An Efficient Ultrasound Image Compression and Decompression Using DWT and Bayesshrink Algorithm

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Abstract

This paper proposes an idea to compress and decompress an ultrasound image with better reconstruction when compared to the existing systems by using the data-driven threshold for image denoising via wavelet soft-threshold and Bayesshrink algorithm. The threshold is derived in a Bayesian framework. The Wavelet transform is capable of providing the time and frequency information simultaneously. So that it enables the easy application of algorithms for compression and decompression. The reason for choosing an ultrasound image is that they are complex in resolution. This proposed technique achieves high PSNR (Peak Signal to Noise Ratio) and a low MSE (Mean Squared Error), when compared to the existing systems.Thus the experimental result shows that the proposed compression method does indeed remove noise significantly.

Keywords: *Ultrasound Image, Wavelet, Bayesshrink, Bayesian framework, threshold, PSNR, MSE, Compression, decompression*

1. Introduction

Image compression is one of the most typical applications of digital signal processing. The large number of medical imaging techniques, together with the increasing importance of digital imaging in the field of radiology makes the compression of medical images, both for transmission and for storage purpose, more and more important. In recent years, there has been an increased interest in the investigation of efficient methods for medical image compression without significantly degrading the quality. No single approach to the measurement of quality or of diagnosis accuracy has gained universal acceptance. However, three general approaches are popular: computable objective distortion measures such as mean squared error (MSE) or signal to noise ratio (SNR), subjective evaluation based on psychovisual tests or questionnaires with numerical ratings and statistical analysis based on clinical simulations. It goes without saying that lossy compression techniques are acceptable for medical applications only if the clinically useful information is preserved in the decoded image. On the other hand, compression of medical images has become mandatory for clinical picture archiving and communication system (PACS), as well as for the development of computer based telemedicine network [1]. Among the various medical imaging techniques, ultrasonic imaging has become an important modality, mainly because of the nature of the ultrasonic radiation, which poses negligible risk to both the patient and the examiner, and also in part due to its real time capability for observing cardiac structures in motion. However, images produced by sonic methods, are of relatively poor quality. Typical image degradation includes multiplicative and additive high frequency noise, blurring of spatial information perpendicular to the direction of sonic waves propagation, distortion in regions which are adjacent to the transducer and speckle noise [2].

This paper deals with image compression and decompression of ultrasound images. Before any algorithm is applied on an image, it has to be transformed to a simpler form. 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 compression technology used here is the Bayesshrink algorithm. Through compression, the noise ratio is reduced also. To achieve a better comparison, another existing compression algorithm called the Block Truncation Coding is implemented here. The proposed system out performs this system and thereby produces a good result.

The ultrasound images are used as they are complex in their resolution. The discrete wavelet transform is applied here. While the other transforms give a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions. It is easy to implement and reduces the computation time and resources required. Also the compression algorithm used is the Bayesshrink algorithm. It has low complexity and is capable of producing reconstructing a better image and also removes noise. In the existing systems the reconstruction of the image produces a lower PSNR (Peak Signal to Noise Ratio) and higher MSE (Mean squared Error) value.

2. An account of the existing systems

There are quite few existing systems for image compression and decompression as this area have attained importance since it deals with large amount of data.

The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where scalability is important [3]. There is another transform used in the existing systems. It is the discrete cosine transform. Only spatial correlation of the pixels inside the single two dimensional blocks is considered and the correlation from the pixels of the neighboring blocks is neglected. It also does not perform efficiently for binary images [4]. The image used in the proposed system is ultrasound. These types of images are complex in their resolution. Hence a good reconstruction is hard to attain. Two of the most commonly used existing compression algorithms are given below.

2.1.1 Block Truncation Coding

Block Truncation Coding is a type of lossy image compression technique for images. It divides the original images into blocks and then uses a quantizer to reduce the number of grey levels in each block whilst maintaining the same mean. In this method, the pixels are considered as matrices. The mean of the pixel values are calculated and the pixel values are compared with the mean. Based on the values the pixels are converted to zeros and ones, resulting in the encoded image. Two reconstruction levels are also calculated. While decompression, these reconstruction levels are used to reconstruct an image similar to the original [5]. The PSNR and MSE values are calculated from the decompressed image. Most statistical image compression methods are implemented by segmenting the image into non-overlapping blocks, since dividing the images into blocks allows the image compression algorithm adapt to local image statistics [6]. The disadvantage, however, is that the borders of the blocks are often visible in the decoded image.

2.1.2. MSPHIT

SPHIT is a simple and compression algorithm with many unique and desirable properties. A modified version of the SPIHT (Set Partition in Hierarchical Trees) algorithm is MSPIHT. The main difference from the original SPIHT algorithm concerns the memory structure. The SPIHT algorithm, designed mainly for SW implementation, uses dynamic structures, such as linked lists. On the contrary, the MSPIHT algorithm uses static bitmaps which represent the significant information. Its PSNR and BER are considerably higher than the SPIHT method [7][8].

