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Image Decomposition Using Wavelet Transform

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Abstract: ***In this work, image has been decomposed on wavelet decomposition technique using different wavelet transforms with different levels of decomposition. Two different images were taken and on these images wavelet decomposition technique is implemented. The parameters of the image were calculated with respect to the original image. Peak signal to noise ratio (PSNR) and mean square error (MSE) of the decomposed images were calculated. PSNR is used to measure the difference between two images. From the several types of wavelet transforms, Daubechie (db) wavelet transforms were used to analyze the results. The value of threshold is rescaled for denoising purposes. De-noising methods based on wavelet decomposition is one of the most significant applications of wavelets.***

Keywords: Haar, daubechie, Symlet, wavelet, PSNR, image decomposition.

1. Introduction

Image processing is required to remove unwanted noise so that the quality of the processed image does not deteriorate [1-3]. Generally, the noise is removed using some specified filters. Several methods have been reported to remove such noises form the stationary digital images [4]. Discrete wavelet transform (DWT) is one of the recent wavelet transforms used in image processing. DWT decomposes an image into different sub images [5]. Denoising algorithm using DWT requires the decomposition of noised images to get the wavelet coefficients [6-8]. These coefficients are then denoised with wavelet threshold. Finally, inverse transform is applied to the coefficients and get denoised image [9]. This process is called the reconstruction of an image using decomposition or analysis of applied noised image. DWT decomposes an image into different sub band images, namely low-low (LL), low- high (LH), high-low (HL), and high-high (HH). The subband (LL) is the low resolution residual [10] [11]. The wavelet-thresholding de-noising method filters each coefficient from the detail subbands with a threshold function to obtain modified coefficients. The de-noised estimated by inverse wavelet transform of the modified coefficients. Here, the threshold plays an important role in the de-noising process [12]. There are two thresholding methods frequently used. The soft-threshold function and the hard thresholding function. The wavelet thresholding procedure removes noise by thresholding only the wavelet coefficients of the detail sub-bands, while keeping the low resolution coefficients unaltered [13]. Hard thresholding is a keep or kill rule whereas soft thresholding shrinks the coefficients above the threshold in absolute value [14]. 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 [15] [16]. Finding an optimum threshold is a tedious process [17]. 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.

In this paper, wavelet decomposition technique is applied to filter the input image for enhancing the quality. A specific threshold value is determined to decompose the original image. Finally, filter is applied for image enhancement.

2. Experiment

In this experiment, a single decomposition level has been taken into account using a discrete wavelet packet. The input image is decomposed at depth 3 with daubechie (db1) wavelet using default entropy (shannon). The steps taken into consideration are shown in fig. 1 in the form of the flow chart. From the flow chart, it is simple to explain that the original input image is first decomposed. In a program, the image is read in the form of matrix and the image is decomposed upto n levels that produce 2^n different sets of coefficients. For this experiment, the value of n is selected as 3. After decomposition, another output can be taken as the synthesized image. The synthesized image may be little or more noisy as compared to the input image. The synthesized image is then denoised using wavelet transformation by computing various parameters of the selected filter.

The threshold value is selected for different sub-band to determine the scale parameter. Soft thresholding is applied to sub-bands to reconstruct the denoised image. After getting the denoised image, the final step is to calculate the image parameters like PSNR and MSE. PSNR is used to measure the difference between two images. It is defined as

$PSNR = 20 * log10(b/rms)$

where b is the largest possible value of the signal (typically 255 or 1), and rms is the root mean square difference between two images. The PSNR is given in decibel units (dB), which measure the ratio of the peak signal and the difference between two images [18] [19]. An increase of 20 *dB* corresponds to a ten-fold decrease in the rms difference between two images.

