# Comparative analysis of Speech Compression on 8-bit and 16-bit data using different wavelets

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***Abstract*— Audio compression is done in order to minimize the memory requirements of an audio file. This paper presents a novel idea to achieve this by reducing the bit rate of a speech signal without compromising with perceptual quality.LPC coding is the most preferred technique but it provides the loss of information. By selecting an efficient technique of wavelet transform, we apply compression on speech signal using MATLAB software on a core-2duo processor based computing device. The different families of wavelet are used in order to extract data such as compression scores and energy levels of an acoustic signal. The simulation results are taken with different wavelets on 8-bit and 16-bit signal. These simulation comparisons would represent the efficiency of a particular family and thus our aim of less memory consumption by reducing the bit rate of an audio file without effecting the quality and integrity of the signal is achieved.***

***Keywords*— Compression score, Energy Level, Bit rate, Matlab, Wavelet transform**

## I. Introduction

This audio compression is achieved in two ways. Either by compressing the data samples using proper encoding formats else by dynamic adjustments on the range of the signal. The former technique is utilized in this paper. Compression can be either lossy or lossless. Lossless compression reduces bits by identifying and eliminating statistical redundancy. No information is lost in lossless compression. The process of reducing the size of a data file is popularly referred to as data compression which is formally called Source coding. Lossy method reduces bits by removing unnecessary information.

A significant advantage of using wavelets for speech coding is that the compression ratio can easily be varied, while most other techniques have fixed compression ratios keeping all the other parameters constant. Wavelet analysis is the breaking up of a signal into a set of scaled and translated versions of an original (or mother) wavelet [5]. Taking the wavelet transform of a signal decomposes the original signal into wavelets coefficients at different scales and positions. These coefficients represent the signal in the wavelet domain and all data operations can be performed using just the corresponding wavelet coefficients [6][7].

The paper is classified as follows: Section II includes Compression algorithms and techniques which include LPC compression technique and an overview of wavelet transform. Section III includes compression technique using different wavelet and their simulation results. Section IV includes the comparison of result using the parameter compression score and energy recovery. In is, comparison is also shown by graphical representation. Section V includes the conclusion and future scope.

## II. Compression Algorithms and Techniques

An Speech signals has unique properties that differ from a general audio/music signals. First, speech is a signal that is more structured and band-limited around 4 kHz. These two facts can be exploited through different models and approaches and at the end, make it easier to compress. Many speech compression techniques have been efficiently applied. The example below shows how a signal is reduced by 2:1 (the output level above the threshold is halved) and 10:1(severe compression).

Basically speech coders can be classified into two categories: waveform coders and analysis by synthesis vocoders. The first was explained before and are not very used for speech compression, because they do not provide considerable low bit rates. They are mostly focused to broadband audio signals. On the other hand, vocoders use an entirely different approach to speech coding, known as parametric coding, or analysis by synthesis coding where no attempt is made at reproducing the exact speech waveform at the receiver, but to create perceptually equivalent to the signal. These systems provide much lower data rates by using a functional model of the human speaking mechanism at the receiver. Among those, perhaps one of the most popular techniques is called Linear Predictive Coding (LPC) vocoder.

MPEG audio standards include an elaborate description of perceptual coding, psychoacoustic modeling and implementation issues. It is interesting to mention some brief comments on these audio coders, because some of the features of the wavelet-based audio coders are based in those models.

- MP1 (MPEG audio layer-1): Simplest coder/decoder. It identifies local tonal components based on local peaks of the audio spectrum.
- MP2 (MPEG audio layer-2): It has an intermediate complexity. It uses data from the previous two windows to predict, via linear interpolation, the component of the current window. This is based on the fact that tonal components, being more predictable, have higher tonality indices.
- MP3 (MPEG audio layer-3): Higher level of complexity. Not only includes masking in time domain but also a more elaborated psychoacoustic model, MDCT decomposition, dynamic allocation and Huffman coding.