3. Materials and methods of the proposed system

There are quite few existing systems for image compression and decompression as this area have attained importance since it deals with large amount of data. A good reconstruction is the one that produces a visually pleasant image, low MSE and high PSNR. The algorithm used in the proposed system is Bayesshrink, which is an effective compression technique that produces good reconstruction. This proposed technique has been implemented by using four different modules like (i) Discrete Wavelet Transform (ii) Encoding (using Bayesshrink Algorithm) (iii) Decoding (using Bayesshrink Algorithm). The implementation of the proposed technique is shown in Figure.1

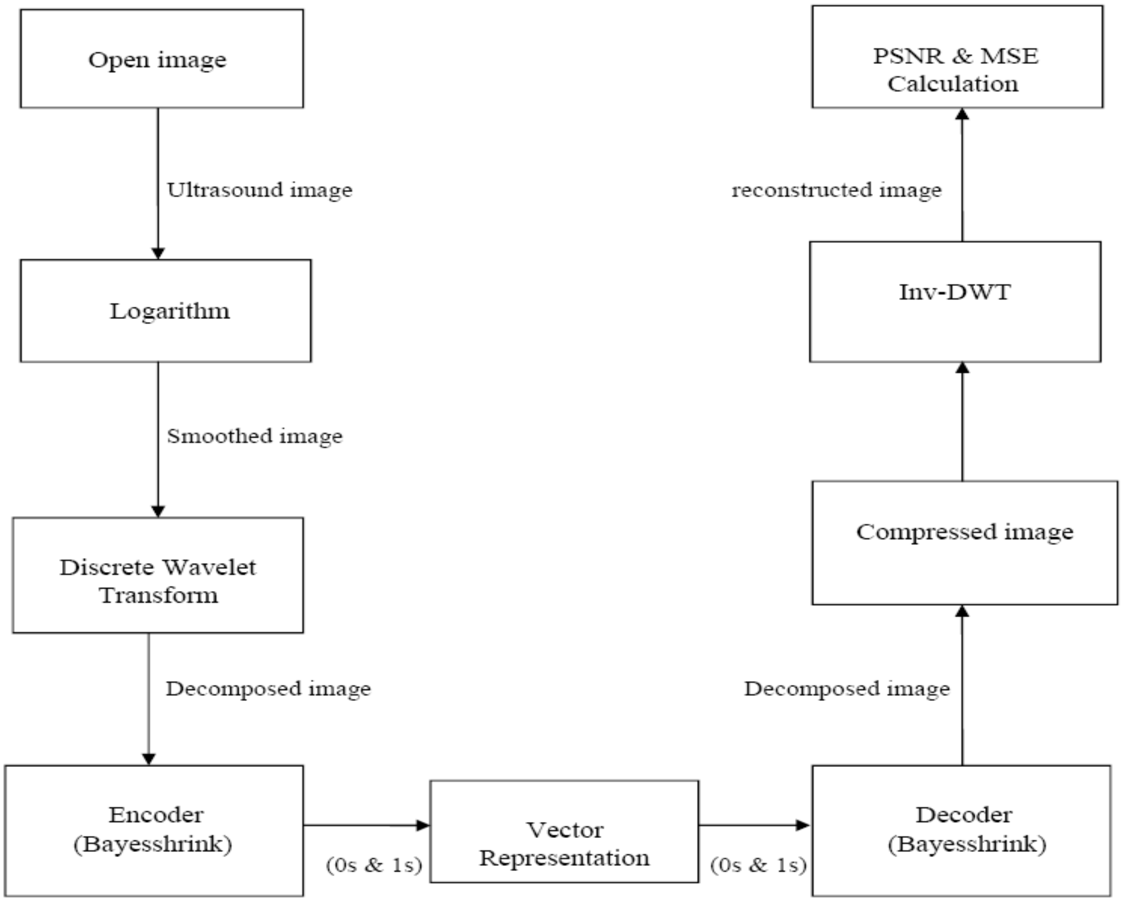

Figure 1. Block diagram of the Proposed System

3.1. Discrete Wavelet Transform(DWT)

Wavelet-based Coding is a new technique where instead of using a fixed wavelet filter for coding and decoding all images, different filters are used for different images. Since there is no single filter that gives the maximum PSNR for all images, adaptive selection and usage of wavelet filters improves the coding performance. Some of the smoothing filters used here are Daubechies wavelet filter (db8) and Median filter. Non linear filters are preferred as they have reduced computational complexity, improved quality and reduced storage space requirements. If the performance of the wavelet filter is poor in the first place, the schemes for quantization and entropy encoding, however elegant they are, may not always provide adequate compensation to maintain significant picture quality. A wavelet filter which produces lowest MSE(Mean Squared Error), highest PSNR(Peak Signal to Noise Ratio) and compression ratio, when an image is transformed and compressed is the best filter. The median filter is normally used to reduce noise in an image. However, it often does a better job of preserving useful detail in the image than some filters like the mean filter.

The Figure.2 depicts how the discrete wavelet transforms works. There are two types of filters used in this transform. They are the high pass filter and low pass filter. In the low pass filter, the low frequency signals are allowed to pass through with no problem but the high frequency signals are attenuated. In the high pass filter, the high frequency signals are passed through and the low pass frequencies are stopped. The low frequency components (smooth variations) constitute the base of an image and the high frequency components (the edges which give the detail) add upon them to refine the image, thereby giving a detailed image. Hence, the smooth variations are demanding more importance than the details.

