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Review Report of Image Processing Using EEMD Algorithm

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Abstract: **This paper proposes a method for image denoising in the filter domain based on the characteristics of the Empirical Mode Decomposition (EMD) and the wavelet technique. The proposed method uses the EMD to the decomposition and double Density wavelet to filter components. Our experimental results show that these image denoising methods are more efficient than the wavelet denoising method.**
Finally, the PSNR (peak signal noise ratio) and the visualization of the denoising image are used as performance comparison indexes.

Keywords: **Double Density Wavelet, Empirical Mode Decomposition, PSNR, image denoising.**

I. INTRODUCTION

Generally, noise reduction is an essential part of image processing systems [1]. An image is always affected by noise in its capture, acquisition and processing. This denoising is used to improve the quality of corrupted by a lot of noise due to the Undesired conditions for image acquisition. Generally, the image quality is measured by the peak signal-to noise ratio (PSNR) or signal-to noise ratio (SNR) [2]. Traditionally, this is achieved by linear processing such as Wiener filtering. A variety of methods has emerged recently on signal denoising using nonlinear techniques in the case of additive Gaussian noise [3].Wavelet technique is the important method of denoising in Image Processing [4]. They make it possible to analyze and identify discontinuities of a signal to one or two dimensions and on different scales. This feature is used for denoising field. However, a limitation of the wavelet approach is the need to predefine the basic functions necessary for the decomposition of the signal. Recently, Huang introduced the EMD method decomposition into sub bands, local and self-adapting for analyzing non stationary signals [5].In this contribution, we combine the Wavelet and EMD techniques to denoising images as a new approach. This contribution uses the EMD as a method of decomposition and the wavelet as method of image denoising.

Decomposition (EMD) based in wavelet technique presents the evaluation criterion. In Sec.4, the experimental results of this proposed method are presented.

II. EMPIRICAL MODE DECOMPOSITION BASED IN WAVELET TECHNIQUE

This is a new filtering method realized in three steps to reduce the noise in images. An edge detector is used primarily to detect the directions of the image edges. Then, the decomposition is performed by an Empirical Modal Decomposition approach [6]. The resulting images were smoothed along the four directions (each image is smoothed in contour direction): horizontal, vertical and diagonals (right and left). Finally, the image is reconstructed as it from different direction; i.e. the image pixel smoothed along the horizontal direction is used to reconstruct the same direction image, and so on. If a contour is not detected, then the average of the smoothed images in the four directions is used to reconstruct the image. Note that the choice of pixels used is based on the direction of the founded contour.

III. INTRODUCTION TO WAVELET

The concept of wavelet was hidden in the works of mathematicians even more than a century ago. In 1873, Karl Weirstrass mathematically described how a family of functions can be constructed by superimposing scaled versions of a given basis function. The term wavelet was originally used in the field of seismology to describe the disturbances that emanate and proceed outward from a sharp seismic impulse [22]. Wavelet means a “small wave”. The smallness refers to the condition that the window function is of finite length (compactly supported) [23]. A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time and are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy [22].

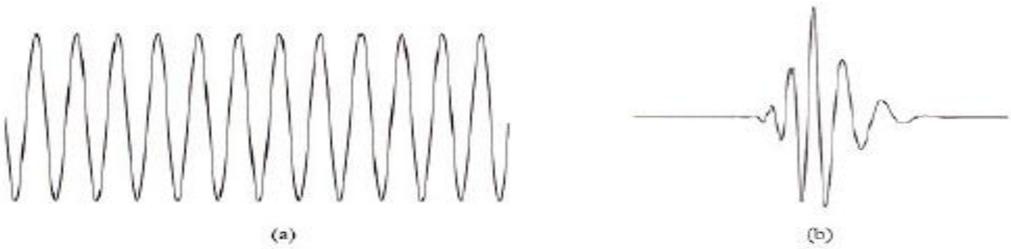

Figure 1.1 Difference between Wave and Wavelet (a) wave (b) wavelet.

In wavelet analysis the signal to be analyzed is multiplied with a wavelet function and then the transform is computed for each segment generated. The Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies; the Wavelet Transform gives good frequency resolution and poor time resolution.