### *A. Linear Predictive Coding*

Linear predictive coding (LPC) is defined as a digital method for encoding an analog signal in which a particular value is predicted by a linear function of the past values of the signal. Human speech is produced in the vocal tract which can be approximated as a variable diameter tube. The linear predictive coding (LPC) model is based on a mathematical approximation of the vocal tract represented by this tube of a varying diameter. At a particular time, t, the speech sample s (t) is represented as a linear sum of the p previous samples. The most important aspect of LPC is the linear predictive filter which allows the value of the next sample to be determined by a linear combination of previous samples.

At this reduced rate the speech has a distinctive synthetic sound and there is a noticeable loss of quality. However, the speech is still audible and it can still be easily understood.

Since there is information loss in linear predictive coding, it is a lossy form of compression.

### *B. Speech Encoding*

LPC coding function will take the speech audio signal and divide it into 30mSec frames. These frames start every 20mSec. Thus each frame overlaps with the previous and next frame.

After the frames have been separated, the LPC function will take every frame and extract the necessary information from it. This is the voiced/unvoiced, gain, pitch, and filter coefficients information.

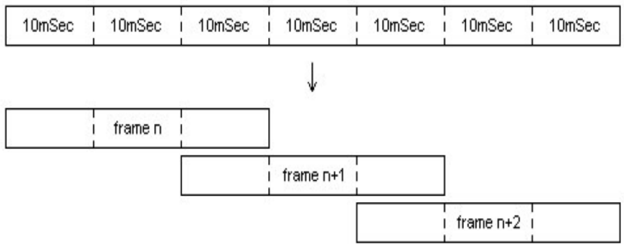



Fig. 2.1 Framing of speech signal into small durations in LPC

To determine if the frame is voiced or unvoiced we need to find out if the frame has a dominant frequency. If it does, the frame is voiced. If there is no dominant frequency the frame is unvoiced. If the frame is voiced we can find the pitch. The pitch of an unvoiced frame is simply 0. The pitch of a voiced frame is in fact the dominant frequency in that frame. One way of finding the pitch is to cross correlate the frame. This will strengthen the dominant frequency components and cancel out most of the weaker ones. If the 2 biggest data point magnitudes are within a 100 times of each other, it means that there is some repetition and the distance between these two data points is the pitch. The gain and the filter coefficients are found using Levinson's method[1].

### *C. Speech Synthesis*

The synthesis part is fairly easy compared to the coding function. First for each frame we need to create an initial signal to run through the filter. This initial signal is also of length 30mSec. Using the information from the variable passed into the synthesis function we will be able to synthesize each frame. After we have synthesized the frames you can put them together to form the synthesized speech signal.

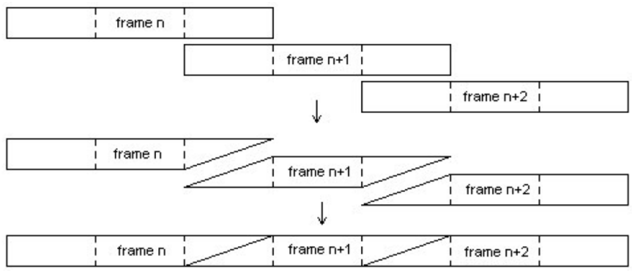



Fig. 2.2 Synthesizing the speech signal by putting back frames together.

The initial 30mSec signal in created based on the pitch information. Remember that if the pitch is zero, the frame is unvoiced. This means the 30mSec signal needs to be composed with white noise. If the pitch is not zero, you need to create a 30mSec signal with pulses at the pitch frequency.

Now that we have the initial signals all you have left to do is to filter them using the gain and filter coefficients and then connect them together.

Putting the frames back together is also done in a special way. This is where the reason for having the frames overlap becomes clear. Because each frame has its own pitch, gain and filter, if we simply put them text to each other after synthesizing them all, it would sound very choppy. By making them overlap, we can smooth the transition from one frame to the next. The figure below shows how the frames are connected. The amplitude of the tip and tail of each frame's data is scaled and then simply added.

Since there is information loss in linear predictive coding, it is a lossy form of compression.