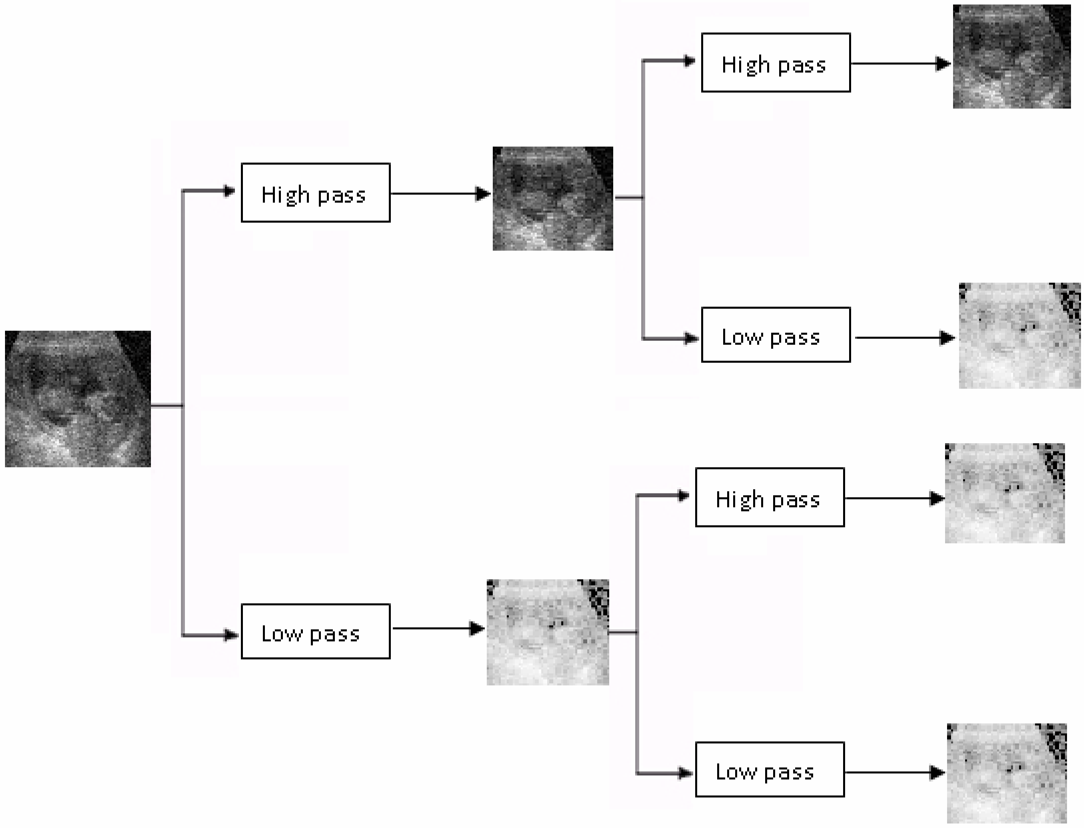

Figure 2. Tree representing the Discrete Wavelet Transform

The signal 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. An image can be decomposed into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL, LH, HL and HH as shown in Figure.2

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. This is because the noise interference is more in the low frequency signals. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded. Usually three level decomposition is done. The LL band is further decomposed to four more sub bands and all the useful information of the image is stored in one corner of the image. Once the image is decomposed, any thresholding algorithm, that is, compression algorithm can be applied. The Figure.3 shows the output of the discrete wavelet transform on an ultrasound image.

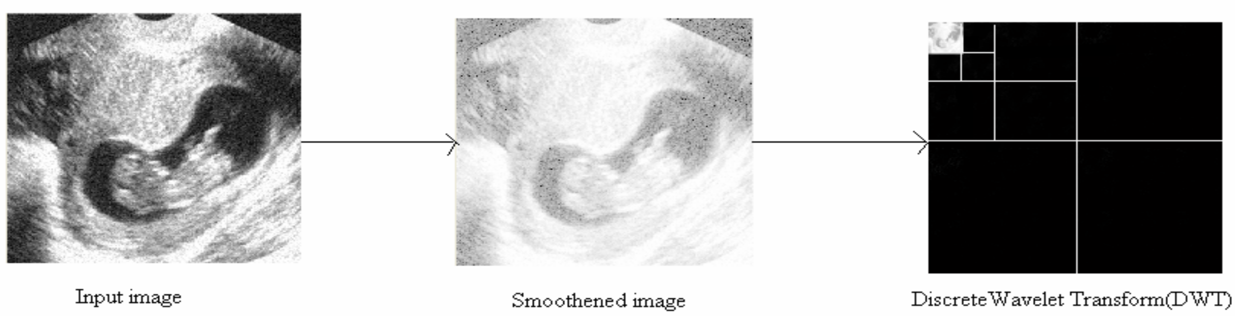

Figure 3. Discrete Wavelet Transform applied on ultrasound image

3.2. Encoding

The decomposed images are encoded using the Bayesshrink compression algorithm. Any regularity in a given set of data can be used to compress the data, i.e. to describe it using fewer symbols than needed to describe the data literally. This hypothesis gives the best compression as it captures the most regularity in the data. This module can also be referred to as the thresholding module. Properly thresholding the wavelet coefficients of a signal corrupted by noise can remove the noise and preserve the signal.

In the bayesshrink method, a threshold is set. There is no close form to find threshold. So we assume the generalized Gaussians for each subband to find the threshold.

$$\lambda = \frac{\hat{\partial}^2_{noise}}{\hat{\partial}_{signal}} \tag{1}$$

In the above equation(1), λ is the thresholding variable. For estimating the noise level (σ^2_{noise}), we use the relation proposed by Donoho given in Equation 2. The signal variance is given in the Equation 3. Here y_{ij} belongs to the sub band HH of the first level decomposition. The median of it is taken and applied in the Donoho's noise variance equation.

$$\sigma^2_{noise} = \left(\frac{Median \quad | y_{ij} |}{0.6745} \right)^2 \tag{2}$$

Where y_{ij} belongs to the sub band HH of the first level decomposition. The signal variance is taken in the threshold equation is calculated using the formula given below

$$\hat{\sigma}_{signal} = \sqrt{\max\left(\hat{\sigma}^2_y - \hat{\sigma}^2_{noise}, 0 \right)} \tag{3}$$

This threshold value (λ) is compared with all the pixels in the image. If the threshold value is greater than the pixel, then the pixel is left as such. If not, it is replaced with 0. This constitutes the encoded image. The small coefficients in the subbands are dominated by noise, while coefficients with large absolute value carry more signal information than noise. Replacing noisy coefficients (small coefficients below certain value) by zero and an inverse wavelet transform may lead to reconstruction that has lesser noise. After this phase the MDL principle is applied.

