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Performance Analysis of Image and Audio Compression Technique using Discrete Wavelet Transform

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Abstract—

Signal compression reduces the number of bits of information required to store or transmit the signals. We have implemented a compression algorithm of Electro-cardiogram (ECG) signals using DiscreteWavelet Transform. The ECG signal to be compressed is decomposed to the desired level using the Daubechies family of wavelets. Threshold value selection should be such that the quality of the ECG signal is not distorted on reconstruction and a good amount of data reduction is also achieved. Also we have proposed an audio and image compression technique . We have also calculated file Compression Ratio and Energy retention in reconstructed signals.

Keywords—Wavelet Transform, threshold, energy retention, Daubechies

I. INTRODUCTION

Data Compression is using fewer bits than the original representation so that data can be transmitted over network easily if also we have a limited bandwidth[1]. Data compression is broadly divided into two categories lossless and lossy[11]. In lossless compression techniques no. of bits are reduced by identifying and eliminating statistical redundancy. No information is lost in lossless compression. Wavelets are mathematical functions that satisfy certain requirements. As the name suggest “wavelet”, it should integrate to zero, “waving” above and below the x-axis [2]. As opposed to fourier transform, which uses sines and cosines as basis functions, wavelet transform uses more complicated basis functions, called wavelets. Using discrete wavelet transform large and noisy data can be easily and quickly transformed. The data are coded by the wavelet coefficients. There are many applications of wavelets such as in biomedical applications, wireless communications and computer graphics [3]. One of the most visible application of wavelet is image compression. There is a large amount of spatial redundancy in a typical image where adjacent pixels have almost the same values. These pixel values are highly correlated [4].

Using the specific local properties of wavelets, we intend to compress various signals in our application assignment. The compression of continuous time-series data or signal (1D, 2D) is done for the purpose of reducing storage and transmission speed in various applications. The compression schemes using wavelet decomposition reduce redundancy and identify sparsity in the signal characteristics before coding the resulting coefficients.

ECG (ELECTROCARDIOGRAM) records the electrical activity of heart over a period of time. The overall electrical depolarisation of heart is captured at each moment throughout the cardiac cycle. These orderly pattern of depolarisation give rise to the characteristics of ECG tracing. These ECG signal convey a vast information about the structure and function of heart, any abnormality related to heart can be seen in ECG. But due to several artifacts, signal gets corrupted, Like

- Power line interference
- Electrode contact noise
- Instrumentation noise etc.

So our motive is to remove this kind of noisy signal and to make data representation efficient.

Also, We have compressed image and audio signals using discrete wavelet transform. This paper is organized as follows, Section II discuss about discrete wavelet transform. Section III includes wavelet audio compression technique. Section IV includes the results which simulated using MATLAB. In Section V there is a brief conclusion.

II. DISCRETE WAVELET TRANSFORM

The most important discovery for wavelet analysis is to construct perfect filter banks that could reconstruct using the coefficient sequences. The input signals are passed through high pass and low pass filters and are down sampled by two. The signal is reconstructed by up sampling and passing through high and low synthesis filters. The perfect reconstruction of the signal is based on the choice of the filter. DWT can be formed by cascading the analysis filter bank with itself number of times. DWT is a digital signal decomposition with dydadic frequency scaling.

A. DWT of an Image

DWT of an image as a 2D signal can be derived from 1D DWT. There exist three wavelet functions that scan details in horizontal, vertical and diagonal directions. This may be represented as a four-channel perfect reconstruction filter bank as shown in Fig. 1. Now, each filter is 2-D with the subscript indicating the type of filter (HPF or LPF) for separable horizontal and vertical components. The resulting four transform components consist of all possible combinations of high- and low-pass filtering in the two directions. By using these filters in one stage, an image can be decomposed into four bands. There are three types of detail images for each resolution: horizontal (HL), vertical (LH), and diagonal (HH). The operations can be repeated on the low–low band using the second stage of identical filter bank. Thus, a typical 2-D DWT, used in image compression, will generate the hierarchical pyramidal structure shown in Fig. 1(b). Here, we adopt the term "number of decompositions" to describe the number of 2-D filter stages used in image decomposition. A wavelet transform measures gray-level image variations at different scales. In the frequency domain, the contrast sensitivity function of the HVS depends on frequency and orientation of the details.

