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Review on Image Denoising using Enhanced Empirical Mode Decomposition Algorithm

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***Abstract* - In this paper, a new technique which is combination of Enhanced Empirical Mode Decomposition (EEMD), has been presented along with the standard wavelet thresholding techniques like hard thresholding to denoise the image. The massive amount of data required for images is a primary reason for the development of many sub areas within the field of computer imaging such as image segmentation and compression. Whatever may be the way of transmission, the data tends to get noisy and thereby the further processing does not lead to good results. Hence, it is very essential to keep the data close to originality. In order to achieve this in terms of the concerned work, wavelet transforms have been applied: Discrete wavelet transform and enhanced empirical mode decomposition.**

I. INTRODUCTION

The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Visual information, transmitted in the form of digital images, has become a major method of communication for the 21st century. Image processing is any form of signal processing for which the input is an image, such as photographs or frames of video and the output of image processing can be either an image or a set of characteristics or parameters related to the image. Most image processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. There are applications in image processing that require the analysis to be localized in the spatial domain. The classical way of doing this is through what is called Windowed Fourier Transform. It is a fascinating and exciting area to be involved in today with application areas ranging from the entertainment industry to the space program. One of the most interesting aspects of this information revolution is the ability to send and receive complex data that transcends ordinary written text. Image processing is a field that continues to grow, with new applications being developed at an ever increasing pace. Central idea of windowing is reflected in Short Time Fourier Transform (STFT). The STFT conveys the localized frequency component present in the signal during the short window of time. The same concept can be extended to a two-dimensional spatial image where the localized frequency components may be determined from the windowed transform. This is one of the basis of the conceptual understanding of wavelet transforms. Hence, wavelet transforms have been kept as the main consideration in this paper. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. 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.

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 noise $Z(i, j)$,

$$B(i, j) = A(i, j) + Z(i, j) \quad ...(1.1)$$

The problem is to estimate the desired signal as accurately as possible according to some criteria. In the wavelet domain, the problem can be formulated as

$$Y(i, j) = W(i, j) + N(i, j) \quad ...(1.2)$$

where $Y(i, j)$ is noisy wavelet coefficient; $W(i, j)$ is true coefficient and $N(i, j)$ noise. In this paper work, the algorithm has been carried out by using variety of inputs.

It was used with Wavelet transform’s thresholding principle to denoise the image and proved to be less computational complex. But EMD also experiences some problems, such as the presence of oscillations of very disparate amplitude in a mode, or the presence of very similar oscillations in different modes, named as “mode mixing”.Fourier based methods are often employed for restoration. Despite the power of these techniques, they rely on a projection onto a linear set of predefined bases. As image features like noise, texture, incident illumination effects; often corresponds to variations in spatial frequencies. This limits the abilities of fourier methods when processing real world images that often display non linear and non stationary behaviour. To avoid all these problems a new method name Empirical Mode Decomposition was formulated for image restoration.

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II. OBJECTIVES

The objective is to denoise the noisy image. For this purpose enhanced empirical mode decomposition is used followed by wavelet thresholding. EEMD is the enhanced version of empirical mode decomposition (EMD) as EMD suffers from mode mixing problem. After breaking noisy image into different IMFs, each IMF is filtered by wavelet thresholding technique. A basic flow chart depicting the above said precedes shown in figure 1.

The main algorithm, followed in order to fulfill the aim of this paper, is as follows:

Step 1: Read the original standard image (LENA.bmp, low_key.jpg, high_key.jpg, medium_key.jpg).

Step 2: Resize the loaded image to a standard size of 128 × 128. The images taken for testification have a lot of variation in their sizes and hence cannot be compared on the same basis. For large sized images, such as 512× 512 , the computation time for denoising is found to be more. And if the image size is taken smaller than 128× 128 , then the useful data is liable to get lost.

