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Advance Source Coding Techniquesfor Audio/Speech Signal: A Survey

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Abstract

Speech & Audio coding is widely used in application such as digital broad casting, Internet audio or music database to reduce the bit rate of high quality audio signal without comprising the perceptual value. Techniques have also been emerging in recent years that offers enhanced quality bit rate over traditional methods. Wideband audio compression is generally aimed at a quality that is nearly indistinguishable from consumer compact-disc audio. Sub band & transform coding methods contained with sophisticated perceptual coding techniques dominate in this area with good quality bit rates.

*Keywords:*Bit rate, Compression, LPC, Fast Fourier Transform, .Wavelet Transform.

1. Introduction

Compression of audio signal has found application in many areas, such as multimedia signal coding, high fidelity audio for radio broadcasting, and audio transmission for HDTV, audio data transmission / sharing through Internet etc. Speech compression converts input speech data stream into a reduced size data stream, by eliminating inherent redundancy associated with speech signals. Compression techniques reduces overall program execution time also storage requirement of processor. Compression helps to reduce the data transfer rate and bandwidth requirement with security for data to be transfer. However, in speech compression schemes it is more important to ensure that compression schemes retain the integrity of the speech. For large amount of exchange & transmission of audio information through internet & wireless systems, efficient (i.e. low bit rate) audio coding algorithms need to be devised [1]. The basic task of high quality audio coding system is to compress the digital audio data in a way [1]the compression is as efficient as possible & the reconstructed audio sounds as close as possible to the original audio before compression.

This paper highlights the state of the art for digital compression of speech & audio signals. The scope is limited to surveying the most important & prevailing methods, approaches and activities of current interest without attempting to give a tutorial presentation ofspecific algorithms or a historical perspective of the evolution of speech coding methods. No attempt is made to offer a complete review of the numerous contributions that have been made in recent years. Nevertheless, the major ideas & trends are covered here & attention is focused on those contributions which have had the most impact on current technology. Hencethe efforts are taken to present the comparative study of various types of source coding techniques such as:

A. Linear Predictive coding (LPC)
B. Code Excited Linear Predictivecoding (CELP)
C. Sub-band coding
D. Transform coding
   i. Fast Fourier Transform (FFT)
   ii. Discrete Cosine Transform (DCT)
   iii. Continuous Wavelet Transform (CWT)
   iv. Discrete Wavelet Transform (DWT)
E. Variance Fractal Compression (VFC)

In [2], low level audio descriptor for psychoacoustic noise is proposed. It removes the compression noise than any other descriptor. Here, matching the descriptors' structure to the compression scheme is essential.

Also in [3], Karhunen Loeve Transform (KLT) is proposed to minimize mean square error distortion with optimality in transform.

In [4], Cascaded Long Term Prediction (CLTP) filter is proposed for polyphonic signal. While LTP is well working for single periodic component, which is not the case with general audio signal as it consist of multiple periodic signals. LTP is effective for long period stationary signals.

1.1 Linear Predictive coding (LPC):

Linear Predictive coding (LPC) is one of the most powerful and useful speech analysis techniques for encoding good quality speech at a low bit rate. It provides extremely accurate estimates of speech parameters, and is relatively efficient for computation. LPC starts with the assumption that the speech signal is produced by a buzzer at the end of a tube. The glottis (space between the vocal cords) produces the buzz, which is characterized by its intensity (loudness) and frequency (pitch). The vocal tract (throat and mouth) forms the tube, which is characterized by its resonances, called as formants. LPC analyzes the speech signal by estimating formants, removing their effects from the speech signal, and estimating the speech intensity and frequency of the remaining buzz. The process of removing the formants is called inverse filtering, and the remaining signal is called residue. Because speech signal vary with time, this process is done on short chunks of speech signal, called as frames. The basic problem of LPC system is to determine the formants from the speech signal. The solution used is the difference equation, which expresses each sample of signal as a linear combination of previous sample. Such equation is called as a linear Prediction and hence the name given is linear Prediction coding [5].

Linear Prediction is an integral part of many modern speech coding systems and is commonly used to estimate the autoregressive (AR) filter parameters. It describes spectral envelope of speech segment. The prediction coefficient is minimized difference between observed signal and the predicted signal [7], but the minimization criteria is not optimal in many cases. e.g. if the excitation is not Gaussian. In this case the coefficients are found for short term and long term signals in two different steps and hence gives suboptimal solution. Whereas the common LP analysis tries to cancel the pitch harmonics by putting some of the poles very close to the unit circle [8].

