may often be confused with the median, mode or range. The mean is the arithmetic average of a set of values, or distribution; however, for skewed distributions, the mean is not necessarily the same as the middle value (median), or the most likely (mode). For example, mean income is skewed upwards by a small number of people with very large incomes, so that the majority has an income lower than the mean. By contrast, the median income is the level at which half the population is below and half is above. The mode income is the most likely income, and favors the larger number of people with lower incomes. The median or mode is often more intuitive measures of such data.

In monochrome raster images there is a type of noise, known as the salt and pepper noise, when each pixel independently become black (with some small probability) or white (with some small probability), and is unchanged otherwise (with the probability close to 1). An image constructed of median values of neighborhoods (like 3×3 square) can effectively reduce a noise in this case.

4. 2D WAVELET ANALYSIS

In terms of 2D signal analysis, the properties of that particular signal are to be known. Here some special Biomedical Images (Figure-4). We analyzed a signal named *kidney.png*. Its properties are as follows:

Width	308 pixels
Height	242 pixels
Horizontal resolution	72 dpi
Vertical resolution	72 dpi
Bit depth	8
Frame count	1

4.1 Procedure

a) To load the image first the following code has to type on the MATLAB command window.
   I = imread ('kidney.png');
b) Now to add built in noise to the loaded image the following codes is to be typed.
   J = imnoise(I,'salt and pepper',0.02);
c) Now to see the original image and the noisy image the following codes need to be typed respectively.
   Imshow (I)
   Figure, imshow (J)
d) For further analysis this image needs to be saved in “mat” format. And it is saved from the workspace.
e) Two file is found named “I” and “J”. Where “I” is the original image and “J” is the image with noise.
f) Now to analyze the image the “Wavelet Toolbox” requires opening. To open it, the following code has to type in command prompt.
   wavemenu
g) After that the Wavelet 2D tool needs to open from the Wavelet window for analyzing the two mat files respectively.
h) Now it is analyzed to find out its statistical data (Table-2).

VOL. 5, NO. 1, JANUARY 2010 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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i) The statistical data of the image are as follows.
j) Different noise is added to the original image and then has to repeat the steps 2-9 for each of the noisy images. The codes are following.
   J = imnoise(I,'speckle');
   J = imnoise(I,'poisson');
   J = imnoise (I,'gaussian');
k) The following obtained data are now ready to compare with each other to find out the noise which distorts the data added (Table-2 and Graph 1).
l) The next step is to de-noising the each of the noisy images individually in order to find out which noise can be reduced more.
m) After that the de-noised images are further analyzed and the statistical data are
n) Collected for more advance comparison (Table-3 and Graph-2). And finally, it is found that-Gaussian noises do lots of damage of the 2D data.

Table-2. Statistical values of kidney.png original image.

Kidney original image			
Mean	103	Maximum	255
Median	73	Minimum	23
Mode	71.72	Range	232
Standard Deviation	55.89	Median absolute Deviation	12
Mean absolute deviation			49.53

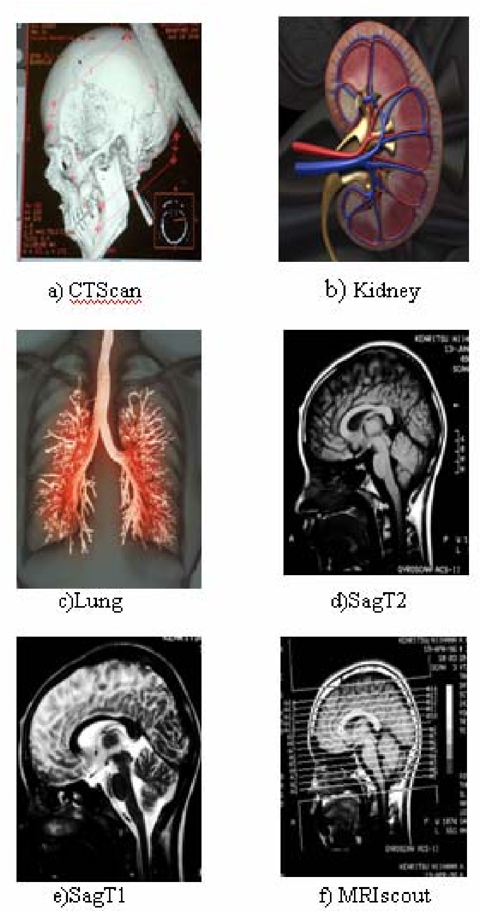
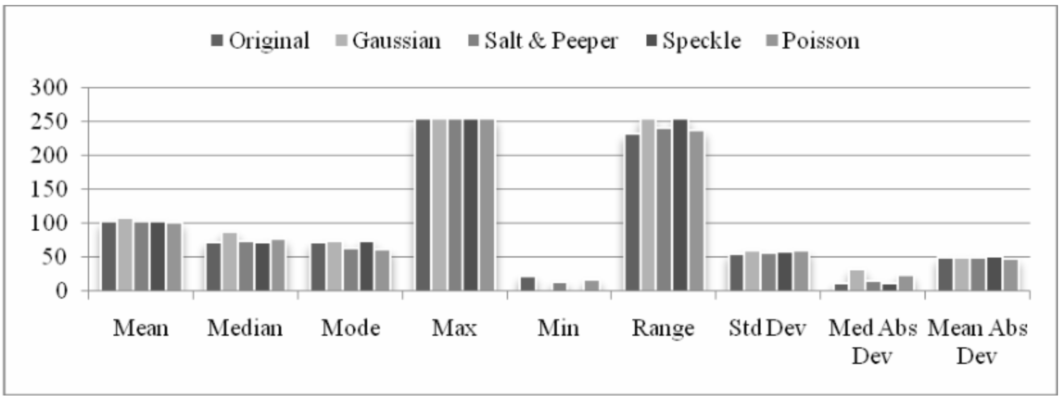