Step 3: Noise is added to the standard test images using the following type of available noise:

• Gaussian noise - This type of noise adds normal distributed noise to the original image. The noise is independent of the image it is applied to. The value of the pixel is altered by the additive Gaussian noise as

$J(k, l) = x(k, l) + n$

where n is the noise, $n \sim N(0, v)$, being distributed normally with variance v . The noisy pixels which are generated are anywhere between black and white, distributed according to the Gaussian curve. The width of the curve is adjusted with the variance parameter. In our case, variance is taken 0.09 which is quite within the permissible limits of [0 1].

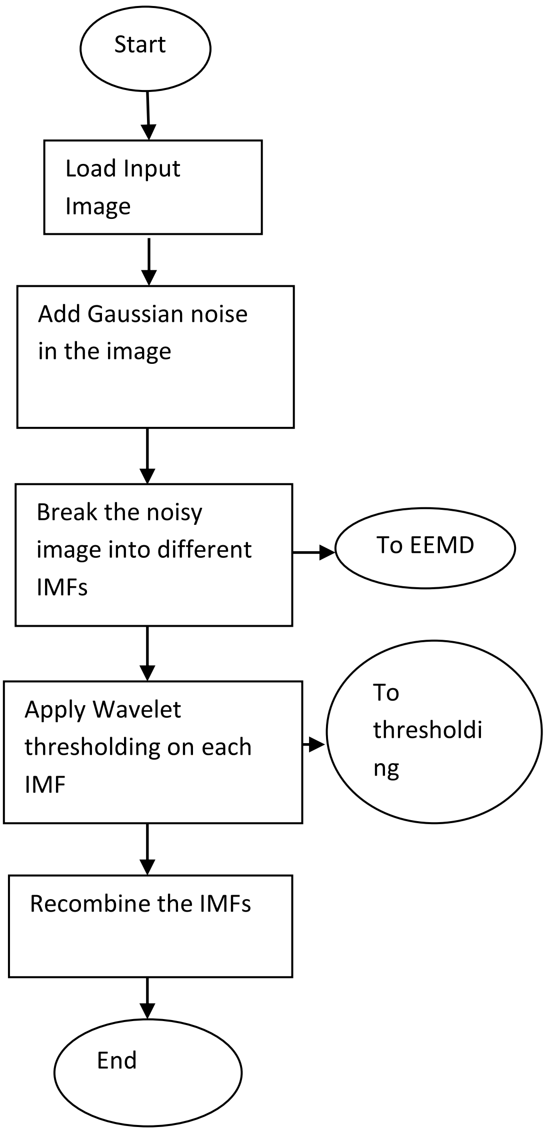


Fig 1: Flow Chart of proposed algorithm

Step 4: Make the noisy image to undergo EEMD transform, and then each IMF is undergone through DWT denoising algorithm. It breaks the each IMF into four different coefficients named Approximation, diagonal, vertical and horizontal coefficients. Among all these approximation coefficient has maximum information of image.

Step 5: After the noisy image is decomposed into approximation and detail coefficients using wavelet transform, it is made to undergo the following thresholding rules having various threshold values. In addition, two cases have been considered- one where the low pass components are not thresholded and the other being the one where the low pass components have been thresholded. The thresholding techniques applied are as follows,

• Soft Thresholding – refers to the procedure where firstly the input elements with absolute value lower than the set threshold value, are set to zero and are then scaled to the non-zero coefficients toward zero. It eliminates discontinuity and gives more visually pleasant images.

$x = abs(y)$

$x = sign(y).*(x^{3}\ thld).*(x - thld)$

where y is the input, thld is the threshold value and x is the thresholded output.

• Hard Thresholding – refers to the procedure where the input elements with absolute value lower than the set threshold value, are set to zero. It is discontinuous at the point where $x = thld$ and yields abrupt artifacts in the recovered images especially when the noise energy is significant.

$x = (abs(y) > thld).*y)$

Step 6: After the decomposed image coefficients are thresholded using the above mentioned three threshold values with each of the thresholding technique, the denoised image is reconstructed using inverse wavelet transforms- IDWT.