The coefficients of the difference equation are prediction coefficients. Prediction coefficients represent the formants, so the LPC system needs to estimate these coefficients. The estimate is done by minimizing the mean square error between predicted signal and actual signal[9]. This is the main problem in principle. Because in order to work for this, the tube must not have any side branches. (Side branches introduces more zeros results more complex equations [5]. This problem is observed in nasal sound. Another problem in LPC is that, any inaccuracy in the estimation of formants leaves more speech information in residue without which quality sound won't be reconstructed. To avoid this, the residue signal may be sent with the compressed one. Unfortunately, the faithful compression will not be achieved. To avoid this problem, LPC is modified as Code Excited Linear Predictive coding (CELP).

1.2 Code Excited Linear Predictive coding (CELP):

It uses codebook, a table of typical residue signals set by the system designers [10]. In operation, the analyzer compares residue to all the entries in the code book, chooses the closest matching entry and just sends the code for that entry. The synthesizer receives this code, retrieves the corresponding residue from the codebook and uses that to excite the formant filter. This is called as Code Excited Linear Predictive coding (CELP) [11].For CELP to work well, the code book must be big enough to include all the various kinds of residues. But if the code book is too big, it will be time consuming to search through, and will require large codes to specify the desired residue [12]. The biggest problem is that such a system would require a different code for every frequency of the source (pitch of the voice) which would make the code book extremely large.

CELP coders are capable of producing good quality speech at around 4.8Kbps. Below this, they suffer from distortion introduced by coarse quantization of model parameters due to limited number of bits [13]. Also, the frame-by-frame analysis coupled with the high processing demands introduces delay which can degrade quality of conversation and introduce difficulties in related speech processing components, such as echo cancelling[11].

Most recently, MPEG-4 CELP (2Kbps in narrowband version and 4Kbps in Wideband) and MPEG-4 BSAC (Bit Slice Arithmetic Coding) coder (up to 1Kbps) have been introduced. In this, a core layer produces the lowest bit rate and provides the minimum information to obtain a basic quality for the decoded signal and several enhancement layers within contains additional information to improve quality, but still the coding efficiency is not comparable [14].

1.3 Sub-band coding:

Audio and voice signals have highly non-stationary characteristics. Therefore, attempts to compress such signals typically rely on block processing, where blocks of input samples are first decomposed by a filter bank into sub-band signals [15]. These sub-band signals are in turn analyzed to extract the time varying signal parameters, which are then input to a coding algorithm. Finally, the coding algorithm transmits a compressed version of input sample. [16]

We can optimize a given Sub-band coding algorithm for non -stationary signals by introducing time varying filter banks; where for each block of input samples we alter the structure of the decomposition filter bank such that a particular coding criterion is optimized. In one of the paper [17], we investigated the time varying filter bank design methods represented in [18] [19]. These methods employ respectively, boundary and entry/exit filters to achieve independent block processing where samples from adjacent blocks do not affect each other. Boundary or entry/exit filters exhibits following characteristics.

- The number of boundary filters and the number of corresponding switching operations increase with the filter length and the depth of the filter bank. These numbers at the synthesis bank are doubled. This creates significant challenges to the design and implementation of computationally efficient time varying filter banks.
- Individual sub band signals at the output of time varying filter bank exhibit severe block effects in the form of abrupt level changes at block boundaries. This reduces sub band coding efficiency. Thus the traditional design techniques do not yield suitable adaptive structure [16].

In [20], a speech coder based on sub-band coding at 2.4Kbps is proposed. At the receiver Mel-frequency Cepstral Coefficient (MFCC) technique is used to extract the speech parameters along with vector quantization and Huffman coding.

1.4 Transform coding:

Transform coding is the type of data compression for natural data like audio signal or photographic images. In this, the knowledge of the application is used to choose the information to discard, thereby lowering its bandwidth [13]. The remaining information can then be compressed via variety of methods. FFT, DCT, CWT, DWT, DPWT [21] are the types of transform coding used for data transform into another mathematical domain for suitable compression.

