

## SPEECH SIGNAL CODING FOR VOIP APPLICATIONS USING WAVELET PACKET TRANSFORM

<sup>A</sup>N.Rama Tej Nehru, <sup>B</sup>P.Sunitha <sup>A</sup>M.Tech student, <sup>B</sup> Assoc. Professor.  
Department of ECE, Pragati Engineering College, A.P,  
India.

<sup>A</sup>ramtejnehru@gmail.com, <sup>B</sup>sunitha4949@gmail.com.

**ABSTRACT** -This paper presents a unique approach for coding of speech signal by using wavelet Packet Decomposition. A key technology that enables speech and audio signals with less mass storage device and bandwidth is coding technique. It will be enforced effectively by Wavelet Packet Transform (WPT) using different threshold methods i.e. global dependent and level dependent. The performance of those threshold methods using wavelet Packet Decomposition in speech signal coding is presented along with the different types of wavelets like Daubechies (db1-db10) at different levels of decomposition(Level 1-level 4). Further the performance analysis of the threshold methods are compared in terms of percentage of zero coefficients and retained signal energy using wavelet transform and wavelet Packet decomposition.

**Keywords:** Coding, Wavelet Packet Decomposition Wavelet threshold methods, Wavelets, Percentage of zero coefficients, retained signal energy.

### I. INTRODUCTION

Since speech signal contains more number of redundant data, how to compress speech signal by maintaining prime quality at low bit rates is still a very important topic. In order to reduce redundancy and make full use of the human's auditive masking effect by using a variety of source coding techniques, not only can compress the coding rate by many times, but also has the ability to regain high intelligibility and acceptability of speech signals[1,2]. Coding is a process of converting an input data into another data that has a smaller size. Coding is possible only because data is normally represented in the computer in a format that is longer than necessary i.e. the input data has some amount of redundancy associated with it. The main objective of coding systems is to eliminate this redundancy.

When coding is used to reduce storage requirements, overall program execution time may be reduced. This is because reduction in storage will result in the reduction of disc access attempts. With respect to transmission of data, the data rate is reduced at the source by the compressor, it is then passed through the communication channel and returned to the original rate by the expander at the receiving end. The coding algorithms help to reduce the bandwidth requirements and also provide a level of security for the data being transmitted. In most of the cases, direct methods are superior than transform based methods with respect to its system simplicity and

error. The transform methods usually achieve higher coding ratio compared to direct

method. Compressor using wavelet packet (WP) based techniques are efficient than discrete wavelet transform (DWT) based method for Time Series coding.

Therefore, a speech coding system focuses on reducing the amount of redundant data while preserving the integrity of signals. Since speech signal is a non-stationary signal, consists of time varying spectral components. Fourier Transform only provides *what spectral components exist*, not where in time they are located. Need some other ways to determine *time localization of spectral components*.

The different transformation of speech signals from time to frequency domains for the purpose of coding aim at representing them with the minimum number of coding parameters. [1, 2] Speech is non-linear random process. Wavelet transform devotes a lot to deal with time-varying, non-stationary signal. Wavelet transform has excellent resolution in both time and frequency domain [10]. Wavelet transform with detail of signal, decomposes the high-frequency, and the signal was decomposed to the time-frequency space which has a certain correspondence with critical band of speech. The result of wavelet transform is called "wavelet coefficients" [6]. In [3, 4] the coefficient conversion of wavelet can classify into two types, Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). This article investigates the improvement speech coding technique based on the model wavelet transform which is focused in the frequency lossless. There are some related researches works which used wavelet transform for speech coding. The DWT is used as a tool for Hindi speech recognition is presented in [5]. It studies the recognition of isolated words in Hindi Language speech. The mother wavelets are selected to use 3 families, Daubechies (db), Coiflets (coif) and Discrete Meyer Wavelet (dmey). It is found that Daubechies 10, 5-level decomposition and the Discrete Meyer wavelet give comparable performance, while the Daubechies 8, 3-level decomposition provides the poorest performance. An innovative method for speech coding by detecting the end points of the speech signals prior to compressing was proposed in [6].