MatLab Implementation [7]

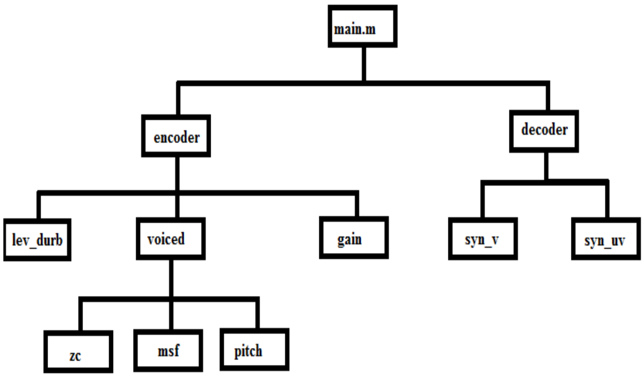



Fig. 2.3 Flow chart of LPC depicting the various functions and their control transfer

**LPC RESULT:**

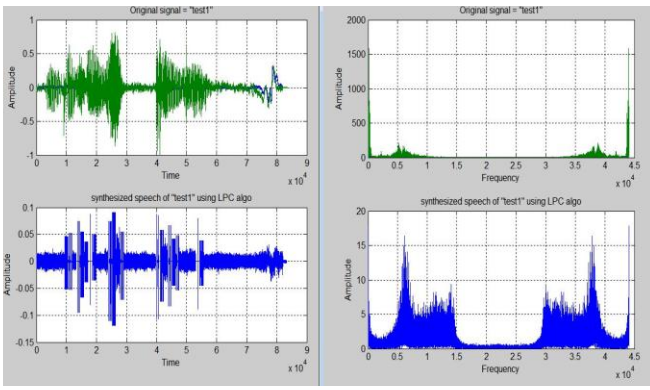



Fig.2.4 LPC algorithm applied on speech signal.

*D. Wavelet Transform*

The fundamental idea behind wavelets is to analyse according to scale. The wavelet analysis procedure is to adopt a wavelet prototype function called an *analysing* wavelet or *mother* wavelet. Any signal can then be represented by translated and scaled versions of the mother wavelet.

Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques such as Fourier analysis miss aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Furthermore, because it affords a different view of data than those presented by traditional techniques, it can compress or de-noise a signal without appreciable degradation

A wavelet prototype function at a scale *s* and a spatial displacement *u* is defined as:

$$\psi_{s,u}(x) = \sqrt{s}\,\psi\left[\frac{(x-u)}{s}\right]$$

A major drawback of Fourier analysis is that in transforming to the frequency domain, the time domain information is lost. When looking at the Fourier transform of a signal, it is impossible to tell when a particular event took place.

An advantage of wavelet transforms is that the windows vary. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. A way to achieve this is to have short high-frequency basis functions and long low-frequency ones.

Thus, applying wavelet transform on a speech signal helps in compressing it to meet the stringent demands of memory consumption while maintaining the quality and integrity of signal[2].

## III. COMPRESSION USING DIFFERENT WAVELET

So our previous results which were performed by LPC showcased the need for a better algorithm, which not only processes signals with less loss but also maintains the accuracy of detailed contents (low frequency) of the audio signal.

*A. Haar Wavelet*

We moved to wavelet analysis using the simplest member of its family i.e. Haar wavelet. Applying the haar wavelet transform on the signal turned out to be a great success. In comparison of both the outputs, the wavelet resulted in preserving the details of the signal using translation and scaling properties of wavelet as well as the auditory results were remarkably enhanced.