1.4.1 Fourier Transform:

It is one of the methods for signal and image compression. FT decomposes a signal defined on infinite time interval into a λ-frequency component where λ can be real or complex number [22]. FT is actually a continuous form of Fourier series. FT is defined for a continuous time signal $x(t)$ as,

$$x(f) = \int_{-\infty}^{\infty} x(t).e^{-i\omega t}.dt \text{ ------------ } 1$$

The above equation is called as analysis equation. It represents the given signal in different form; as a function of frequency. The original signal is a function of time, whereas after the transformation, the same signal is represented as a function of frequency. Consider following two different signals.

$$x1(t) = \sin(2\pi * 100 * t) \quad for\ 0 \le t < 0.1\, Sec$$

$$= \sin(2\pi * 500 * t) \quad for\ 0.1 \le t < 0.2\, Sec \text{---- } 2$$

And

$$x2(t) = \sin(2\pi * 500 * t) \quad for\ 0 \le t < 0.1\, Sec$$

$$= \sin(2\pi * 100 * t) \quad for\ 0.1 \le t < 0.2\, Sec \text{----} 3$$

A plot of these signals is shown below.

T=0 to 0.2 sec, sin(2π*100*t) and sin(2π*500*t)

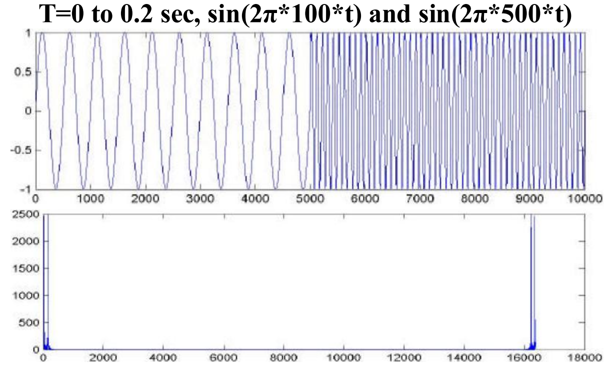

Fig. 1 Signal $x1(t)$ and its FFT

T=0 to 0.2 sec, sin(2π*100*t) and sin(2π*500*t)

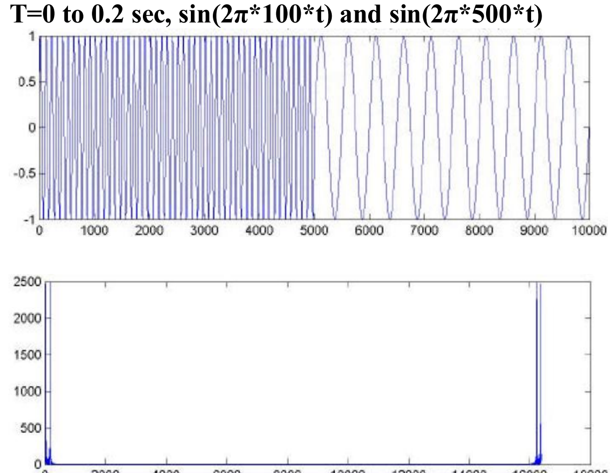

Fig. 2 Signal $x2(t)$ and its FFT

The above example demonstrates the drawback in Fourier analysis of signals. It shows that the FT is unable to distinguish between two different signals.

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The two signals have same frequency components, but at different times. In general FT is not suitable for the analysis of a class of signals called as non-stationary signals. This problem can be solved by Continuous Wavelet Transform.

In FT, all data smoothened by removing all spike and anomaly on the other hand this is not the case with DWT [23].

1.4.2 Wavelet Transform:

The wavelet transform belongs to the family of filter banks. It consists of a low pass filter followed by decimation of factor 2. For an N sample input frame, two N/2 sample output frames are called approximation and detail; with bandwidth about half of input signals bandwidth. The low frequency band is further filtered to provide details at lower resolution levels. The details are not further filtered. This method gives good frequency selectivity at the cost of temporal resolution [24]. But for high frequency area, the poor frequency selectivity is not acceptable in speech/audio coding.

Wavelet is a waveform of effectively limited duration that has zero average value. It is the latest method of compression where it's ability to describe any type of signals both in time and frequency domain [25] [26] [27].

Consider a real or complex valued continuous time function $\psi(t)$ with following properties.

1. The function integrates to zero.

i.e. $\int_{-\infty}^{\infty} \psi(t)\,.dt = 0$ ------- 4

And

2. It is square integral or equivalently, has finite energy.

$\int_{-\infty}^{\infty} |\psi(t)|^2 .dt < 0$ -------- 5

The function is called mother wavelet if it satisfies equation no. 4 and 5 these two properties. Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet.