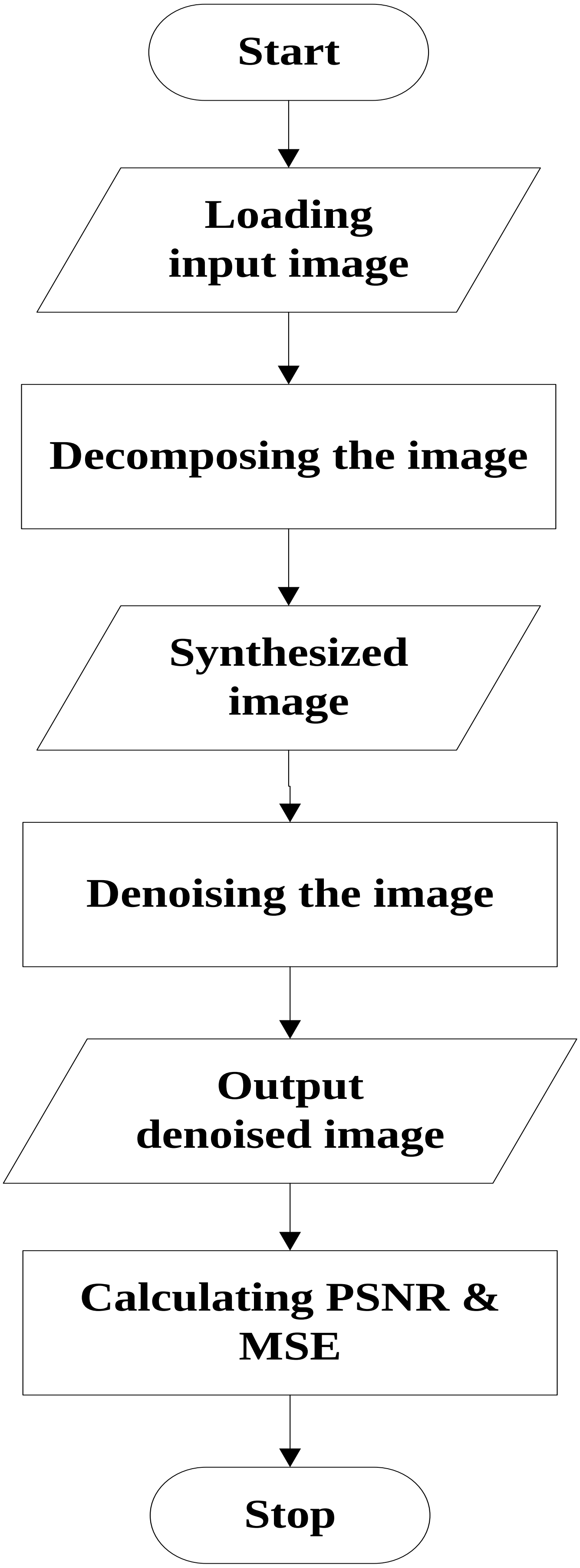

Figure 1: Work flow showing procedural steps used in experiment.

There are many versions of signal-to-noise ratios, but the PSNR is very common in image processing, probably because it gives better-sounding numbers than other measures. Mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated [20].

3. Results and Discussions

Fig. 2 shows the original input image that has to be processed using wavelet transformation. In the orthogonal wavelet decomposition procedure, the generic step splits the approximation coefficients into two parts.

Figure 2: Original inpuit image

After splitting we obtain a vector of approximation coefficients and a vector of detail coefficients, both at a coarser scale. The information lost between two successive approximations is captured in the detail coefficients. Then the next step consists of splitting the new approximation coefficient vector, successive details are never reanalyzed. Figure 3 shows the decomposed image at depth 3 with daubechie (db1) wavelet.

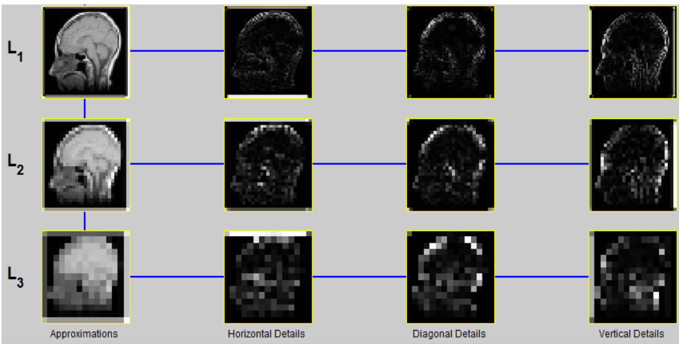

Figure 3: Decomposed wavelet image

In the corresponding wavelet packet situation, each detail coefficient vector is also decomposed into two parts using the same approach as in approximation vector splitting. This offers the richest analysis. The complete binary tree is produced in the one-dimensional case or a quaternary tree in the twodimensional case. Figure 4 shows the synthesized image using wavelet transformation.

Figure 4: Synthesized image

Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. It removes noise by killing coefficients that are insignificant relative to some threshold. Soft thresholding shrinks coefficients above the threshold in absolute value. Figure 5 shows the reconstructed image after denoising. Different threshold levels were used to optimize the good quality output. Hence, the 3 different threshold levels selected were, L1= 141.2, L2=87.92 and L3=57.

Figure 5: Denoised output image

Finally, the PSNR and MSE are calculated and the results showed that the value of MSE is 0.3632. The MSE and PSNR were calculated in-between the original input image and that of the output reconstructed image. Similarly, the value of PSNR is found to be 52.53 with compression ratio of 84.78%.

4. Conclusion

From the obtained results, this can be concluded that the denoising of digital input images using daubechie wavelet is effective for image reconstruction. An input digital image is processed using daubechie (db) at depth 3. Analysis shows that half of the interpolation factor was used for exclamation of the different frequency subbands. During compilation, the decomposed image has been denoised to generate a super resolved imaged. The proposed experiment shows good and economical denoising method while calculating PSNR and MSE. A visual result confirms that the proposed technique is better than the conventional and image enhancement technique.

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