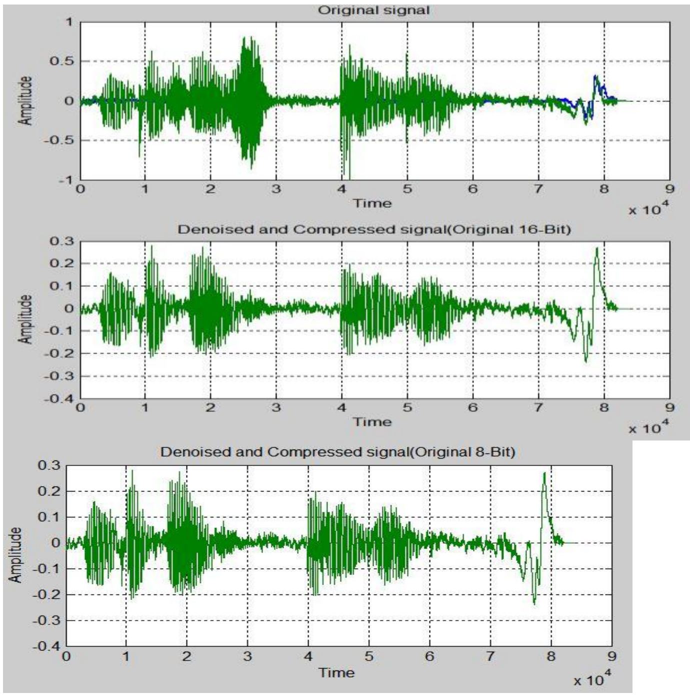



Fig. 3.1 Compression I/O in time domain of both the 16-bit and 8-bit versions using haar wavelet.

## *B. Daubechies Wavelets*

The Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform—by computing running averages and differences via scalar products with scaling signals and wavelets. For the Daubechies wavelet transforms, the scaling signals and wavelets have slightly longer supports, i.e., they produce averages and differences using just a few more values from the signal. This slight change, however, provides a tremendous improvement in the capabilities of these new transforms. They provide us with a set of powerful tools for performing basic signal processing tasks. These tasks include compression and noise removal for audio signals and for images, and include image enhancement and signal recognition[4].

Using certain predefined functions we applied the denoising and compression algorithms and also deduced the compression scores w.r.t. original signal. Output was in accordance to the auditory behavior within required quality levels.

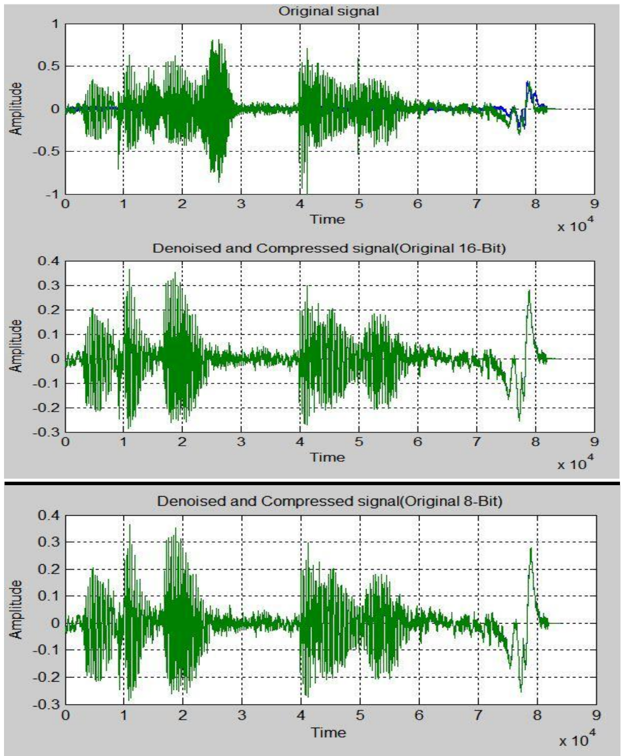
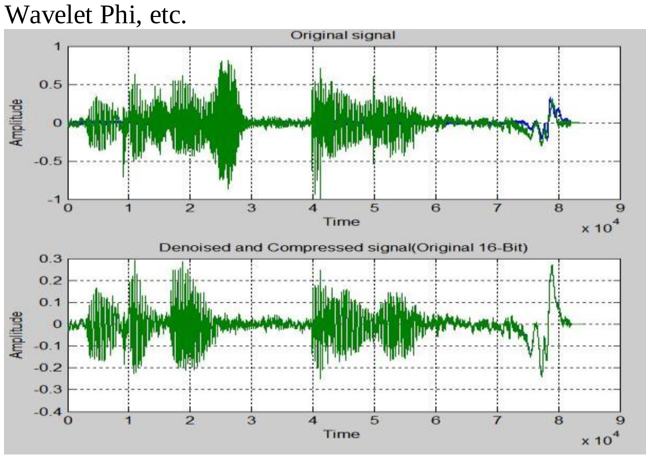



Fig. 3.2 Compression I/O in time domain of 16-bit and 8-bit versions using Daubechies Wavelet.

