A Novel Speech Compression Technique using Optimized Wavelet Transform to Improve the Quality of Auditory Perception under Low SNR Conditions

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***Abstract* - Speech compression in poor environment, where the signal energy is weak due to acoustical disturbances, can improve the efficiency of transmission while reducing the bandwidth if intelligibility and/or quality can be preserved by selecting appropriate energy based wavelets. We propose an Optimized Wavelet Transform (OWT) to improve speech perception by incorporating masking techniques in the algorithm to reduce the noise effect. Adaptive Wavelet Selection followed by optimized quantization exploit a robust Dynamic Dictionary Scheme (DDS) to perform efficient compression while preserving speech intelligibility and perceptual quality. An additional lossless coding technique inevitably increases the compression ratio while preserving the quality of the signal. Finally, decompressing the compressed signal undergoes tonal and noise masking by applying a global threshold based on Sub-Band Perceptual Factor (SBPF) and Perceptual Entropy (PE), which improves the quality of the signal. Performance of the proposed algorithm is obtained in terms of Normalized Root-Mean Square Error (NRMSE), Compression Ratio (CR), Performance Evaluation of Speech Quality (PESQ), Re-construction Distortion Length (RDL), Signal to Noise Ratio (SNR) for various voiced and unvoiced signals recorded in low SNR conditions. All the signals are derived from NOIZEUS data base and some samples are recorded and normalized to operate at sampling frequency of 8KHz.**

Keywords - speech compression, optimized wavelet transform, auditory perception quality, low SNR

I. INTRODUCTION:

In the last few years, there has been exponentially up surge in multimedia data communication over transmission network thus demanding more efficient transmission paradigm while preserving the quality constructs of the original data. Speech signal has always been a dominating signal for communication that demands quality communication inevitably over communication network, even under low Signal to Noise Ratio (SNR) conditions. The limited number of channels available for cellular and telephone services put a demand before the researchers to concentrate on storage and transmission equipment, which drags the necessity of speech compression under the acoustical disturbances. According to Harshalata Petkar [1], DWT is the lossy compression technique for speech compression used to solve the problem faced by Palestinian cellular company, Jawwal for accommodating more users, without varying the parameters of the speech. P.M. Kavathekar et al., identified the necessity of speech compression in real – time scenario and implemented the same using FPGA. But DWT as it is a lossy compression techniques it retains detailed coefficients and decompressed signal is reconstructed from those coefficients by making other coefficients to be zero increases the compression ratio at a compensation of intelligibility/ quality of the signal [2]. Undeniably, there is an array of applications environment where identifying original signal under high disturbances or noise is must. M. Herrera et al., developed a perceptual audio compressor with a remarkable compression ratio using time-frequency localization based on principles from psychoacoustics and information theory [3].

These all key factors make it inevitable to develop a robust audio processing mechanism or vocoders to enable quality speech or audio communication. Speech compression is one of the broad research domains which often provide a broadened horizon for improvement and innovation. A major objective of speech compression is representing the speech signal with few bits by removing non – essential signals so that the reconstructed signal quality should be acceptable [4]. Compressive Sensing (CS) gives inbuilt compression, sensing & security to signal in just one single step reducing complexity & storage, but reconstruction quality is traded with available processing power at decoder [5-7]. Maher K. Mahmood Al-Azawi et al., proposes chaotic encryption with large key size along with compressive sensing to improve the compression ratio further [8]. Though, numerous efforts have been made on exploiting efficacy of the algorithms such as Linear Predictive Models, Discrete Cosine Transform, classical Fast Fourier transform etc., to perform speech compression, it has been still an open research area to augment existing systems or develop more efficient speech compression paradigm.

With this motivation, in this research work a highly robust and novel Optimized Wavelet Transform (OWT) based speech compression technique has been developed. Unlike classical wavelet techniques in the research work EWT comprising Adaptive Wavelet Selection (AWS) is developed followed by Optimized Wavelet Coefficient Quantization (OWCQ). These two key contributions (i.e., AWS and OWCQ) exploit a robust Dynamic Dictionary Scheme (DDS) to perform efficient compression while preserving speech intelligibility and perceptual quality. In proposed method, AWS incorporates Adaptive DWT selection and Transform Coefficient Bit Allocation (ADWT-TCBA) scheme so as to exploit efficacy of the masking effect in human hearing process. This makes proposed system more efficient in reducing the total number of bits needed to represent each frame of audio signal at certain defined noise or distortion level. Noticeably, in the proposed method the applied DDS scheme plays vital role in minimizing statistical redundancies allied with the original signal or the audio source. Here, both encoder as well as decoder maintain dictionary which is updated (at encoder/decoder) by applying the same set of rules and decoded audio frames. In the proposed DDS model for each individual audio frame a Best Matching Entry Factor (BMEF) is estimated in dictionary. Similarly, a Residual Signal Fraction Factor (RSFF) is estimated as the difference between BMEF of current frame and previous frame. Hence the proposed method encodes both frame and RSFF using optimized wavelet mechanism and transmits a minimum number of bits, reducing the transmission bandwidth. Also, In the DDS method least distance between the each frame of the decoded signal and perceptually nearest entry in the dictionary is estimated and compared against pre-specified threshold value. If the difference is less than the defined threshold, the dictionary remains unchanged; otherwise the decoded signal has been applied to update the dictionary by substituting the least used entry of the dictionary in the decoded signal.