The MDL (Minimum Description Length) Principle is that any regularity in a given set of data can be used to compress the data, i.e. to describe it using fewer symbols than needed to describe the data literally. This hypothesis gives the best compression as it captures the most regularity in the data. Each pixel is compared with its neighboring pixel. It is done horizontally, vertically and diagonally starting from the left corner. This takes place in the form of sub bands. Hence bits with the same MSBs are encoded at a time and sent as a cluster to the decoder. To compare the reconstructed image with the existing system, the PSNR value is estimated by using Equation 4.

$$PSNR = 10 \log_{10} \left[\frac{255^2}{MSE} \right] \tag{4}$$

Where, MSE denotes the Mean Square Error between the original and denoised images, and is given as

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{i=1}^{N} \left(x(i,j) - p(i,j) \right)^2 \tag{5}$$

Where, M - Width of image, N - Height of Image, P - Processed Image, X - Original Image

The above is the numerical analysis of the Bayesshrink algorithm. The encoded image is given in the Figure.4. Here the decomposed image as a result of discrete wavelet transform is thresholded using the Bayesshrink compression algorithm and the encoded image is obtained. The next module deals with the reconstruction of the image from the encoded image.

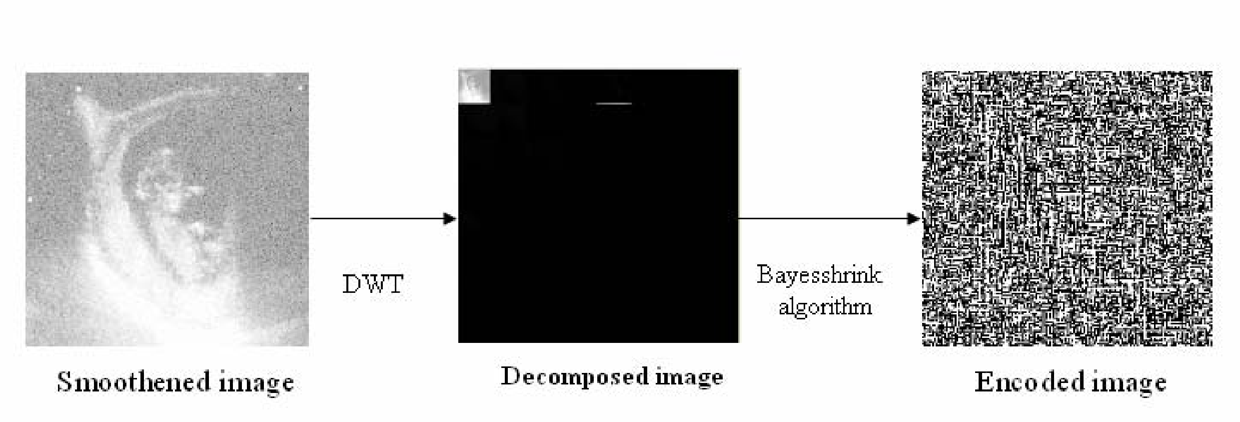

Figure 4. Representation of the Encoding process

3.3. Decoding

The decoder receives the image in the form of zeros and ones as a cluster from the encoder because bits with the same MSBs are encoded at a time and sent as a cluster. The same algorithm is applied to decompress the image. From the reconstructed image, the PSNR (Peak signal to noise ratio) and MSE (mean squared error) is calculated. This value is found to be improved than the existing systems. Also since the minimum description length method is used, perfect reconstruction is possible. Compression and decompression also removes the noise interference in the image and thus providing a good image. The decoded image is given in the Figure.5

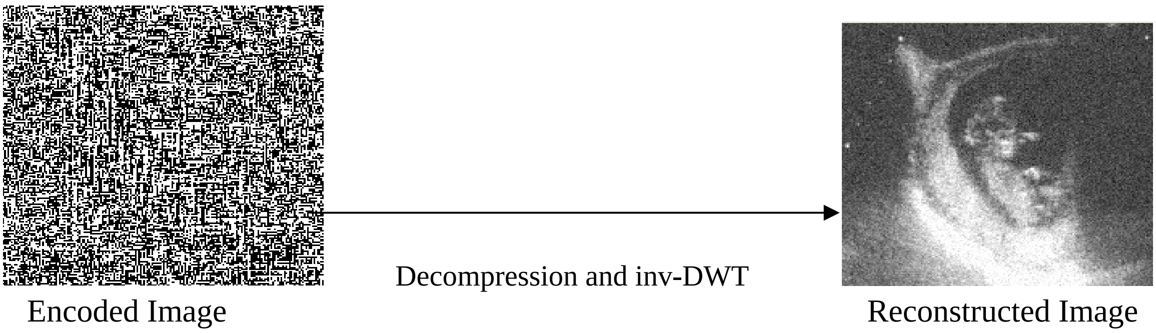

Figure 5. Representation of the Decoding process

The inverse discrete wavelet transform, which is the reverse of the discrete wavelet transform. The thresholding used here is the soft thresholding. Another type of thresholding is the hard thresholding. Soft thresholding is commonly used nowadays as it is more efficient. Hard thresholding is “keep or kill” procedure and is more intuitively. Moreover, it is also found to yield visually more pleasing images. In the Figure.6, the overall step followed to attain reconstruction is represented. In this figure, the prefilter is the median filter. The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values

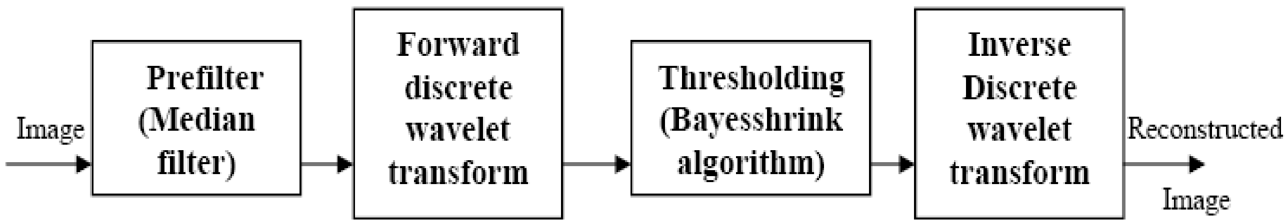

Figure 6. Steps in Reconstruction

The quality of any image after decompression is calculated with the PSNR (Peak Signal to Noise Ratio) and MSE (Mean Squared Error). PSNR is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. If the PSNR value is high then it is a reconstruction with high quality. The MSE value must to low to attain a good reconstruction and PSNR value. The PSNR value generated by the block truncation method is compared with the PSNR value generated by the Bayesshrink algorithm. It is seen that soft thresholding Bayesshrink algorithm together with discrete wavelet transform produce a better result.