## *C. Symlet Wavelet*

Symlet Wavelet, also known as "least asymmetric" wavelet, defines a family of orthogonal wavelets. Symlet Wavelet[*n*] is defined for any positive integer *n*. The scaling function ($\phi$) and wavelet function ($\psi$) have compact support length of 2*n*. The scaling function has *n* vanishing moments. Symlet Wavelet can be used with such functions as Discrete Wavelet Transform and Wavelet Phi, etc.



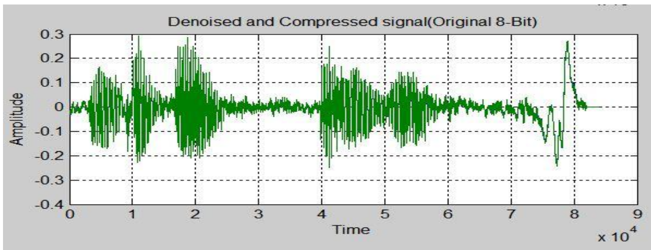



Fig. 3.3 Compression I/O in time domain of 16-bit and 8-bit versions using symlet Wavelet.

## D. *Coiflet Wavelets*

Coiflet Wavelet defines a family of orthogonal wavelets. Coiflet Wavelet[*n*] is defined for positive integer *n* between 1 and 5. The scaling function ($\phi$) and wavelet function ($\psi$) have compact support of length $6n-1$ [4].

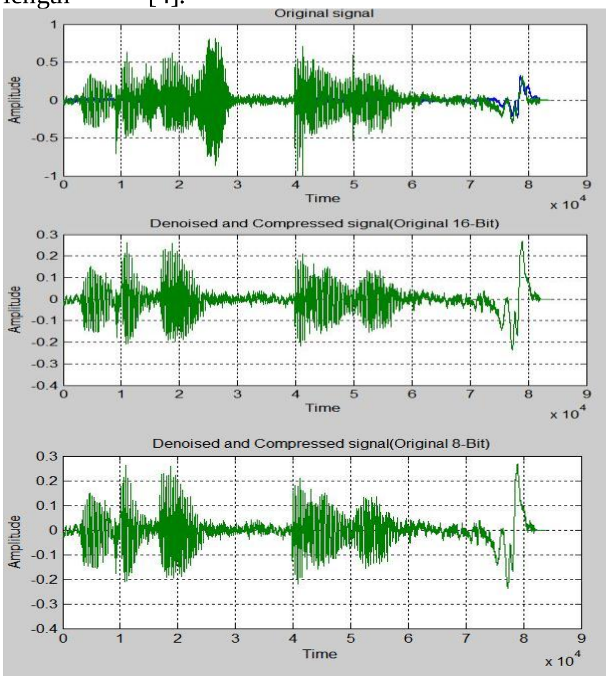



Fig. 3.4 Compression I/O in time domain of 16-bit and 8-bit versions using coiflet Wavelet.

## E. *B-Splines Wavelet*

BSpline Function[...][*u*] gives the point on a B-spline curve corresponding to parameter *u*. BSpline Function[...][*u*, *v*, ...] gives the point on a general B-spline manifold corresponding to the parameters *u*, *v*, ....

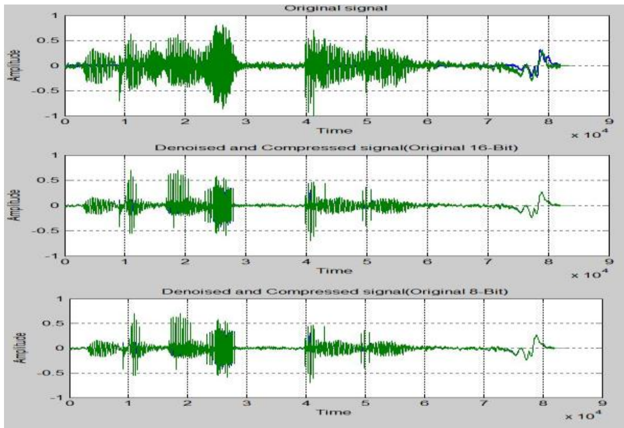



Fig.3.5 Compression I/O in time domain of 16-bit and 8-bit versions using Bspline Wavelet.

