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A Survey on Implementation of Discrete Wavelet Transform for Image Denoising

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Abstract- Image Denoising has been a well studied problem in the field of image processing. Images are often received in defective conditions due to poor scanning and transmitting devices. Consequently, it creates problems for the subsequent process to read and understand such images. Removing noise from the original signal is still a challenging problem for researchers because noise removal introduces artifacts and causes blurring of the images. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. This paper deals with using discrete wavelet transform derived features used for digital image texture analysis to denoise an image even in the presence of very high ratio of noise. Image Denoising is devised as a regression problem between the noise and signals, therefore, Wavelets appear to be a suitable tool for this task, because they allow analysis of images at various levels of resolution.

Key words**:** Image, De-noising, Wavelet Based, Transformation

I. INTRODUCTION

In everyday life, digital images processing have many applications it includes digital cameras, intelligent traffic monitoring, handwriting recognition on checks, signature validation and so on. However, it is not uncommon that images are contaminated by noise due to several unavoidable reasons. Poor image sensors, imperfect instruments, problems with data acquisition process, transmission errors and interfering natural phenomena are its main sources. Therefore, it is necessary to detect and remove noises present in the images. Reserving the details of an image and removing the random noise as far as possible is the goal of image Denoising approaches.On the other hand, image Denoising from natural and unnatural images is still a challenging problem in image processing. Indeed, wavelets transform based approaches have efficient noise reduction ability in photographic images and promising results are reported in these references. Over the pastdecade,wavelet transform have received a lot of attention Over the past decade, wavelet transforms have received a lot of attention from researchers in many different areas. Both discrete and continuous wavelet transforms have shown great promise in such diverse fields as image compression, image de-noising, signal processing, computer graphics, and pattern recognition to name only a few. In de-noising, single orthogonal wavelets with a single-mother wavelet function have played an important role. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. Crudely, it states that the wavelet transform yields a large number of small coefficients and a small number of large coefficients. Simple de-noising algorithms that use the wavelet transform consist of three steps.

- Calculate the wavelet transform of the noisy signal.
- Modify the noisy wavelet coefficients according to some rule.
- Compute the inverse transform using the modified coefficients.

One of the most well-known rules for the second step is soft Thresholding. Due to its effectiveness and simplicity, it is frequently used in the literature. The main idea is to subtract the threshold value T from all wavelet coefficients larger than T, arising from the standard discrete wavelet transform and to set all other coefficients to zero.The problem of Image de-noising can be summarized as follows. Let A(i,j) be the noise-free image and B(i,j)the image corrupted with independent Gaussian noise Z(i,j),
$B(i,j)= A(i,j)+\sigma Z(i,j)$ ……(1)
where Z(i,j) has normal distribution N(0,1). The problem is to estimate the desired signal as accurately as possible according to some criteria. In the wavelet domain, if an orthogonal wavelet transform is used, the problem can be formulated as
$Y(i,j)= W(i,j)+N(i,j)$ ……(2)
where Y(i,j) is noisy wavelet coefficient; W(i,j) is true coefficient and N(i,j) noise, which is independent Gaussian. .

II. DISCRETE WAVELET TRANSFORM

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time-frequency representation of the signal .The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image de-noising. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. An image can be decomposed

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into a sequence of different spatial resolution images using DWT.In case of a 2D image,anNlevel Decomposition can be performed resulting in 3N+1 different frequency bands namely, LL,LH, HL and HH as shown in figure 1. These are also known by other names, the sub-bands may be respectively called a1 or the first average image, h1 called horizontal fluctuation, v1 called vertical fluctuation and d1 called the first diagonal fluctuation. The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded.The Discrete Wavelet Transform (DWT), which is based on sub-band coding is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. The foundations of DWT go back to 1976 when techniques to decompose discrete time signals were devised. Similar work was done in speech signal coding which was named as sub-band coding. In 1983, a technique similar to sub-band coding was developed which was named pyramidal coding. Later many improvements were made to these coding schemes which resulted in efficient multi-resolution analysis schemes. In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales.