Figure-4. a) CT Scan; b) kidney; c) Lunge; d) Sag T2; e) Sag T1 and f) MRI scout of different biomedical images.

Table-3. Comparative statistical value of different noisy images.

	Mean	Median	Mode	Max	Min	Range	Std Dev	Med Abs Dev	Mean Abs Dev
Original	103	73	71.72	255	23	232	55.89	12	49.53
Gaussian	108.1	88	73.95	255	0	255	60.93	33	50.95
Salt and peeper	103.7	73	73.95	255	0	255	58.37	13	51.37
Speckle	102.5	78	62.22	255	17	238	60.27	24	49.21
Poisson	103	74	64.61	255	14	241	56.76	15	49.58



Graph-1. Graphical comparison between the statistical values of different noisy images.

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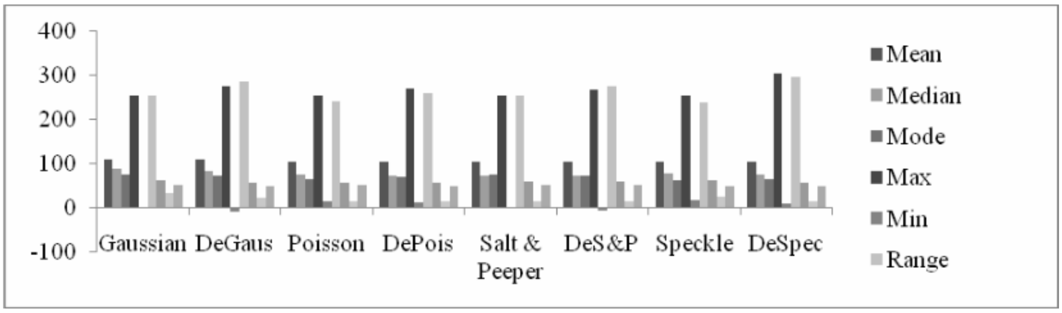
Table-4. Comparative statistical value of different noisy and de-noised images.

	Mean	Median	Mode	Max	Min	Range	Std Dev	Med Abs Dev	Mean Abs Dev
Gaussian	108.1	88	73.95	255	0	255	60.93	33	50.95
De Gaus	108.1	82	72.65	275	-10	285	56.66	21	49.08
Poisson	103	74	64.61	255	14	241	56.76	15	49.58
De Pois	103	73	70.57	270	11	259	55.91	13	49.35
Salt and peeper	103.7	73	73.95	255	0	255	58.37	13	51.37
De S and P	103.7	73	71.75	267	-8	275	58.41	13	51.35
Speckle	102.5	78	62.22	255	17	238	60.27	24	49.21
De Spec	102.5	74	64.43	305	8	297	57.2	15	48.75



Graph-2. Graphical comparison between the statistical values of different noisy and de-noised images.

5. CONCLUSIONS

From the above analysis of the 2D signal, it is decided that; Salt and Peeper noise is the less destructive noise for 2D data and most of the data can be reconstructed easily though effected by the noise. On the other hand it is found that-Gaussian noises do lots of damage of the 2D data. It almost diminishes the information of the data and is hardly reconstructed. But most of the cases it cannot be reconstructed when it is effected by Gaussian noise.

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