In [7] applies the Wavelet Packet Transform (WPT) to process speech signal to obtain optimal wavelet tree to allocate the dynamic bits, and then uses the modified Set Partitioning in Hierarchical Trees (SPIHT) coding algorithm to compress the coefficients from the wavelet packet transform. It indicates that it can gain better high coding. However the quality signal reconstruction is still

not perfect according to loss of frequency. Thus this article is concerned to compare the frequency lossless of the new model wavelet for speech coding.

This paper is organized by various sections, section-II describes to brief introduction to DWT, Section – III gives Wavelet Packet Decomposition, Section IV Wavelet Packet Based Speech Coding Technique, section – V gives Results and discussion, section – VI describes conclusion followed by References.

**II. INTRODUCTION TO DWT**

Similar to the Fourier series expansion, the DWT maps a continuous variable  $\Psi(t)$  into a sequence of coefficients, the resultant coefficients are called discrete wavelet transform of  $\Psi(t)$ . Its representation involves the decomposition of the signals in wavelet basis function  $\Psi(t)$  given by

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} [(t-b)/a] \quad a, b \in R \quad -(1)$$

Where a, b are called scale and position parameters as respectively

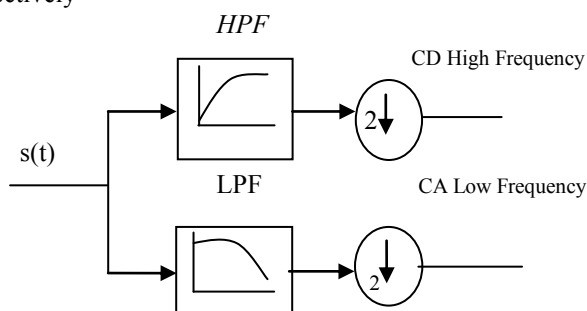


Fig 1: Single level, wavelet decomposition (analysis).

The multi resolution analysis is given by S. Mallet and Mayer proves that any conjugate mirror filter characterizes a wavelet  $\Psi$ . The wavelet decomposition of a signal  $x(t)$  based a multi resolution theory can be obtained using filter [10], the filter based wavelet decomposition is shown in fig. 1.

The above arrangement has used two wavelet decomposition filters which are high pass and low pass respectively followed by down sampling by 2 producing half input data point of high and low frequency. The high frequency coefficients (CD) and low frequency coefficients are called approximate coefficients (CA). The signal can be reconstructed back by inverse wavelet transform. The corresponding filter bank structure for reconstruction is shown in figure 2.

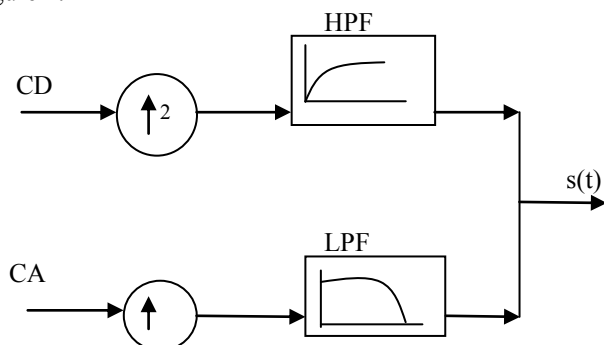


Fig 2: single level wavelet reconstruction (synthesis)

**III. INTRODUCTION TO WAVELET PACKET TRANSFORM**

It is a wavelet transform where the discrete-time or sample signal is passed through more filters than the discrete wavelet transform (DWT). In the DWT, each level is calculated by passing only the previous wavelet approximation coefficients through discrete-time low and high pass quadrature mirror filters. However in the WPD, both the detail and approximation coefficients are decomposed to create the full binary tree. For n levels of decomposition the WPD produces  $2^n$  different sets of coefficients (or nodes) as opposed to  $(3n + 1)$  sets for the DWT. However, due to the down sampling process the overall number of coefficients is still the same and there is no redundancy.