Step 7: Repeat wavelet denoising for each IMF and then recombine all IMFs by adding them to reconstruct the image.

III. RESULTS

In our work we have developed a graphical user interface which facilitates a step by step demonstration of our work. GUIs (also known as graphical user interfaces or UIs) provide point-and-click control of software applications, eliminating the need to learn a language or type commands in order to run the application. The user interface developed is shown in figure 2.

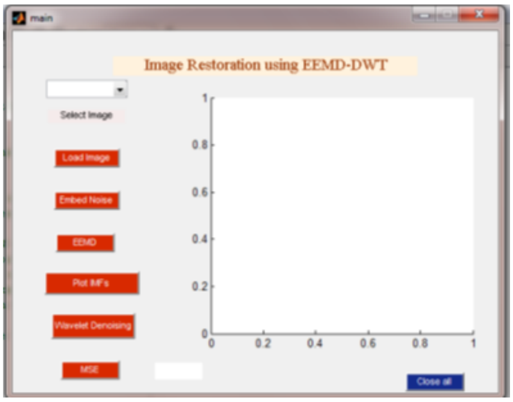
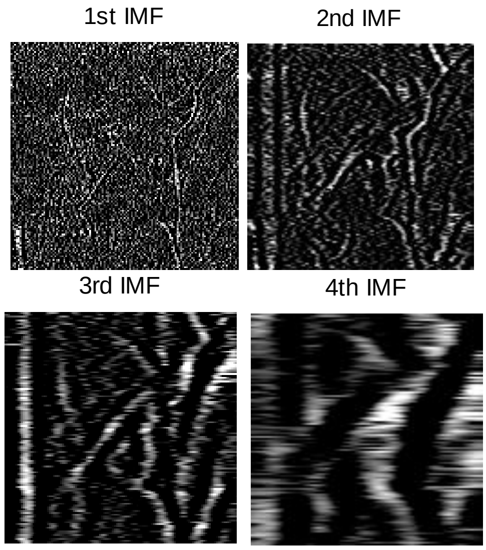


Fig 2: GUI used for proposed work

Initially we have loaded the lena image as input. As described in the algorithmic steps of previous chapter Gaussian noise is added into the input image after resizing it into 128*128. Figure 3(a) to (c) show the original, resized and noisy image after addition of Gaussian noise. Gaussian is chosen as it is the most common noise added when image is passed through any communication channel. The original image is resized into 128*128 pixels keeping major information. To denoise it first EEMD algorithm is applied to the noisy image. This algorithm calculates 6 IMF for this image. The number of IMFs calculated depends upon the information in the image as in each iteration cubic spline envelope is calculated and IMFs are calculated till maximum and minimum cubic spline envelope can be detected. Here in this case only 7 IMFs can be calculated. These IMFs have some information of the image as shown in figure 4. The information contained in the 1st IMF is maximum and decreases further. This is because initially maximum and minimum envelope developed contains highest peaks values for both and value decreases for further IMF. That's why last IMF has no information and can be considered as residual.