## F. *Reverse Bior Splines*

Reverse Biorthogonal Spline Wavelet defines a family of biorthogonal wavelets. Reverse Biorthogonal Spline Wavelet [*n*, *m*] is defined for positive integers *m* and *n* where $m + n$ is even. The scaling function ($\phi$) and wavelet function ($\psi$) have compact support. The functions are symmetric..

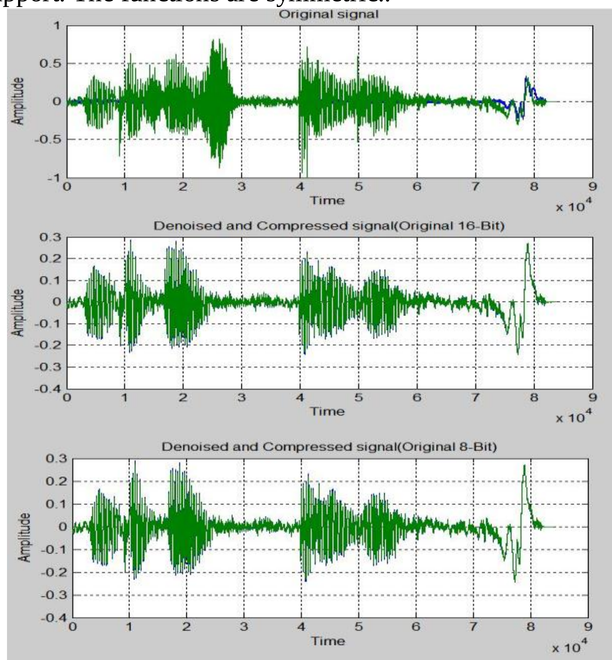



Fig. 3.6 Compression I/O in time domain of 16-bit and 8-bit versions using reverse bior spline Wavelet.

# IV. MATLAB AUDIO COMPRESSION SCORES AND ENERGY

| SIGNAL | TYPE | SIZE(BIT)@ BITRATE(KBPS) | COMPRESSION SCORES | ENERGY RECOVERY |
|---|---|---|---|---|
| Original Signal(8-Bit) | --- --- | 164kb @ 705 | 0 | 100 |
| Original Signal(16-Bit) | --- --- | 328kb @ 1411 | 0 | 100 |
| Haar Applied(8-Bit) | L3 | 164kb @ 705 | 98.4792 | 42.2013 |
| Haar Applied(16-Bit) | L3 | 328kb @ 1411 | 98.4375 | 42.2292 |
| Daubechies Applied(8-Bit) | L3 D6 | 164kb @ 705,328kb @ 1411 | 98.4699 | 42.3482 |
| Daubechies Applied(16-Bit) | L3 D6 | | 98.4375 | 42.3747 |
| Sym Applied(8-Bit) | L3 D6 | 164kb @ 705 | 98.4699 | 42.0721 |
| Sym Applied(16-Bit) | L3 D6 | 328kb @ 1411 | 98.4375 | 42.1006 |
| Coiflets Applied(8-Bit) | L3 D5 | 164kb @ 705 | 98.4699 | 43.3749 |
| Coiflets Applied(16-Bit) | L3 D5 | 328kb @ 1411 | 98.4375 | 43.4020 |
| ReverseBior Applied(8-Bit) | L3 D3 .5 | 164kb @ 705 | 98.4714 | 57.8868 |
| ReverseBior Applied(16-Bit) | L3 D3 .5 | 328kb @ 1411 | 98.4375 | 57.9500 |

Graphical Representation

Thus after computing the requisite data in terms of compression scores and energy recovery percentage, we plot bar graphs and pie charts to depict the complete scenario graphically. FIG. 4.1 below represents the compression scores of 8-bit audio signal. In this we could figuratively see that there is close approximation in the numerical values of compression we have applied. Thus, a bit of uniformity in broader terms but precisely there's a lot of variation present.