From the point of view of coding, the standard wavelet transform may not produce the best result, since it is limited to wavelet bases that increase by a power of two towards the low frequencies. It could be that another combination of base produces a more desirable representation for a particular signal. The best basis algorithm finds a set of bases that provide the most desirable representation of the data relative to a particular cost function. There were relevant studies in signal processing and communications fields to address the selection of sub band trees (orthogonal basis) of various kinds, e.g. regular, dyadic, irregular, with respect to performance metrics of interest including energy. Compaction e.g. entropy, sub band correlations and others. Discrete wavelet transform theory or continuous in the variable offers an approximation to transform discrete or sampled signals. In contrast, the discrete sub band transform theory provides a perfect representation of discrete signals.

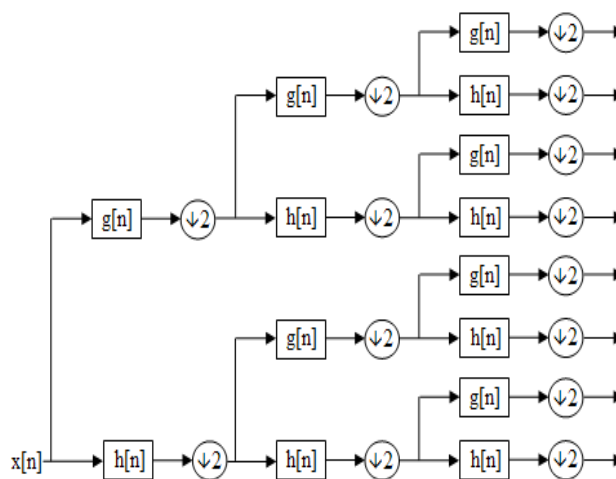


Fig3: Wavelet Packet Decomposition over 3 levels. Where  $g[n]$  &  $h[n]$  are low-pass approximation & high-pass detail coefficients.

#### IV. WAVELET PACKET BASED SPEECH CODING TECHNIQUE

The idea behind signal coding using wavelet packets is primarily linked to the relative Scarceness of the wavelet domain representation for the signal. Wavelets concentrate speech information (energy and perception) into a few neighboring coefficients. Therefore as a result of taking the wavelet transform of a signal, many coefficients will either be zero or have negligible magnitudes. Another factor that comes into picture is taken from psychoacoustic studies. Since our ears are more sensitive to low frequencies than high frequencies and our hearing threshold is very high in the high frequency regions, we used a method for coding by means of which the detail coefficients (corresponding to high frequency components) of wavelet transforms are thresholded such that the error due to thresholding is in audible to our ears. Since some of the high frequency components are discarded, we should expect a smoothened output signal

##### A) Choice of Wavelet:

The choice of the mother- wavelet function used in designing high quality speech coders is of prime importance. Several different criteria can be used in selecting an optimal wavelet function. The objective is to minimize reconstructed error variance and maximize signal to noise ratio (SNR). In general optimum wavelets can be selected based on the energy conservation properties in the approximation part of the wavelet coefficients. A suitable criterion for selecting optimum mother wavelets is related to the amount of energy a wavelet basis function can concentrate into the level 1 approximation coefficients.

##### B) Wavelet Packet Decomposition:

Wavelets work by decomposing a signal into different resolutions or frequency bands, and this task is carried out by choosing the wavelet function and computing the Wavelet Packet Transform (WPT) . Signal coding 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 WPT usually depends on the type of signal being analyzed or some other suitable criterion such as entropy.

##### C) Truncation of Coefficients:

After calculating the wavelet transform of the speech signal, coding involves truncating wavelet coefficients below a threshold. From the experiments that we conducted, we found that most of the coefficients have small magnitudes. Speaking in general terms, more than 90% of the wavelet coefficients were found to be insignificant, and their truncation to zero made an imperceptible difference to the signal. This means that most of the speech energy is in the high - valued coefficients, which are few. Thus the small valued coefficients can be truncated or zeroed and then be used to reconstruct the signal.