4. Experimental results

This proposed method has been implemented by using MATLAB software. The output of each module has been shown as follows

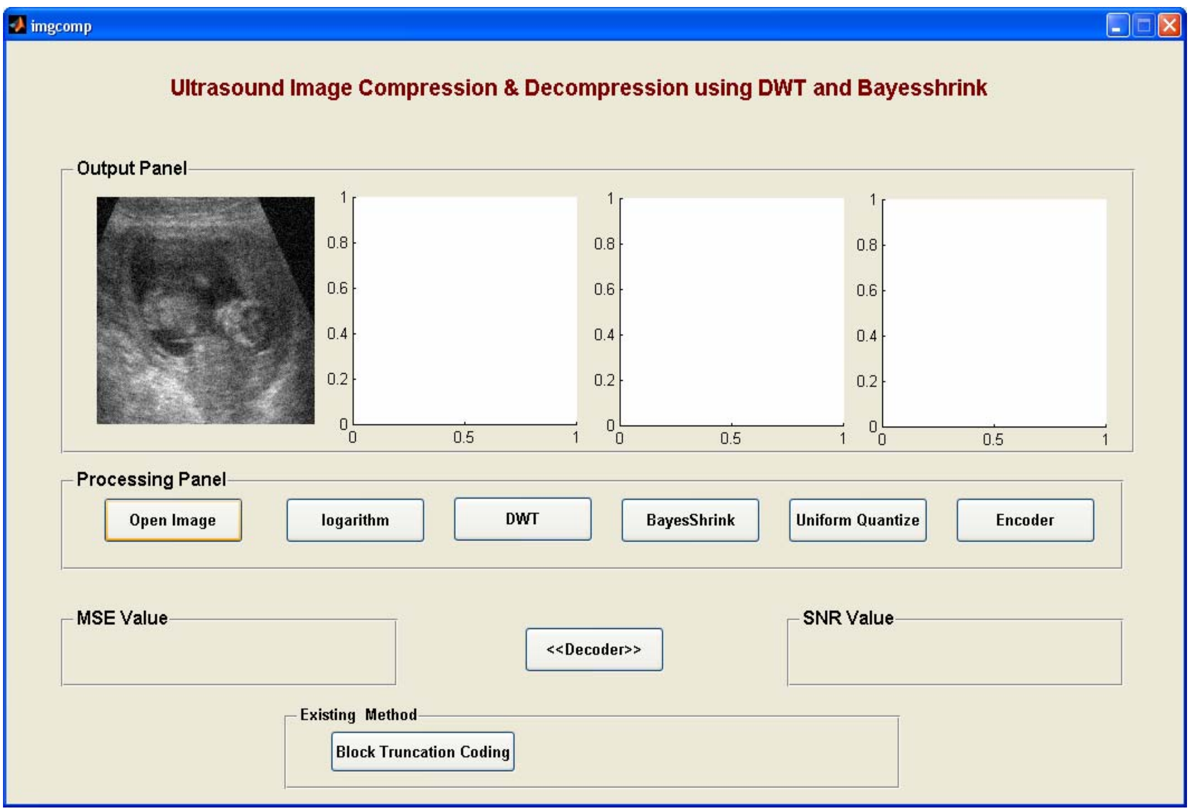

Figure 7. Opened image in the GUI window

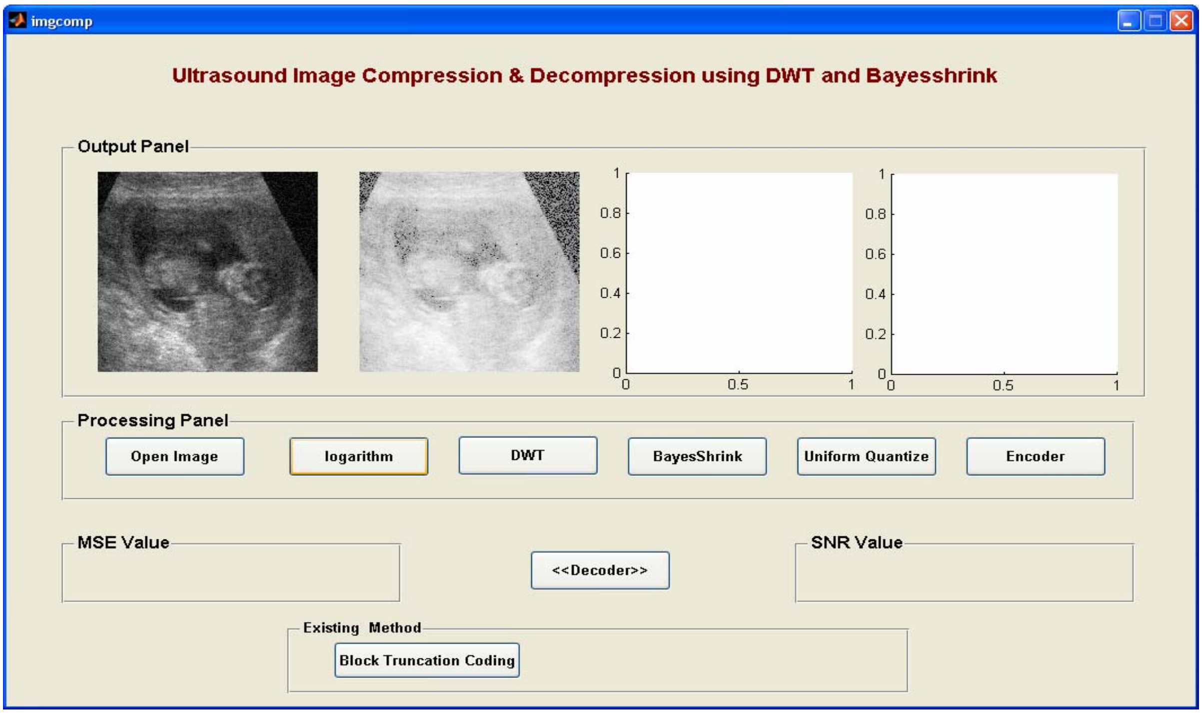

Figure 8. Smoothing process

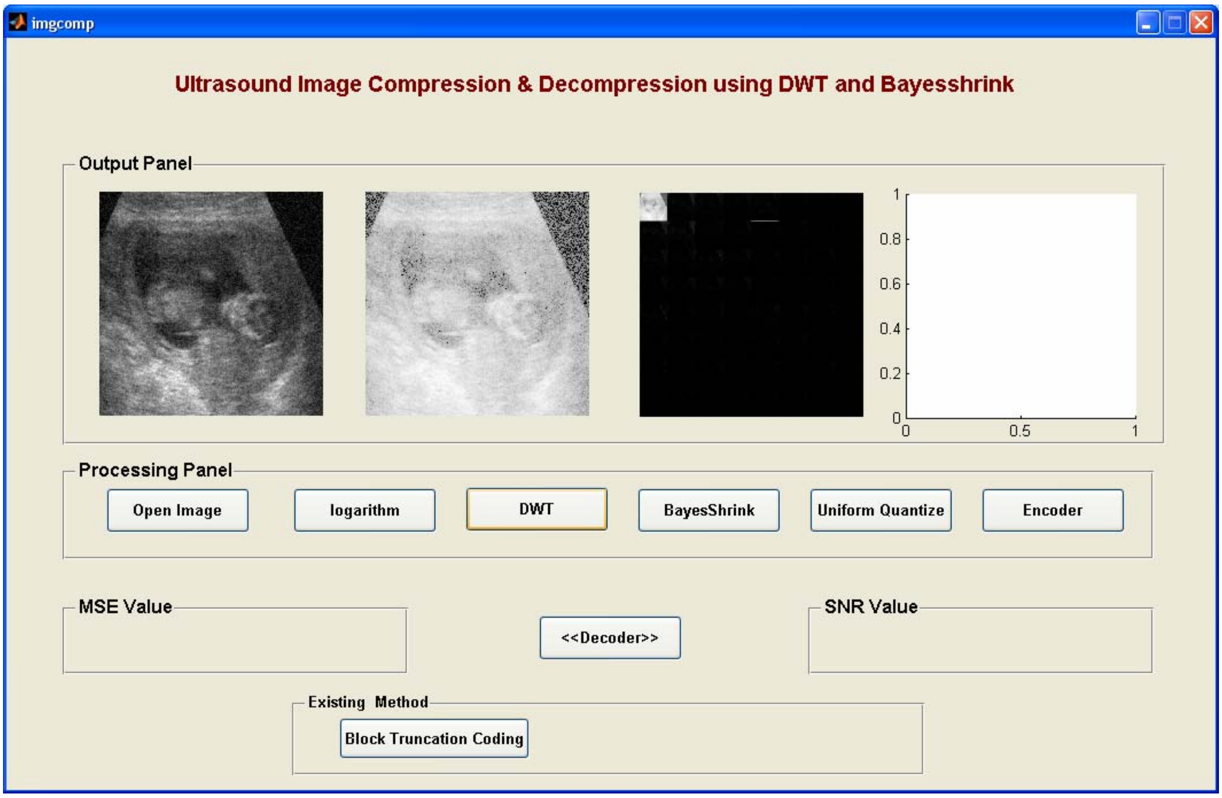

Figure 9. Discrete Wavelet Transform

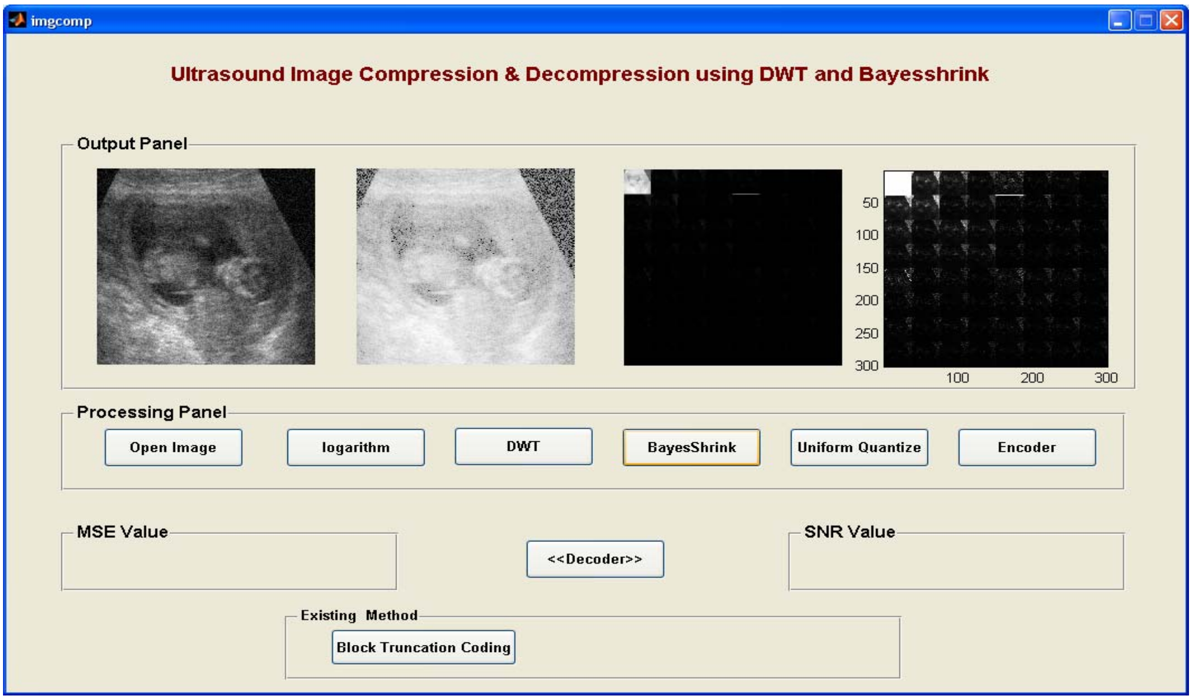

Figure 10. Bayesshrink thresholding

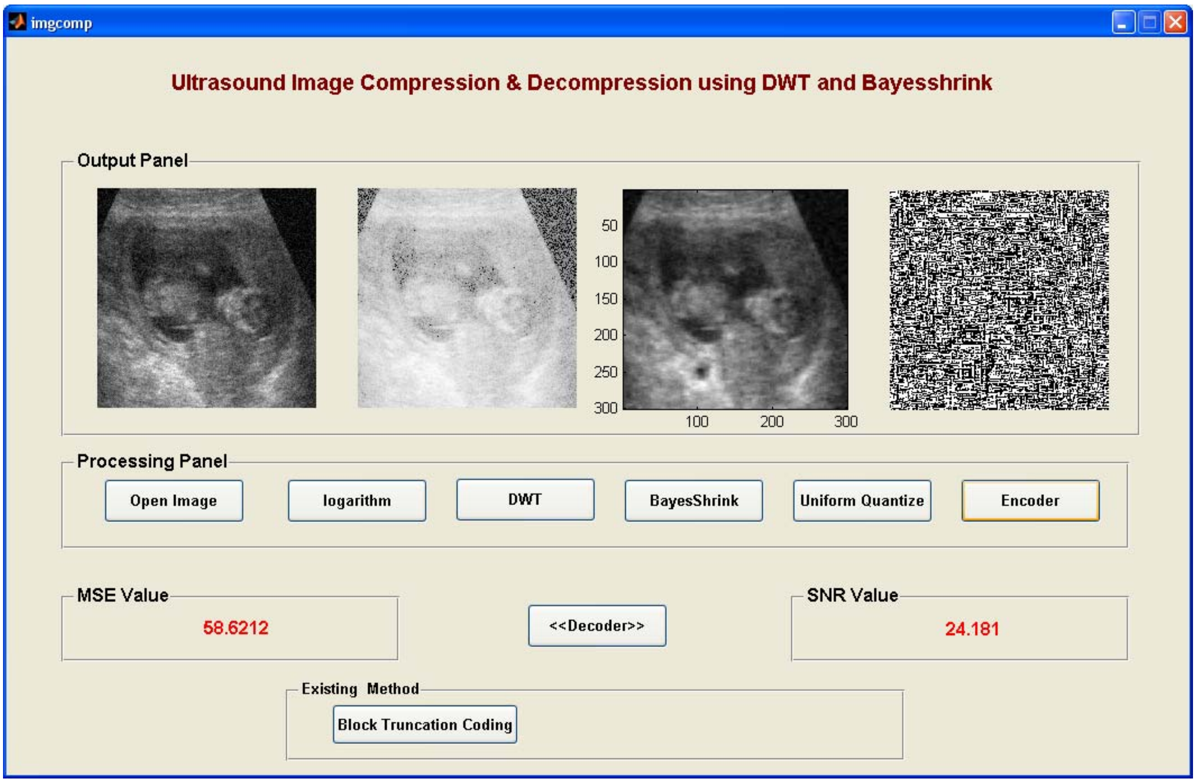

Figure 11. Encoding operation

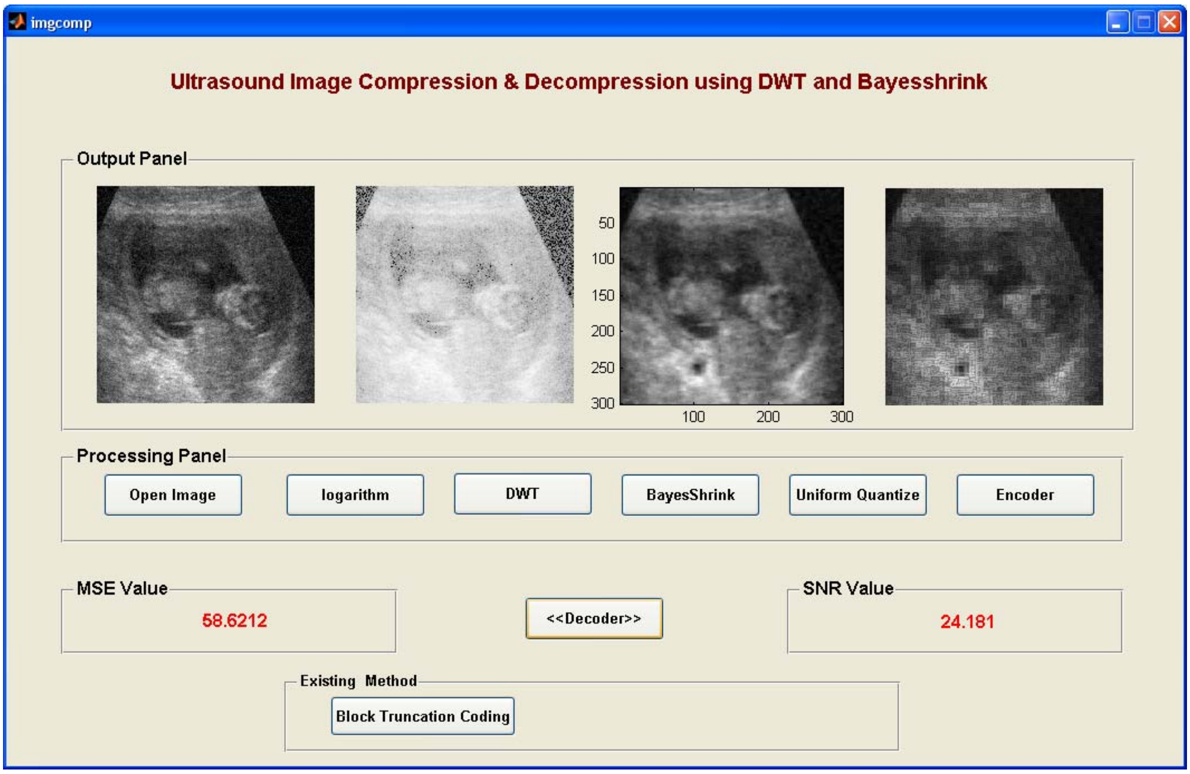