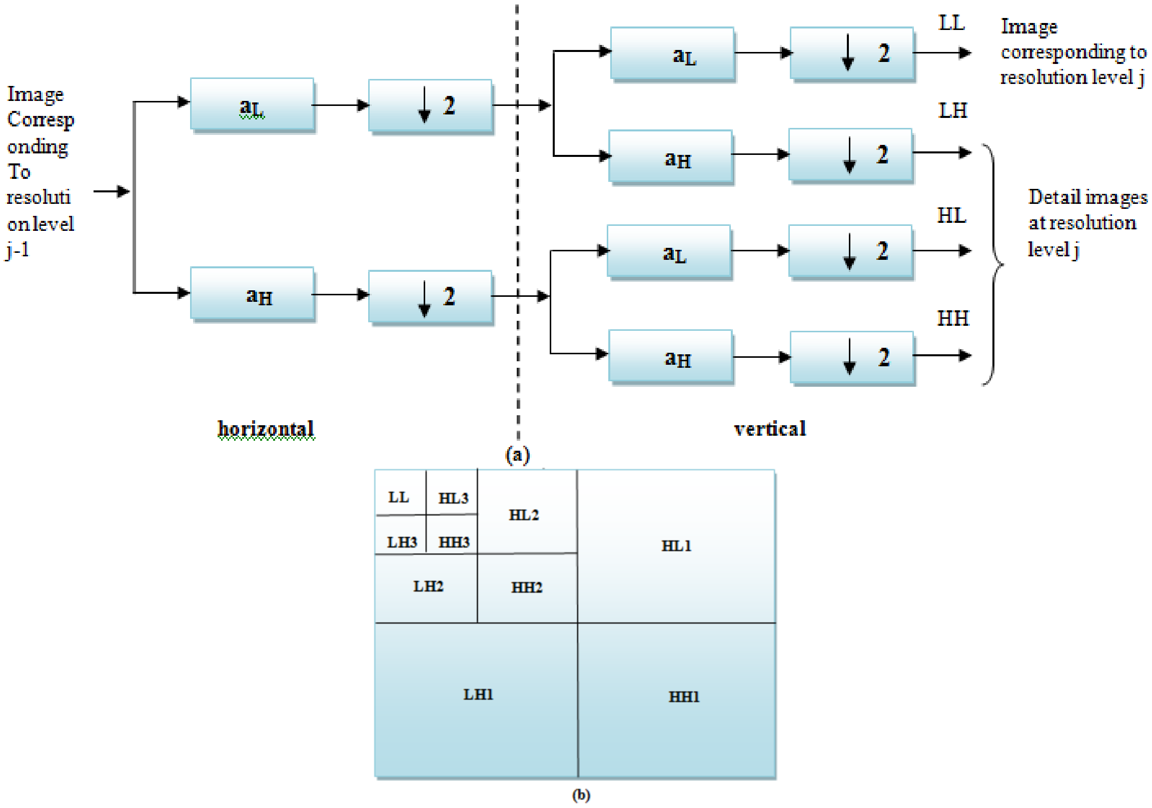

Fig.1 (a) One filter stage in 2-D DWT (b) Pyramidal structure of a wavelet decomposition

III. WAVELET AUDIO COMPRESSION TECHNIQUE

Audio Compression can be classified into three categories[5]:-

Waveform Coding: The Signal that is transmitted as input is tried to be reproduced at the output which would be very similar to the original signal.

Parametric Coding: In this, signals are represented in the form of small parameters which describes the signals very accurately.

Transform Coding: In this method the signal is transformed into frequency domain and then only dominant feature of the signal is maintained.

To compress the audio signal wavelets concentrate the signal information (energy and perception) into a few neighbouring coefficients [6]. Wavelet transform of a signal results many coefficients which are either be zero or have negligible magnitudes. We have to treat these small valued coefficients as insignificant data and thus discard them to achieve data compression.

A. Choice of Wavelet

The prime importance in designing the high quality audio coders is the choice of mother wavelet function. For an optimum wavelet audio compressor, the wavelet that has compact support in both time and frequency in addition to a significant vanishing moment has to be chosen. In general optimum wavelets can be selected based on the energy conservation properties in the approximation part of the wavelet coefficients. Wavelets with more vanishing moments provide better reconstruction quality, as they introduce less distortion into the processed speech and concentrate more signal energy in a few neighbouring coefficients.

However the computational complexity of the DWT increases with the number of vanishing moments and hence, for real time applications it is not practical to use wavelets with an arbitrarily high number of vanishing moments [7].

B. Wavelet Decomposition

Wavelets work by decomposing a signal into different resolutions or frequency bands, and choosing the wavelet function and computing the Discrete Wavelet Transform (DWT) carries out this task [8]. Signal compression is based on the concept that selecting a small number of approximation coefficients (at a suitably chosen level) and some of the detail coefficients can accurately represent regular signal components. Choosing a decomposition level for the DWT usually depends on the type of signal being analyzed or some other suitable criterion such as entropy. For the processing wof speech signals decomposition up to scale 5 is adequate [9], with no further advantage gained in processing beyond scale 5.