Two different approaches are available for calculating thresholds:

##### 1. Global threshold:

It involves taking the wavelet expansion of the signal and keeping the largest absolute value coefficients. In this case you can manually set a global threshold, a coding performance or a relative square norm recovery performance. Thus, only a single parameter needs to be selected. The coefficient values below this value should be set to zero, to achieve coding.

Figure4 shows the setting of global threshold for a typical speech signal.

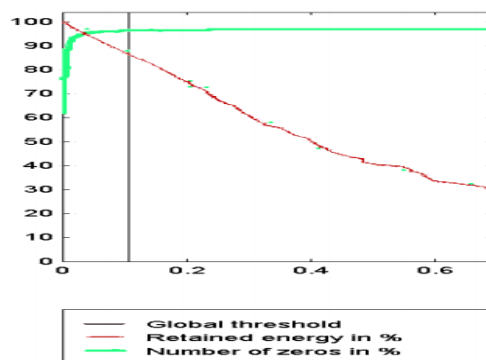


Fig4: Global thresholding of a speech signal

In this figure, the X- axis represents the coefficient values .The black (dark) vertical line moves to right or left, thereby changing the threshold. The intersection of this line with green line indicates the percentage of zero coefficients below this threshold. Its intersection with the red line indicates the percentage of signal energy retained after truncating these coefficients to zero.

##### 2. Level dependent thresholding:

This approach consists of applying visually determined level dependent thresholds to each decomposition level in the Wavelet Transform. The following figure shows the level - dependent thresholding. The truncation of insignificant coefficients can be optimized when such a level dependent thresholding is used.

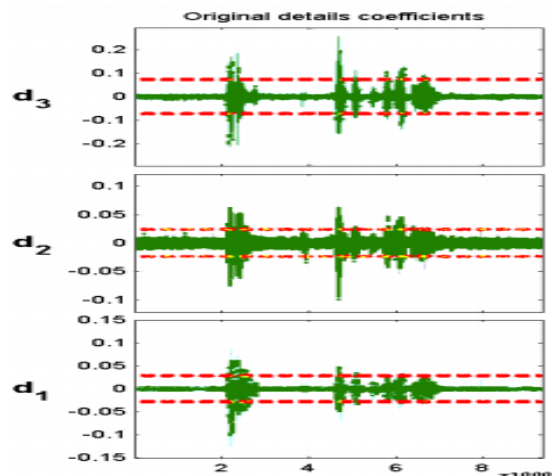


Fig5: Level dependent thresholding of a speech signal

Encoding Signal coding is achieved by first truncating small - valued coefficients and then efficiently encoding them. One way of representing the high- magnitude coefficients is to store the coefficients along with their respective positions in the wavelet transform vector.