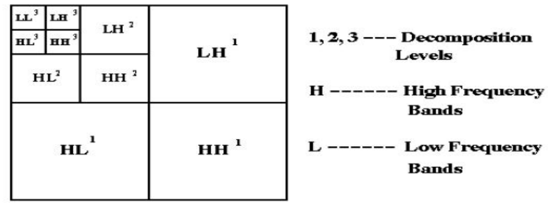

Figure 1: 2D-DWT with 3-Level decomposition

III. WAVELET BASED IMAGE DE-NOISING

All digital images contain some degree of noise. Image Denoising algorithm attempts to remove this noise from the image. Ideally, the resulting de-noised image will not contain any noise or added artifacts. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The methodology of the discrete wavelet transform based image de-noising has the following three steps as shown in figure 2.

1. Transform the noisy image into orthogonal domain by discrete 2D wavelet transform.
2. Apply hard or soft Thresholding the noisy detail coefficients of the wavelet transform.
3. Perform inverse discrete wavelet transform to obtain the de-noised image.Here, the threshold plays an important role in the Denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details. Normally, hard Thresholding and soft Thresholding techniques are used for such de-noising process. Hard Thresholding is a keep or kill rule whereas soft Thresholding shrinks the coefficients above the threshold in absolute
value. It is a shrink or kill rule.

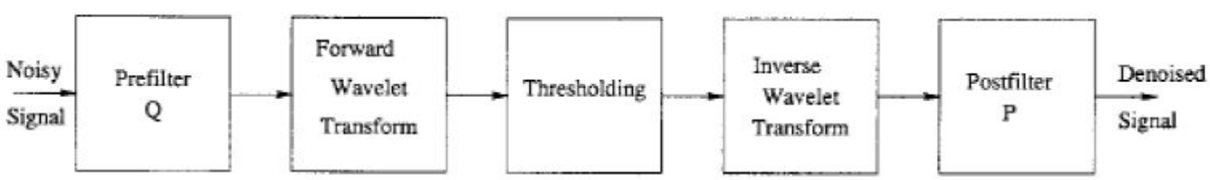

Figure2: Diagram of wavelet based image De-noising

IV. MULTI-RESOLUTION ANALYSIS USING FILTER BANKS

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up sampling and down sampling (sub sampling) operations. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in figure 2.2. This is called the Mallet algorithm or Mallet-tree decomposition. Its significance is in the manner it connects the continuous-time mutiresolution to discrete-time filters. In the figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G_0 while the high pass filter is denoted by H_0.At each level, the high pass filter produces detail

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information, d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n].

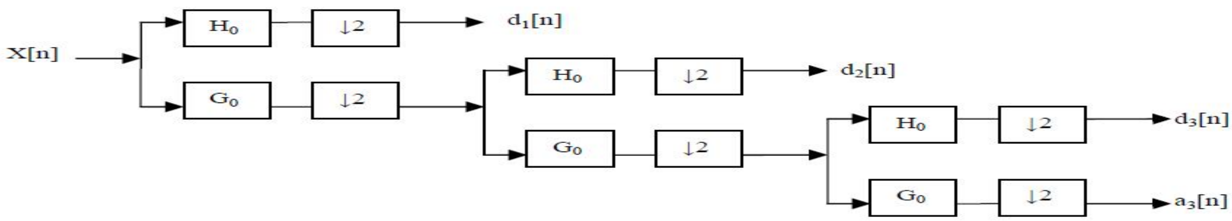

Figure 2.2 Three-level wavelet decomposition tree.

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainity in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale. With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition. Figure 2.3 shows the reconstruction of the original signal from the wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain and H the original signal. The Mallat algorithm works equally well if the analysis filters, G_0 and H_0, are exchanged with the synthesis filters, G1andH1.