C. Truncation of Coefficients
Compression involves truncation of wavelet coefficients below a threshold after calculating the wavelet transform of the speech signal. In an experiment which is conducted on a male spoken sentence [6], shows that most of the coefficients have small magnitudes. More than 90% of the wavelet coefficients have less than 5% of the maximum value. This means the most of the speech energy is in the high valued coefficients, which are few [6]. Thus the small valued coefficients can be truncated or zeroed and then be used to reconstruct the signal.
Now, to truncate small valued coefficients, there are two thresholding techniques are used: Global Thresholding and By-Level Thresholding. In Global Thresholding the wavelet expansion of the signal is taken and the largest absolute value coefficient is kept regardless of the scale in the wavelet decomposition tree. Global thresholds are calculated by setting the % of coefficients to be truncated. In By Level thresholding visually determined level dependent thresholds are applied to each decomposition level in the wavelet transform. Level dependent thresholds are calculated using the Birge-Massart strategy [10].

D. Encoding Coefficients
After truncating the small valued coefficients these are efficiently encoded. One way to represent the high magnitude coefficients is to store the coefficients along with their respective positions in the wavelet transform vector [8]. Another way is to encode consecutive zero valued coefficient[6] , with two bytes. One byte to indicate a sequence of zeros in the wavelet transforms vector and the second byte representing the number of consecutive zeros. For further data compactness a suitable bit-encoding format, can be used to quantize and transmit the data at low bit rates. A low bit rate representation can be achieved by using an entropy coder like Huffman coding or arithmetic coding.

Algorithm for Audio compression
- Step 1: Select the mother wavelet.
- Step 2: Select the no. of vanishing moment.
- Step 3: Select the decomposition level.
- Step 4: Input the audio.
- Step 5: Decompose the audio up to selected decomposition level.
- Step 6: Calculate the threshold.
- Step 7: Truncate the wavelet coefficients which are below threshold.
- Step 8: Encode the zero-valued coefficients.
- Step 9: Decode the zero- valued coefficients.
- Step 10: Reconstruct the audio

IV. RESULTS
A. Performance Metrics
1) Compression Ratio: The compression ratio (CR) is defined as the ratio of the number of bits representing the original signal to the number of bits required to store the compressed signal. All data compression algorithms are used to minimize data storage by eliminating the redundancy wherever possible to increase the compression ratio. Compressed data must also represent the data with better fidelity while achieving high compression ratio. A high compression ratio is typically desired.

$$\text{CR} = \frac{Original\ Size}{Compressed\ Size}$$

2) Energy Retention: The L2(R) norm of a signal gives its energy. The energy retention (ER) parameter is defined as

$$\text{ER} = \frac{\text{Energy Content of Reconstructed Signal}}{\text{Energy Content of Original Signal}} \text{ X } 100$$

Higher the ER, The closer we have reached towards the original signal. From the compression algorithm used we have seen that better the compression ratio (CR), the more approximated is the reconstructed signal. Hence, the ER value decreases. Generally by the wavelet decomposition and reconstruction technique we are almost able to retain 99% of energy of the original signal.
3) SNR (Signal To Noise Ratio):

$$\text{SNR} = 10.\log_{10}\left(\frac{\sum_x 2}{\sum_e 2}\right)$$

Σx^2 is the mean square of the speech signal and Σe^2 is the mean square difference between the original and reconstructed signals.
4)PSNR (Packet Signal to Noise Ratio): It is Defined as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

The PSNR (in dB) is defined as:

$$\text{PSNR} = 10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

B. Results

Fig:2(a) shows the original ECG data of lead-1 and lead-2 signals for 2048 sample taken from MIT-BIH ECG Compression test database. Fig:2(b) shows the reconstructed lead-1 and lead-2 signals with Thr-1 and Thr-2 of 24.0353 and 23.1429 respectively. The wavelet used for decomposition and reconstruction is Daub-4.