Figure 12. Decoding operation

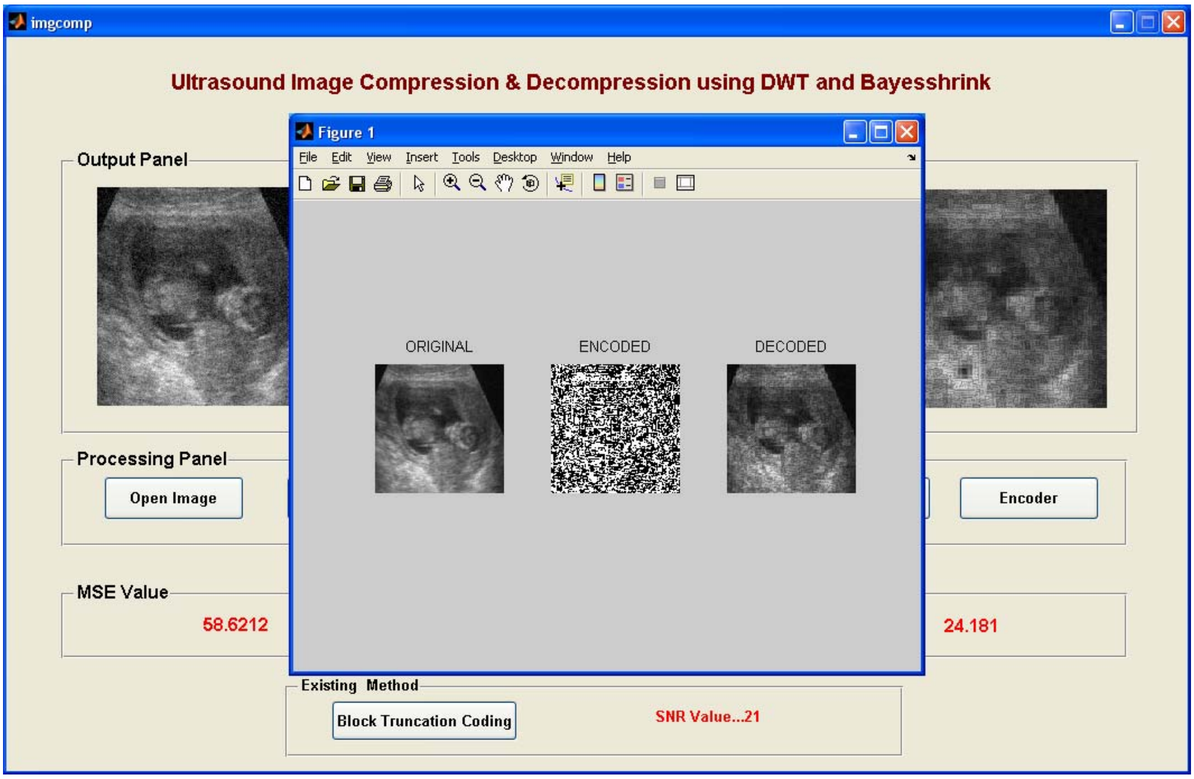

Figure 13. Encoding, Decoding and PSNR calculation

5. Conclusions and future scope

From the results, it is clear that the ultrasound image compression and decompression led to a better PSNR (Peak Signal to Noise Ratio) and lower MSE (Mean Squared Error) when compared to the existing systems. The discrete wavelet transform is the effective decomposition technique to reduce storage, transmission, and processing. The existing system with block truncation coding is compared with the proposed Bayesshrink algorithm. Though there is greater compression level with larger block sizes, in the block truncation method, quality reduces with the increase in block size due to the nature of the algorithm. The compression algorithm which uses Bayesshrink used in the proposed system, , is an efficient and subband adaptive nature. It is based on the modeling of subband coefficients. The image denoising algorithm uses soft thresholding to provide smoothness and better edge preservation at the same time. Also the issue of denoising was solved through compression. Hence the reconstructed image is far better when compared to the images reconstructed using other techniques.

In the future, this system can be improvised to achieve a better image quality by preventing the loss of bits during transmission in the channel. This can be done by using error correcting techniques in the decoding side. Also other new algorithms can be applied instead of the algorithms and methods used to attain a higher quality in image.

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