An arbitrary signal can be analyzed in terms of scaling and translation of a single mother wavelet function (basis). Wavelets allow both time and frequency analysis of signals simultaneously because of the fact that the energy of wavelets is concentrated in time and still possesses the wave-like (periodic) characteristics. As a result, wavelet representation provides a versatile mathematical tool to analyze transient, time-variant (non stationary) signals that are not statistically predictable especially at the region of discontinuities-a feature that is typical of images having discontinuities at the edges.

1.2 Mathematical Representation of Wavelet.

Wavelets are functions generated from one single function (basis function) called the prototype or mother wavelet by dilations (scaling) and translations (shifts) in time (frequency) domain.

If the mother wavelet is denoted by y (t), the other wavelets $\varphi_{a,b}(t)$ can be represented as

$$\varphi_{a,b}(t) = (1 * \varphi(\left(\frac{t-b}{a}\right)/\sqrt{a})$$

Where a and b are two arbitrary real numbers. The variables ‘a’ and ‘b’ represent the parameters for dilations and translations respectively in the time axis.

The mother wavelet can be essentially represented as

$$\varphi_{a,b}(t) = \varphi_{1,0}(t)$$

For any arbitrary a ≠1 and b = 0, we can derive that

$$\varphi_{a,0}(t) = (1 * \varphi(\left(\frac{t}{a}\right)/\sqrt{a})$$

As shown above, $\varphi_{a,0}(t)$ is nothing but a time-scaled (by a) and amplitude-scaled (by a) version of the mother wavelet function y (t).

IV. TYPES OF WAVELET TRANSFORMS

There are mainly two types of Wavelet Transforms-

- Continuous Wavelet Transformation (CWT)
- Discrete Wavelet Transformation (DWT)

Since our algorithm is to be based on discrete wavelet transform, so we will discuss only the concepts of DWT (leaving CWT as such) in the following paragraphs. Two commonly used abbreviations are DWT and IDWT.

DWT stands for Discrete Wavelet Transformation. It is the Transformation of sampled data, e.g. transformation of values in an array, into wavelet coefficients.

IDWT is Inverse Discrete Wavelet Transformation: procedure converts wavelet coefficients into the original sampled data.

Here the case of square images has been considered. Let us take an N by N image.

V. COMPOSITION PROCESS

The inverse process is shown in Figure 1.4. The information from the four sub-images is up-sampled and then filtered with the corresponding inverse filters along the columns. The two results that belong together are added and then again up-sampled and filtered with the corresponding inverse filters. The result of the last step is added together in order to get the original image again. Note that there is no loss of information when the image is decomposed and then composed again at full precision.

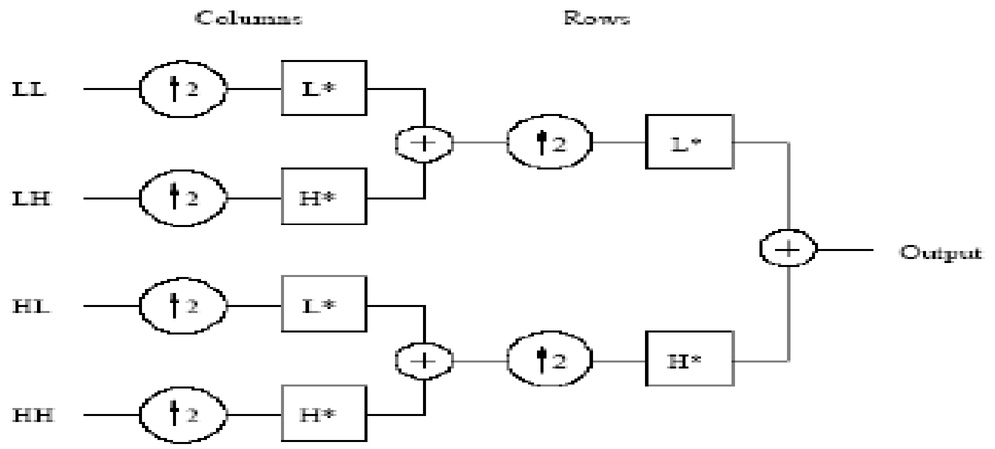

Figure 1.4 One composition steps of the four sub images

With DWT we can decompose an image more than once. Decomposition can be continued until the signal has been entirely decomposed or can be stopped before by the application at hand.