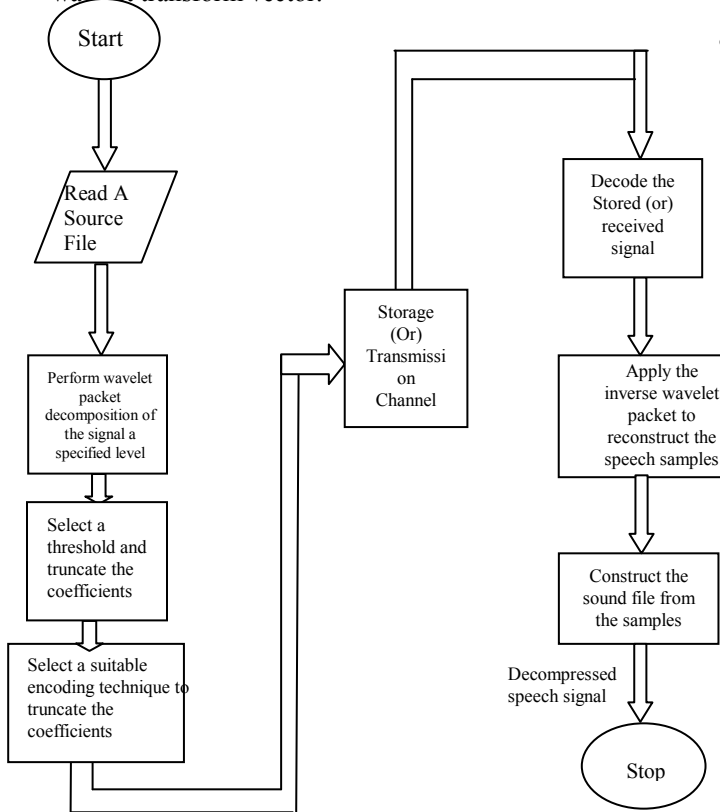


Fig6: Proposed Speech Coding Technique using Wavelet Transform

V. RESULTS AND DISCUSSIONS

This paper compares the performance analysis of wavelet threshold methods in coding of speech signal using Wavelet form and Wavelet Packet Transform. Threshold methods have been applied on the speech signal spoken in English language, taken from a female speaker at a sampling frequency of 8 KHz. All the threshold methods are tested with wavelets like Dabauchies (db1-db10)at four different levels of decomposition i.e. level1,level2,level3,level4. Further the performance analysis of the threshold methods are compared in terms of percentage of zero coefficients, retained signal energy.

A) Performance Measures

1. Retained signal energy:

This indicates the amount of energy retained in the compressed signal as a percentage of the energy of original signal. When compressing using orthogonal wavelets, the Retained energy in percentage is defined by:

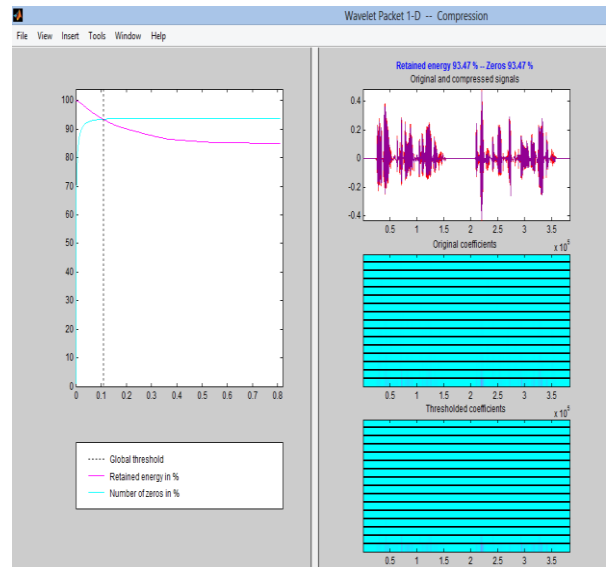
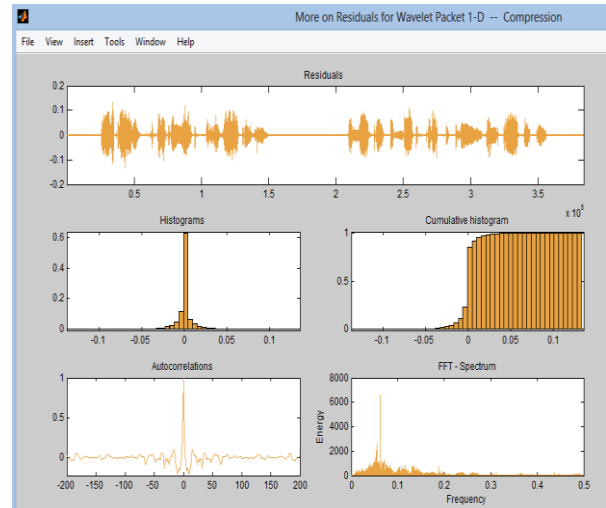
$$RE (\%) = \frac{100 * (vector - norm(coeffs of the current decomposition, 2))^2}{(vector - norm(original signal, 2))^2} \quad - (2)$$

Where  $\sigma_x$  and  $\sigma_e$  are respectively the mean square of the speech signal and the mean square difference between the original and reconstructed signals.