Fig 3(a) Input image (b) resized Image (c) Noisy Image



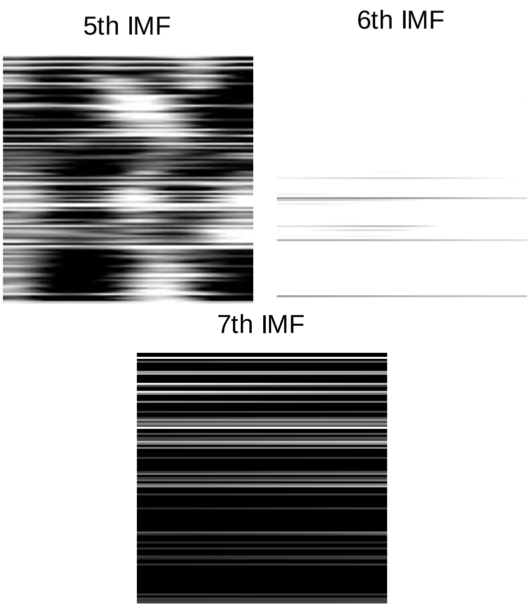


Fig 4: All 7 IMFs of input image

Now each IMF is passed through the wavelet packet filters which break each IMF into 4 different coefficients. The approximation coefficient has the maximum information so it will be considered for thresholding purpose. For denoising wavelet packet thresholding is used and in that also hard thresholding is used to denoise. MATLAB's image processing toolbox has inbuilt function 'ddencmp' to automatically determine thresholding and even type of thresholding. 'wpdencmp' is the MATLAB command which denoise the noisy image. After denoising all IMFs by above said method filtered image is shown in figure 4.6. when all IMFs are denoised by above process then they will be recombined by just adding them.

Image = IMF1+IMF2+..........IMF7

Result of this is shown in figure 5. the mean square after adding Gaussian noise is 10.1830.

Fig 5: Denoised Image

Images have been categorized into three types: low key image, medium key image and high key image and they are categorized on the basis of histogram as shown in figure 6 below.

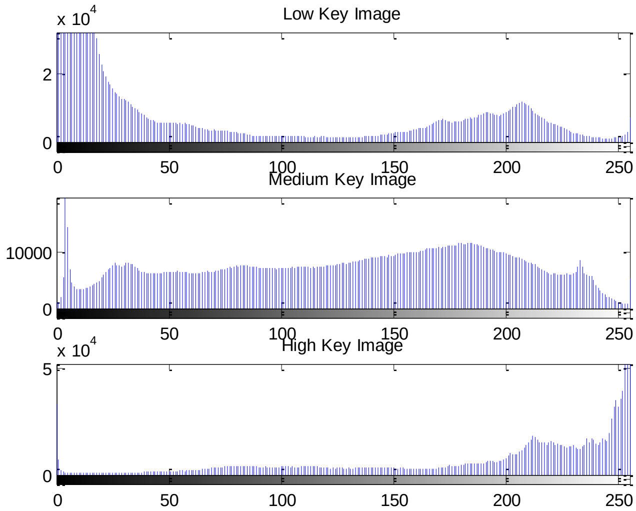


Fig 6: Histograms of images

These all images are taken as input and a table 4.1 shows the MSE values for different input images.

Table 4.1: MSE values for different images

	MSE
Lena	20.3076
Low Key Image	17.4914
Medium Key Image	20.129
High Key Image	16.5206

A bar chart showing this is shown in figure 7 which clearly depicts the MSE value for different images. It clearly shows that for high type of images MSE is lowest as addition of noise affects less on high intensity image.

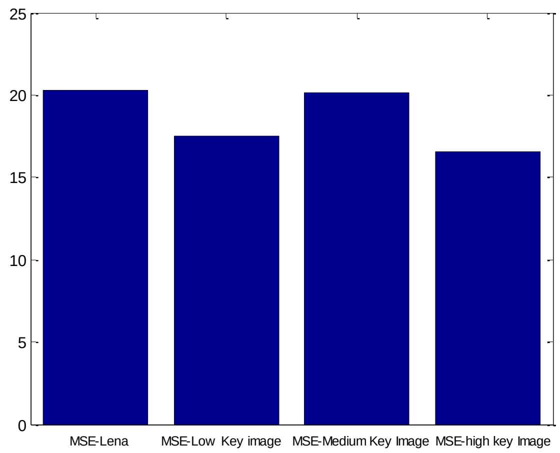


Fig 7: bar graph showing MSE values for different input images

IV. CONCLUSION

This paper presents a comparative analysis of various image denoising techniques using wavelet transforms. A lot of combinations have been applied in order to find the best method that can be followed for denoising intensity images. The image formats that have been used in this work are JPG, BMP, TIF and PNG, but all has to be converted into BMP. The analysis, of all the obtained experimental results, demonstrates that EEMD-DWT outperforms DWT for denoising all of the above mentioned images (whether the low pass components are thresholded or are kept as such).

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