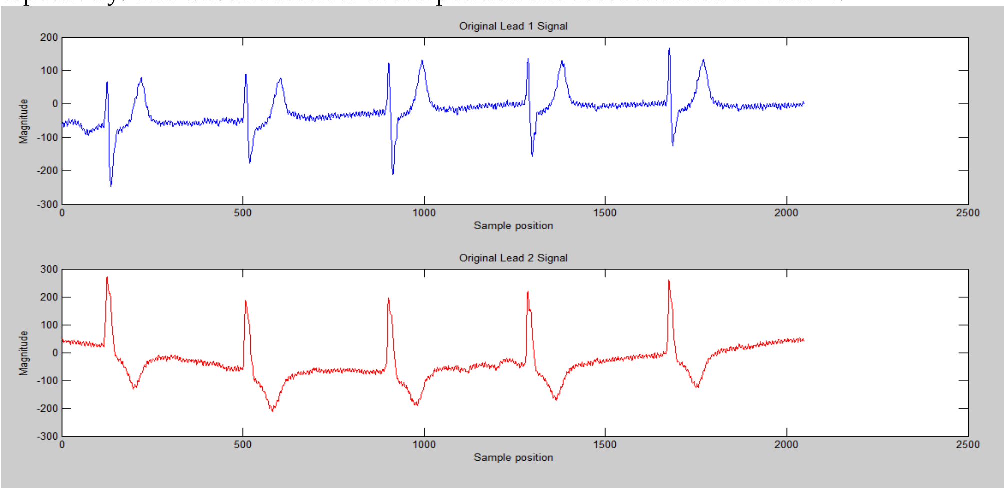

Fig.2 (a) Original Data

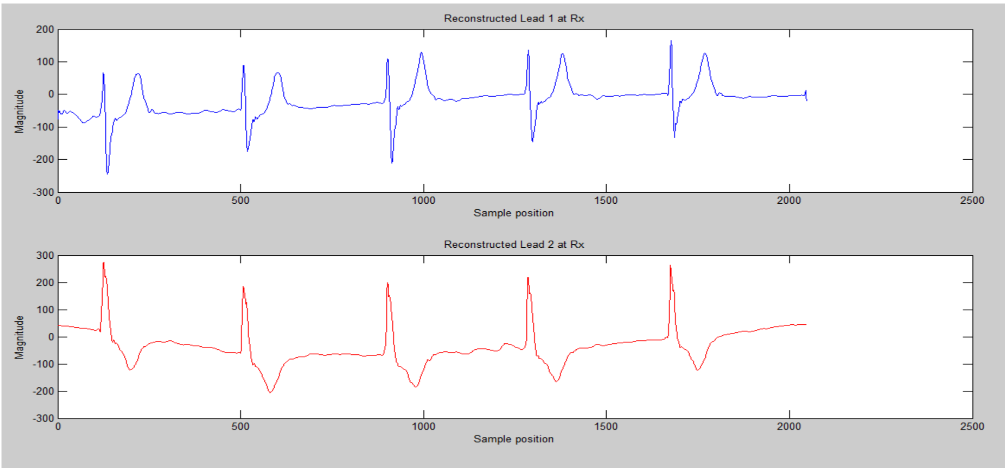

Fig.2 (b) Reconstructed Data

Fig.3 shows the plot of compression ratio versus decomposition level for different daubechies wavelets. Here the threshold value depends on the particular wavelet and are not same for the plots.

Fig:4 shows the plot of Energy Retention in lead-1 versus decomposition level for different daubechies wavelets. Here the threshold value depends on the particular wavelet and are not same for the plots.