2. Percentage of zero coefficients:

It is given by the following relation:

$$\% \text{ of Zeros} = \frac{100 * (\text{no. of zeros of the current decomposition})}{\text{no. of coeff.}} \quad - (3)$$



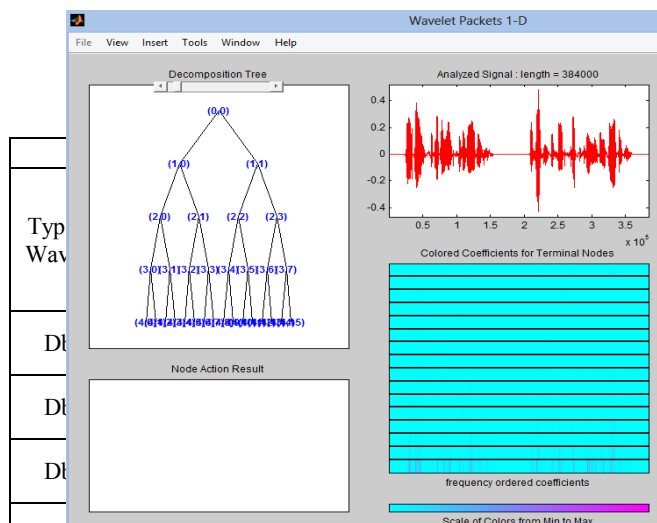


TABLE I PERFORMANCE ANALYSIS OF DAUBCHIES WAVELETS AT DIFFERENT LEVELS OF DECOMPOSITIONS

Type of Wavelet	Balance Sparsity Norm						
	Decomposition at Level-3		Decomposition at Level-4				
	No. Of Zeros %	Threshold value	RE(%)	No. Of Zeros %	Threshold value	RE(%)	No. Of Zeros %
Db4	75.0	0.1739	86.02	86.0	0.1235	89.84	89.84
Db5	75.0	0.2279	86.96	86.9	0.1435	91.13	91.13
Db6	74.9	0.2773	86.98	87.0	0.1563	91.53	91.53
Db7	74.9	0.2878	87.23	87.2	0.1643	91.61	91.61
Db8	74.9	0.3031	87.13	87.1	0.1737	91.74	91.74
Db9	74.9	0.3235	87.22	87.2	0.1683	91.79	91.79
Db10	74.9	0.3054	87.20	87.1	0.1801	91.69	91.69
	74.9	0.3258	87.17	87.2	0.1772	91.93	91.93
	74.9	0.3118	87.22	87.1	0.1798	91.79	91.79
	74.9	0.34	87.21	87.1	0.1723	91.86	91.86

IN TERMS OF THRESHOLD VALUE, RETAINED ENERGY (RE %) AND NUMBER OF ZEROS WITH GLOBAL THRESHOLDING BY BALANCE SPARCITY NORM

TABLE II PERFORMANCE ANALYSIS OF DAUBCHIES WAVELETS AT DIFFERENT LEVELS OF DECOMPOSITIONS IN TERMS OF THRESHOLD VALUE, RETAINED ENERGY (RE %) AND NUMBER OF ZEROS WITH GLOBAL THRESHOLDING BY REMOVAL NEAR ZERO

Type of Wavelet	Global Thresholding, Removal Near Zero											
	Decomposition at Level-1			Decomposition at Level-2			Decomposition at Level-3			Decomposition at Level-4		
	Threshold value	RE(%)	No. Of Zeros %	Threshold value	RE(%)	No. Of Zeros %	Threshold value	RE(%)	No. Of zeros %	Threshold value	RE(%)	No. Of Zeros %
Db1	0.004186	99.98	25.05	0.004186	99.97	32.06	0.004186	99.97	34.27	0.004186	99.97	35.05
Db2	0.004186	99.97	30.85	0.004186	99.97	38.63	0.004186	99.96	40.90	0.004186	99.96	41.86
Db3	0.004186	99.97	34.03	0.004186	99.96	41.95	0.004186	99.96	44.34	0.004186	99.96	45.22
Db4	0.004187	99.97	35.55	0.004187	99.96	43.78	0.004187	99.96	46.25	0.004187	99.96	47.00
Db5	0.004186	99.97	36.15	0.004187	99.96	44.52	0.004187	99.96	46.80	0.004187	99.96	47.66
Db6	0.004187	99.97	36.61	0.004187	99.96	44.76	0.004187	99.96	47.18	0.004187	99.96	48.14
Db7	0.004186	99.77	37.23	0.004186	99.96	45.18	0.004186	99.96	47.49	0.004186	99.96	48.29