The most important difference between FT and WT is that, individual wavelet functions are localized in space. In contrast, Fourier sine and cosine functions are non-local and are active for all time t. This in turn results in a number of useful applications such as data compression, detecting features in images and de-noising signals. The wavelet transform of a signal f(t) is the family $C(a,b)$, given by the analysis equation no. (6) as below.

$$C(a,b) = \int_{-\infty}^{\infty} f(t).\frac{1}{\sqrt{|a|}}\psi*\left(\frac{t-b}{a}\right)dt \quad \text{----6}$$

It depends upon two indices a and b. from an intuitive point of view, the wavelet decomposition consists of calculating a "resemblance index" between the signal and the wavelet located at point b and of scale a. if the index is large, the resemblance is strong and vice versa. The index $C(a,b)$ is called as coefficient.

Revised Example:

Let us consider the same example, demonstrated for FT and how wavelet analysis distinguishes between the two different signals and also gives their frequency content.

$x1(t) = \sin(2\pi * 100 * t) \quad for\ 0 \le t < 0.1\,Sec$

$=\sin(2\pi * 500 * t) \quad for\ 0.1 \le t < 0.2\,Sec$--- **7**

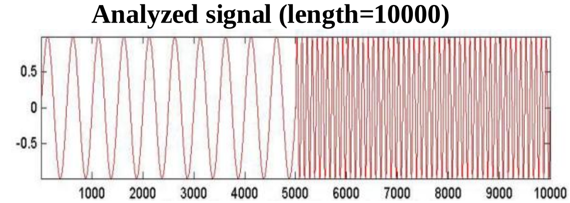
And

$x2(t) = \sin(2\pi * 500 * t) \quad for\ 0 \le t < 0.1\,Sec$

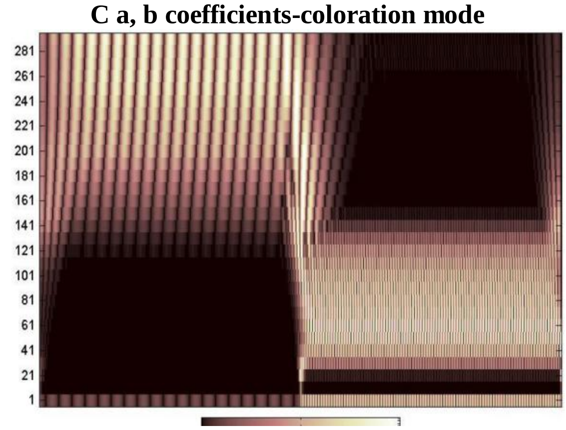
$=\sin(2\pi * 100 * t \quad for\ 0.1 \le t < 0.2\,Sec$----8

The following figures show the signals along with their wavelet scalogram. Note the scalograms of these two signals are entirely different, hence enables the wavelet transform to distinguish between these two signals.

Analyzed signal (length=10000)



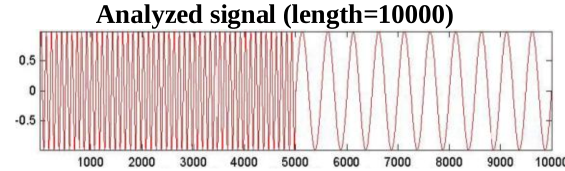
C a, b coefficients-coloration mode



Scale of color for min to max

Fig. 3 $x1(t)$ and it's scalogram

Analyzed signal (length=10000)



C a, b coefficients-coloration mode

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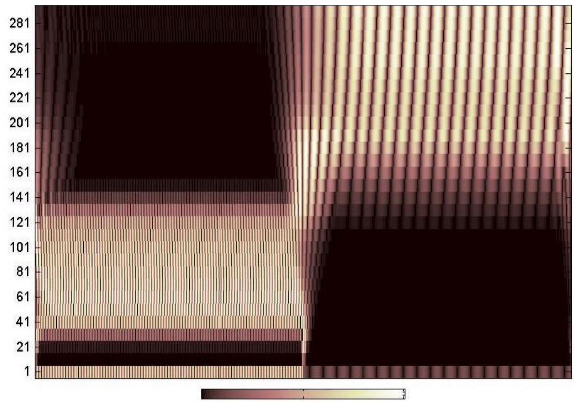

Fig. 4 $x2(t)$ and itsscalogram

There are two types of wavelet transform. Continuous wavelet transform (CWT) discussed above and Discrete Wavelet Transform (DW). The main idea of wavelet transform is same in both of these transforms. However, they differ in the way the transform is being carried out. The period, during the standardization of FFT and DCT based compression technology; Variance Fractal Compression has also advanced. But their compression methodology has not matched the rate-distortion performance of wavelet based codec [28].