VI. DECOMPOSITION PROCESS

To start with, the image is high and low-pass filtered along the rows and the results of each filter are down- sampled by two. Those two sub-signals correspond to the high and low frequency components along the rows and are each of size N by N/2. Then each of these sub-signals is again high and low-pass filtered, along the column data. The results are again down-sampled by two.

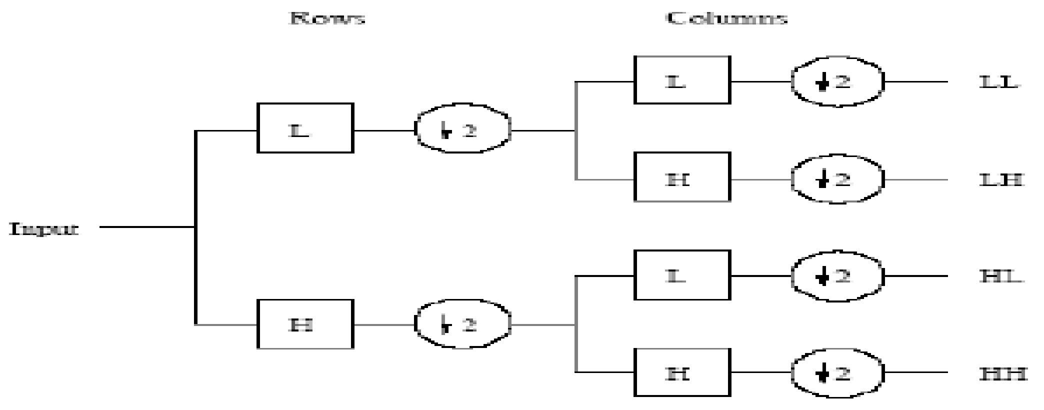

Figure 1.2 One decomposition step of the two dimensional image

As a result the original data is split into four sub-images each of size N/2 by N/2 containing information from different frequency components. Figure 1.2 shows the level one decomposition step of the two dimensional grayscale image. Figure 1.3 shows the four sub bands in the typical arrangement.

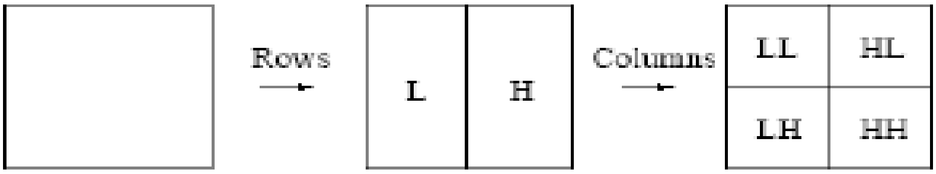

Figure 1.3 One DWT decomposition step

The LL sub band is the result of low-pass filtering both the rows and columns and it contains a rough description of the image as such. Hence, the LL sub band is also called the approximation sub band. The HH sub band is high-pass filtered in both directions and contains the high-frequency components along the diagonals as well. The HL and LH images are the result of low-pass filtering in one direction and high-pass filtering in another direction. LH contains mostly the vertical detail information that corresponds to horizontal edges. HL represents the horizontal detail information from the vertical edges. All three sub bands HL, LH and HH are called the detail sub bands, because they add the high-frequency detail to the approximation image.

Mostly two ways of decomposition are used. They are:

(1) Pyramidal decomposition
(2) Packet decomposition

Pyramidal decomposition is the simplest and most common form of decomposition used. For the pyramidal decomposition we only apply further decompositions to the LL sub band. Figure 1.5 shows a systematic diagram of three decomposition steps. At each level the detail sub bands are the final results and only the approximation sub band is further decomposed.