Db8	0.00418 7	99.97	37.3 1	0.00418 7	99.96	45.7 8	0.00418 7	99.96	48.17	0.00418 7	99.96	49.0 1
Db9	0.00418 6	99.97	37.3 3	0.00418 6	99.96	45.4 3	0.00418 6	99.96	47.93	0.00418 6	99.96	48.8 2
Db10	0.00418 7	99.97	37.5 1	0.00418 7	99.96	45.4 8	0.00418 7	99.96	47.86	0.00418 7	99.96	48.6 7

TABLE III PERFORMANCE ANALYSIS OF DAUBCHIES WAVELETS AT DIFFERENT LEVELS OF DECOMPOSITIONS IN TERMS OF THRESHOLD VALUE, RETAINED ENERGY (RE %) AND NUMBER OF ZEROS WITH WAVELET PACKET TRANSFORM BY BALANCE SPARCITY NORM

Wavelet Packet Transform, Balance Sparsity Norm												
Type of Wavelet	Decomposition at Level-1			Decomposition at Level-2			Decomposition at Level-3			Decomposition at Level-4		
	Threshold value	RE(%)	No. Of Zeros %	Threshold value	RE(%)	No. Of Zeros %	Threshold value	RE(%)	No. Of zeros %	Threshold value	RE(%)	No. Of Zeros %
Db1	0.1632	97.11	50.0 2	0.3532	87.68	75.0 1	0.1775	86.05	86.05	0.1236	90.06	90.0 6
Db2	0.0831	99.28	50	0.2963	94.26	75.0 0	0.2342	86.96	86.96	0.1378	91.32	91.3 2
Db3	0.05256	99.60	50	0.2931	95.98	75.0 0	0.2798	87.03	87.03	0.1592	91.77	91.7 8
Db4	0.05049	99.70	50	0.2847	96.69	75.0 0	0.2938	87.26	87.22	0.1689	91.89	91.8 8
Db5	0.06362	99.74	50	0.2124	96.85	75.0 0	0.3031	87.12	87.13	0.1789	92.08	92.0 8
Db6	0.06624	99.76	50	0.2328	97.00	75.0 0	0.3126	87.31	87.26	0.1767	92.11	92.1 1
Db7	0.0637	99.77	50	0.2135	97.20	75.0 0	0.3054	87.18	87.18	0.1796	92.01	92.0 1
Db8	0.06038	99.77	50	0.2124	97.17	75.0 0	0.3224	87.25	87.25	0.1763	92.24	92.2 3
Db9	0.05966	99.78	50	0.2093	97.12	75.0 0	0.3118	87.20	87.22	0.1883	92.16	92.1 4
Db10	0.05359	99.79	50	0.1916	97.26	75.0 0	0.34	87.19	87.24	0.1821	92.16	92.1 5

TABLE IV PERFORMANCE ANALYSIS OF DAUBCHIES WAVELETS AT DIFFERENT LEVELS OF DECOMPOSITIONS IN TERMS OF THRESHOLD VALUE, RETAINED ENERGY (RE %) AND NUMBER OF ZEROS WITH WAVELET PACKET TRANSFORM BY REMOVAL NEAR ZERO