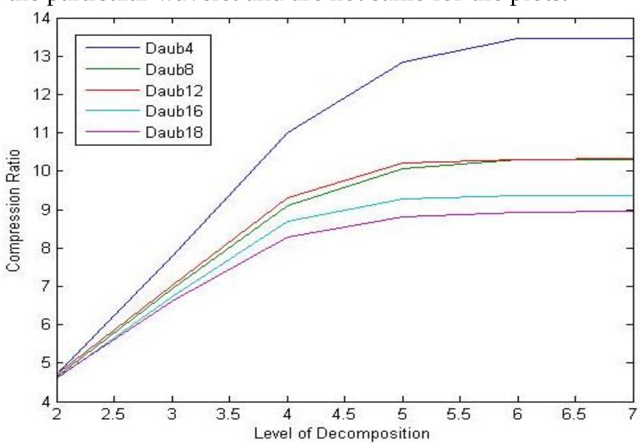

Fig. 3. Compression Ratio Vs levels of decomposition

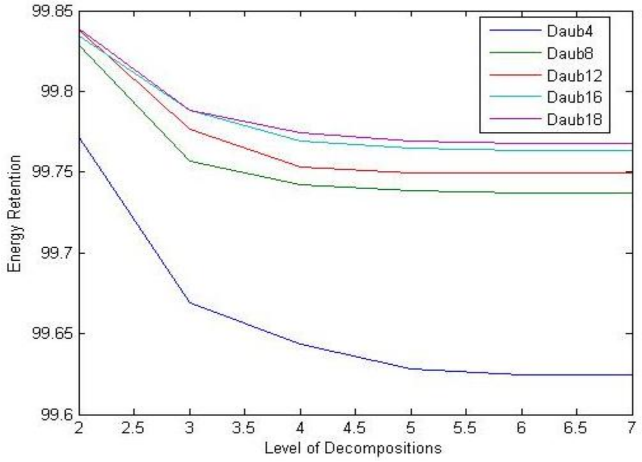

Fig. 4 Energy Retention Vs levels of decomposition

Also We have implemented signal compression algorithm on the audio signal. The audio signal is divided into frames of size 2048 and the compression algorithm is applied to each frame. This has resulted into the compression ratio of 14.8 for Daub-4 wavelet.

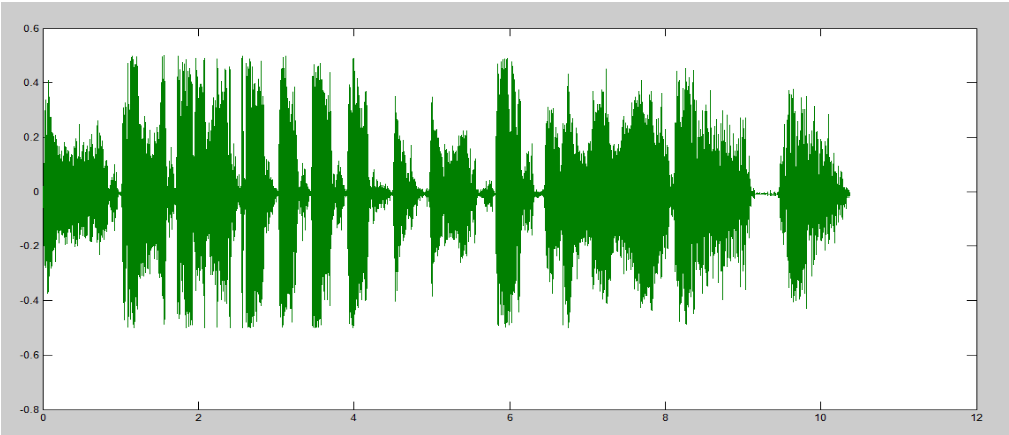

Fig.5(a) Original Audio

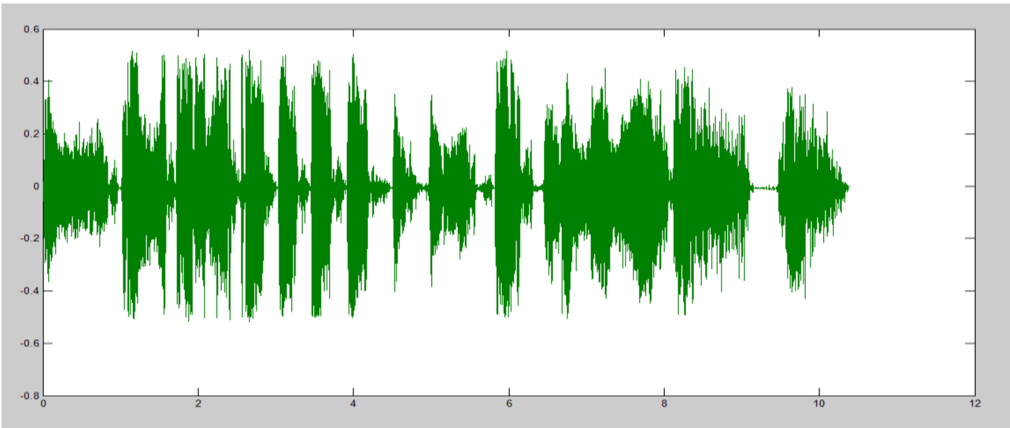

Fig. 5(b) Reconstructed Audio

V. CONCLUSION

As we increase the number of vanishing moments in the used wavelet, we get higher retained energy in the reconstructed signal, i.e. less number of detail coefficients are thresholded to zero due to lower threshold value. Therefore lower compression ratio and better reconstructed signal fidelity. As we increase the level of decompositions for a particular wavelet, we get higher numbers of detail coefficients thresholded to zero as there is increase in threshold value. Therefore higher compression ratio and lower is the reconstructed signal fidelity. Here we should note that lower is the retained energy in the reconstructed signal, higher will be the noise(high frequency) reduction. Better would be the compression ratio in this case.

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