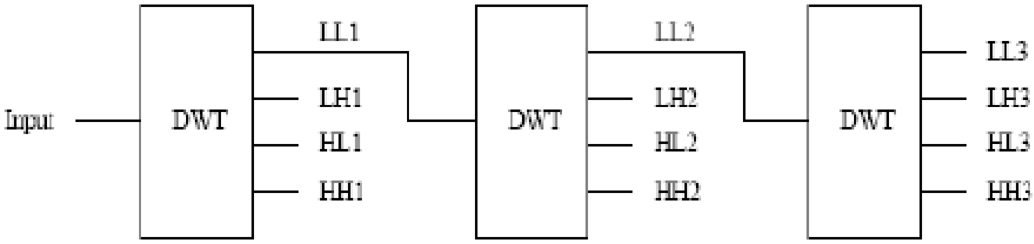

Figure 1.5 Three decomposition steps of an image using Pyramidal Decomposition

Figure 1.6 shows the pyramidal structure that result from this decomposition. At the lowest level there is one approximation sub band and there are a total of nine detail sub bands at the different levels. After L decompositions, a total of D (L) = 3 * L + 1 sub bands are obtained.

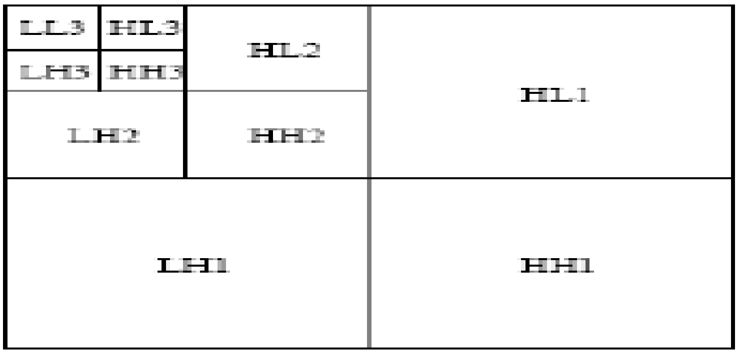

Figure 1.6 Pyramid after three decomposition steps

VII. WAVELET PACKET DECOMPOSITION

For the wavelet packet decomposition, the decomposition is not limited to the appro VIII. ximation sub band only but a further wavelet decomposition of all sub bands on all levels is considered. In figure 1.8, the system diagram for a complete two level wavelet packet decomposition has been shown.

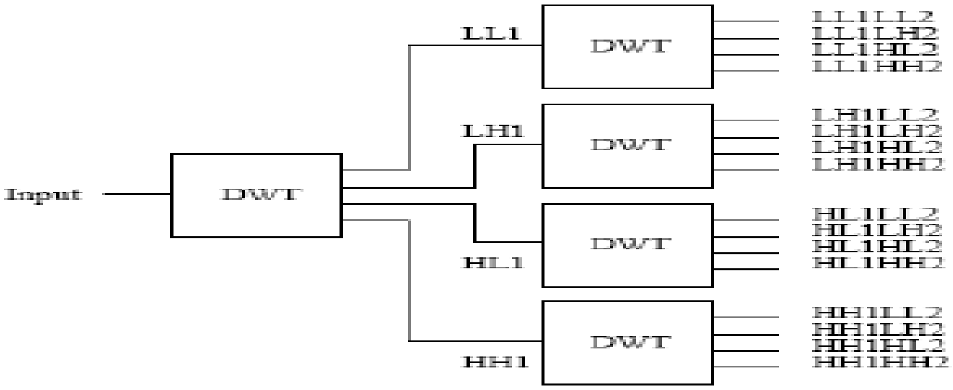

Figure 1.8 Two complete decomposition steps using wavelet packet decomposition

VIII. CONCLUSION

In this paper, a novel unsupervised image clustering method is introduced. The proposed approach exploits ensemble empirical mode decomposition (EEMD) to analyze the histogram of the image under examination. The EEMD algorithm can decompose any nonlinear and non-stationary data into a number of intrinsic mode functions (IMFs). The proposed algorithm uses only a number of the intermediate IMFs of the EEMD decomposition, which have interesting characteristics and provide a novel workspace that is utilized in order to automatically detect not only the different clusters, but also the number of clusters into the image under examination.

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