Wavelet Packet Transform, Removal Near Zero												
Type of Wavelet	Decomposition at Level-1			Decomposition at Level-2			Decomposition at Level-3			Decomposition at Level-4		
	Threshold value	RE(%)	No. Of Zeros %	Threshold value	RE(%)	No. Of Zeros %	Threshold value	RE(%)	No. Of zeros %	Threshold value	RE(%)	No. Of Zeros %
Db1	0.00418 6	99.98	25.0 3	0.00418 1	99.97	32.2 2	0.00418 6	99.97	35.79	0.00418 9	99.97	36.4 2
Db2	0.00418 6	99.97	30.8 5	0.00418 6	99.97	39.5 8	0.00418 6	99.97	42.90	0.00418 6	99.96	44.9 1
Db3	0.00418 6	99.97	34.0 3	0.00418 7	99.96	43.5 4	0.00418 6	99.97	46.96	0.00418 7	99.96	49.2 7
Db4	0.00418 7	99.97	35.5 5	0.00418 6	99.96	46.1 4	0.00418 7	99.97	49.84	0.00418 6	99.96	51.0 5
Db5	0.00418 6	99.97	36.1 5	0.00418 7	99.96	47.1 6	0.00418 6	99.97	50.83	0.00418 6	99.97	51.8 8
Db6	0.00418 7	99.97	36.6 1	0.00418 6	99.96	47.2 1	0.00418 6	99.97	50.89	0.00418 6	99.97	52.8 4

Db7	0.00418 6	99.77	37.2 3	0.00418 6	99.97	47.5 7	0.00418 7	99.97	51.75	0.00418 7	99.97	53.3 5
Db8	0.00418 7	99.97	37.3 1	0.00418 6	99.96	48.5 1	0.00418 6	99.97	52.19	0.00418 6	99.96	53.9 1
Db9	0.00418 6	99.97	37.3 3	0.00418 6	99.96	48.2 1	0.00418 6	99.96	52.56	0.00418 6	99.96	54.3 3
Db10	0.00418 7	99.97	37.5 1	0.00418 6	99.96	48.2 6	0.00418 6	99.96	52.75	0.00418 7	99.97	54.2 1

TABLE V ENTROPY VALUES AT DIFFERENT LEVELS OF DECOMPOSITION

S.No	Name of the Signal	No. of Samples	Entropy
1	Original Signal	384000	1345.3
2	Approximation at Level-1 (CA1)	192000	1119.1
3	Detail at Level-1 (CD1)	192000	14.08
4	Approximation at Level-2 (CA2)	96000	886.41
5	Detail at Level-2 (CD2)	96000	33.14
6	Approximation at Level-3 (CA3)	48000	656.61
7	Detail at Level-3 (CD3)	48000	60.602
8	Approximation at Level-4 (CA4)	24000	449.39
9	Detail at Level-4 (CD4)	24000	91.771

A comparative analysis has been performed between the threshold methods, for different wavelets with different levels of decomposition as shown in tables I,II,III&IV in terms of percentage of zero coefficients, signal energy in the first level approximation, retained signal energy.

It is observed as the level of decomposition is increased from level 1 to level-4, the percentage amount of retained energy will goes on decreasing and %of zero coefficients are increasing. We can also observe that as the level of decomposition increases we can achieve a higher coding factor which means that requires less memory space and band width. Generally higher coding factors are preferable but in the reconstruction process we may lose some information.

**VI. CONCLUSION**

In this paper the performance analysis of different wavelet threshold methods in coding of speech signal is investigated along with 4 different levels of decomposition along with Dabauchies (db1-db10) wavelets. The result shows that as the level of decomposition increases the percentage amount of retained energy will goes on decreasing and percentage of zero coefficients are increasing. Thus the lower levels of decomposition can be preferred as seen from the result performance.

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**Authors Profile:**

P.Sunitha born on April 3<sup>rd</sup> 1983 in Krishna district, received the B.Tech degree in Electronics and Communication Engineering from JNTU college of Engineering , Kakinada in 2006 and M.Tech in Digital Electronics and Communication Systems (DECS) from JNTU Kakinada. She is working towards the Ph.D degree from JNTUK.

She is currently working as an Assoc. Professor in the dept. of Electronics and Communication Engineering in Pragati Engineering College,