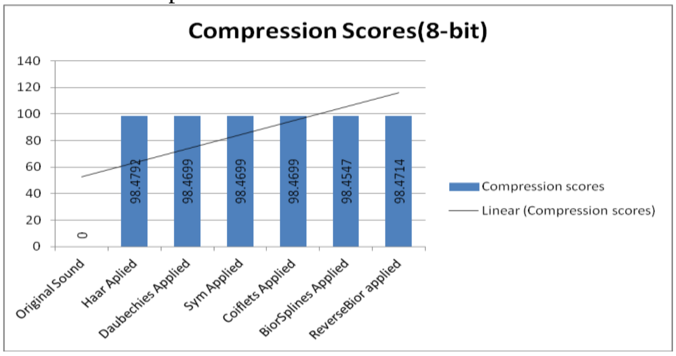



Fig. 4.1 Bar graph with the trend line represents the comparison of different wavelet families for 8-bit speech signal.

The greater the compression score, the better the compressing power of the particular wavelet. Here haar appears to be the best one. But remember the greater the compression the more data we lose.

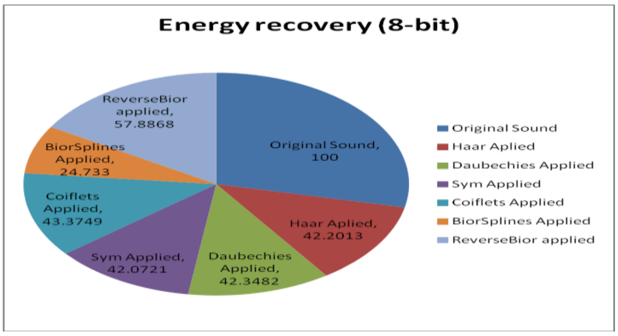



Fig. 4.2 Energy Recovery represented by the pie chart signifies the recovery of original file during reconstruction for 8-bit speech signal.

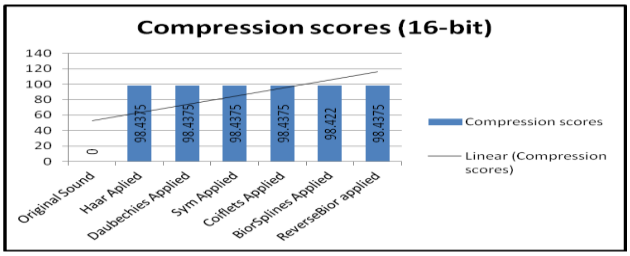



Fig. 4.3 Bar graph with trend line shows the comparison of diff. wavelet families for 16-bit speech signal

Fig below indicates the energy recovery when we move back to original signal from the compressed one. This pie chart shows that reverse still performs the best in maintaining the integrity and originality of the signal.

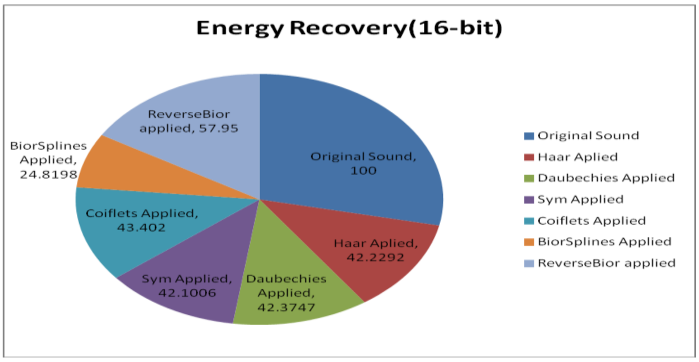



Fig. 4.4 Energy Recovery represented by the pie chart signifies the recovery of original file during reconstruction for 16-bit speech signal.

## V. Conclusion

Thus utilizing MATLAB computational power we have deduced the data in terms of compression scores and energy recovery diagrams. After comparison with all the other families of wavelet we have attained the results. The graphical representation as shown notifies the compression scores and pie charts displaying the energy recovery percentage. The numerical value turns out to be in close approximations with each other. Thus it may appear that daubechies, symlet, coiflet are close contenders yet this is a limitation of one's observation. Symlet is the best for achieving bit reduction without compromising quality. Since auditory nature is good, r/l balancing sufficient, bass and treble perfect with the least noise effect. After compressing the 16-bit, just half the number of bits present, to achieve the less memory consuming and no quality compromised speech signal.

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