Wavelet transforms have two additional advantages over DCT that are important for coefficient compression. The first is the multiresolution representation of the signal by wavelet decomposition that greatly facilitates subband coding. The second advantage of wavelet transform is that it reaches a good compromise between frequency and time resolution of the signal. Wavelet transforms are superior to DCT as their basis function offer good frequency resolution in the lower frequency range, and at the same time they yield good time resolution at a higher frequency range[28]. Noise is extraneous information in a signal that can be filtered out via the computation of averaging and detailing coefficients in the Wavelet transform [29]. Wavelet transform is able to detect and localize disturbances [30]. Also there are several thresholding techniques for wavelet transform coefficients like, Absolute maximum value, hard threshold, soft threshold, Garrote thresholding, firm thresholding [23], global threshold and level dependent threshold [31]. All the data contents/characteristics are recaptured by MRA (Multi Resolution Analysis).

Multi-wavelet Decomposition is discussed in [32] for audio compression the performance of different types of wavelets for composing the transient audio signal is discussed. The wavelets that were investigated for this purpose are Dubechies family of wavelets, called as wavelet packet and multi-wavelets. One of the main challenges to the application of multi-wavelets is the problem of multi-wavelet initialization (pre-filtering). In the case of scalar wavelets, the given signal data is usually assumed to be the scaling coefficients which are sampled at a certain resolution, and hence, multi resolution decomposition can directly be applied on the given signal. Unfortunately, the same technique cannot be applied directly in the multi-wavelet setting. Some preprocessing has to be performed on the input signal, prior to multi-wavelet decomposition. Then it represents a promising substitute for scalar wavelets in audio compression.

1.4.3 Discrete Wavelet Transform:

This is based on sub-band coding, is found to yield a fast computation of wavelet transform. It is easy to implement and reduce the computation time and resources required. In CWT, the signals are analyzed using a set of basic functions which relate to each other by simple scaling and transition. In case of DWT, the time scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cut-off frequencies at different scales [33].

In DWT, a signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression. When a signal passes through these filters, it is splitted in two bands. The low pass filter corresponds to an averaging operation and extracts the coarse information of the signal. The high pass filter corresponds to a differencing operation and extracts the detail information. The output of the filtering operation is then decimated by two [34]. Wavelets can be realized by iteration of filters with rescaling as shown in fig. 5. This is called as Mallat algorithm or Mallatt-tree decomposition.

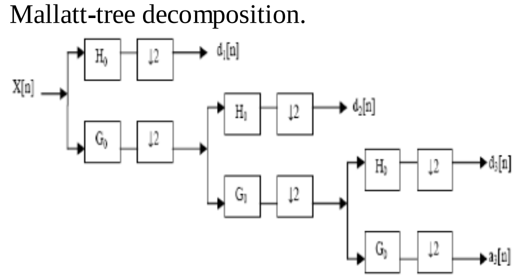

Fig. 5 Three-level wavelet decomposition tree

Here, the signal is denoted by x (n), where n is an integer. The low pass filter is denoted by Go & high pass filter is denoted by Ho. At each level, the high pass filter produces detail information d(n), while the law pass filter produces coarse approximations a(n).

At each decomposition level, the half band filters produce signals spanning only half the frequency

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band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 200 radians, then it now has a highest of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies & thus halves the resolution, the decimation by 2 doubles the scale. The filtering & decimation process is continued until the desired level is reached. The DWT of the original signal is obtained by coefficients concatenation i.e. starting from the last level of decomposition.

For DWT, various wavelet filters such as Harr (2 filters) and Daubechies (up to 10 filters) are used. All the numerical results were done by using Mat lab programming. In [35], the author discussed the use of WT for speech compression. Speech compression is the process of converting human speech signals into efficient encoded representation that can be decoded back to produce a close approximation of the original signals. The input signal used is 8KHz, 8 bit speech [22]. Based on Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), and compression ratio, they concluded D10 wavelet filter gives higher SNR and better speech quality with compression ratio 4.31 times and reduces bit rate.