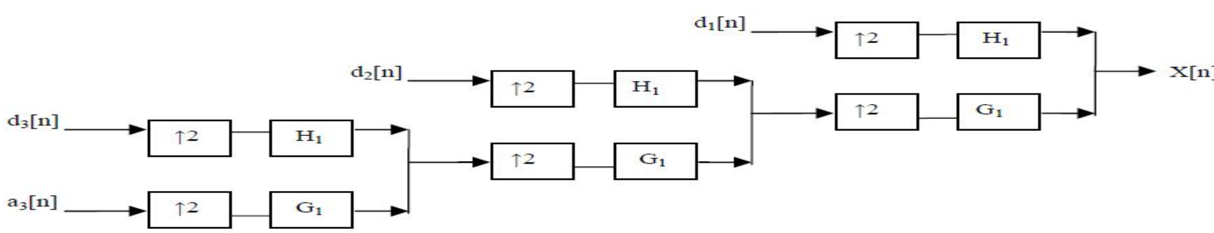

Figure 2.3 Three-level wavelet reconstruction tree.

V. WAVELET FAMILIES

There are a number of basis functions that can be used as the mother wavelet for Wavelet Transformation. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform. Therefore, the details of the particular application should be taken into account and the appropriate mother wavelet should be chosen in order to use the Wavelet Transform effectively. Figure 2.4 illustrates some of the commonly used wavelet functions. Haar wavelet is one of the oldest and simplest wavelet. Therefore, any discussion of wavelets starts with the Haar wavelet. Daubechies wavelets are the most popular wavelets. They represent the foundations of wavelet signal processing and are used in numerous applications. These are also called Maxflat wavelets as their frequency responses have maximum flatness at frequencies 0 and π. This is a very desirable property in some applications. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. These wavelets along with Meyer wavelets are capable of perfect reconstruction. The Meyer, Morlet and Mexican Hat wavelets are symmetric in shape. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application.

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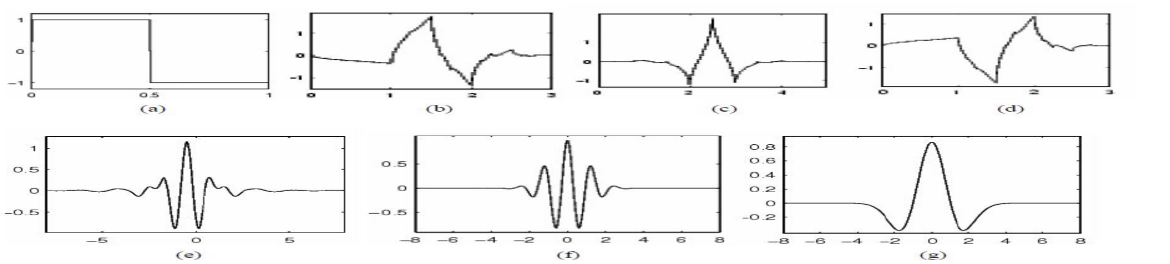

Figure 2.4 Wavelet families (a) Haar (b) Daubechies4 (c) Coiflet1 (d) Symlet2 (e) Meyer (f) Morlet (g) Mexican Hat.

VI. CONCLUSION

In this paper, the image de-noising using discrete wavelet transform is analyzed. In DWT, the most prominent information in the signal appears in high amplitudes and the less prominent information appears in very low amplitudes. Data compression can be achieved by discarding these low amplitudes. The wavelet transforms enables high compression ratios with good quality of reconstruction. Therefore, Wavelets are used in biomedical imaging. For example, the ECG signals, measured from the heart, are analyzed using wavelets or compressed for storage. Wavelets also find application in speech compression, which reduces transmission time in mobile applications. They are used in Denoising, edge detection, feature extraction, speech recognition, echo cancellation and others. At present, the application of wavelets for image compression is one the hottest areas of research. The popularity of Wavelet Transform is growing because of its ability to reduce distortion in the reconstructed signal while retaining all the significant features present in the signal.

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