In [36], the authors use wavelets to compress speech signal. They used spoken English speech to be analyzed to D20 wavelet filter. With this, Cr went higher and SNR was decreased.

In [37], the author did the compression using Battle Lemarie wavelet, Haar and Daubechies(up to 20 filters). The analysis was done by voices and unvoiced speech and the results shows Battle-Lemarie is the best while other filters almost comparable except Haar. While in [31], they analyzed the effect of different compression schemes on speech signal. They used D4, D8, D10 and D20 and their input is Arabic speech signal. Based on SNR, PSNR, they found that, using smooth wavelets like D10, the percentage of truncated coefficients decreased and give better SNR. For unsmooth wavelet, it gives better compression ratio but low SNR.

In [34], the audio compression is evaluated by using WT (up to 10 filters). Here, the main objective is transparent coding of audio and speech signal at the lowest possible data rate. Based on the numerical results, D10 is the best wavelet filter with lowest SNR and highest CR (1.88).

1.4.4 Discrete Wavelet Packet Transform

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. It is used to obtain the critical bands of human auditory system [38]**[**39**].**In wavelet analysis; a signal is split into an approximation & a detail coefficient. The approximation coefficient is then itself split into a second level approximation coefficients & detail coefficients & the process is repeated. In wavelet packet analysis, the details as well as the approximations can be splitted. It gives more than 2^{2n-1} different ways to encode the signal.

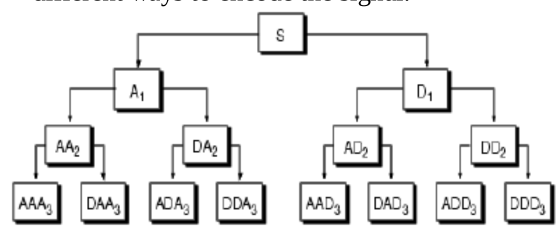

Fig. 6 Level 3 Decomposition using Wavelet Packet Transform

Fig.6 shows the level 3 decomposition using Wavelet Packet Transform. In this the entropy-based criterion is used to select the most suitable decomposition of a given signal. This means, we look at each node of decomposition tree & quantity for the information to be gained by performing each split [39].

The wavelets have several families [36] [39]. The most important wavelets families are Harr, Daubechies, symlet, coiflet, Biorthogonal, reverse Biorthogonal, Meyers, Discrete Approximation of Meyer wavelets, Gaussian, complex, Gaussian, Mexican Hat, Morlet complex Morlet, Ballet Lamarie, Shannon. Out of these wavelet families, Haar, Daubechies wavelets, symlet, coiflet wavelet families are the most important wavelet families. For compression purposes, the best cost functional to be minimized is the number of coefficients superior to a certain threshold. This is the reason; the transform based on Wavelets Packets must be used in compression applications [39]. Use of Psychoacoustic model is also suggested in [34] to achieve perceptually transparent compression of high quality audio signals at about 45Kbps. The filter bank structure adapts according to Psychoacoustic criteria and according to computational complexity that is available at the decoder.

1.5 Variance Fractal Compression:

The fractal compression is based on fractal systems ability to approximate discontinuous

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functions, where audio signals exhibits greater smoothness [32]. It has gained a wide popularity due to its inherent features and efficiency in compressing data in medical field. The fractal dimension values indicate the complexity of pattern in terms of morphology, entropy, spectra or variance. The VFD analysis does not create window artifacts in the Fourier sense, which is often introduced in fractal spectral analysis. Therefore, the VFD is an excellent tool for investigating time series signals by calculating the variance fractal dimensions [40]. This technique can also be integrated into the framework of conventional compression techniques such as vector quantization and transform methods. This direction may also lead to succeed in applying fractal audio coding in practice.

2. Conclusion

As far as the compression ratio, compression factor, reconstruction of audio signal & it is redundancy with original signal, bit rate, PSNR is concerned it is observed that Discrete Wavelet Transform & Discrete Wavelet Packet Transform is better & best respectively. Whereas the use of post filtering at suitable bit rate in both transforms improves the quality of the reconstructed signal. It is also suggested that five is the optimum number of wavelet decomposition level. Since high valve of wavelet decomposition level will require more computation time. The wavelet Packet Transform instead of wavelet transform provides the improvement in PSNR of the reconstructed audio signal.

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