Considering the need of a well characterized and significant masking in audio signal, a complete masking threshold is required to be estimated by exploiting the concept of simultaneous and temporal masking in conjunction with the frequency response of the ear. In addition to the proposed model an Adaptive Zero-Tree Model (AZTM) is used at the decoder end to reduce its complexity and Sub-Band Perceptual Factor (SBPF) is obtained to reach the Perceptual Entropy (PE) as much as possible.

II. PROPOSED METHODOLOGY

A. Adaptive WAVELET selection and DWT:

A wavelet family suitable for one application may not be perfectly suitable for any other application [2]. Hence choosing a wavelet for compressing the different speech signals from the database needs to select the wavelet from a trained dictionary. The Speech signal chosen from the Noizeus data base is segmented into frames of size 32ms each with 16ms overlapped with the successive frames. Energy of each frame is computed and compared with the energy of wavelet function. The difference between the energy levels is computed and stored forming a dictionary. Based on the difference of energy levels the algorithm is trained to select a best wavelet depending on the Best Matching Entry Factor (BMEF). The proposed work transforms each frame of the signal through the best suited wavelet by optimizing the filter bank shown in Fig 2.1. The low pass filtered and down sampled coefficients of each frame is called as approximation or coarser coefficients and the high pass filtered and down sampled coefficients are called the detailed coefficients.

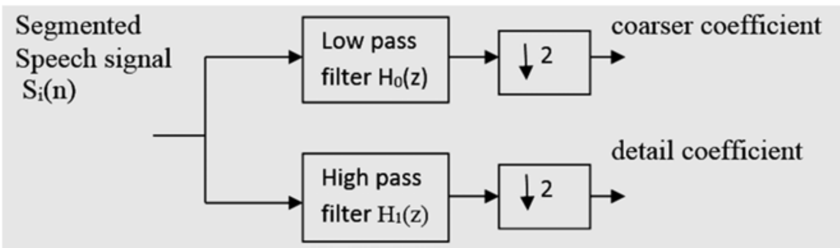

Fig 2.1 Decomposed structure of DWT

In general Quadrature Mirror Filter Banks (QMF) is considered for wavelet decomposition and reconstruction. The design of the band limited filter is the most important design aspect of the wavelet transformation for avoiding aliasing effect due to decimation. The proposed methodology is concentrated on optimizing filter banks in view of preserving the information of the speech signal without any loss due to aliasing.

B. Design of Optimized Wavelet Filter Banks

Filter bank design in wavelet transformation is a key role for improving the performance of the proposed work in maintaining the intelligibility of the signal by eliminating the phase distortion and distortion due to aliasing during the process of analysis-synthesis. To eliminate the phase distortions in the decomposition process the band limited low pass FIR filter design before decomposition is quite necessary. Here FIR filter using Kaiser Window with length equal to the frame length of input is chosen to avoid the

DOI 10.5013/IJSSST.a.19.06.28 ISSN: 1473-804x online, 1473-8031 print

phase distortion. The Kaiser window based on zeroth order Bessel's function is:

$$w(n) = I_0 \begin{cases} \left(\beta(1-[(n-\alpha)/\alpha]^2)^{\frac{1}{2}}\right) & 0 \le n \le N-1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $I_0(.)$ is the Bessel's function, α and β are variable parameters that controls the shape and width of side lobe amplitudes, N is the length of the frame. If low pass filter transfer function is $H_0(z)$ and high pass filter transfer function is $H_1(z)$, then $H_1(z) = H_0(-z)$ avoids the amplitude distortion at coarser coefficients. The filter is designed to a particular cut-off frequency, ω_c and is represented as $H_0(e^{j\omega})$ then:

$$H_0(e^{j\omega}) = H_d(e^{j\omega})W(e^{j\omega}) \tag{2}$$

$$h_0(\mathrm{n}) = \mathrm{h_d}(\mathrm{n}) * w(n) \tag{3}$$

where $H_d(e^{j\omega})$ is the desired filter frequency response and $W(e^{j\omega})$ is the frequency response of the window, $H_0(z)$ is the z-transform of $h_0(\mathrm{n})$. The optimization can be achieved by minimizing the error between the magnitude responses of ideal (MI) and desired filter (MD) i.e.:

$$e = MI - MD \tag{4}$$

If $e > 0$ then increase ω_c by step size, else if $e < 0$ then decrease ω_c by step size and repeat the process till the error is minimum.

C. Sub-band Tonal and Noise Masking, Threshold:

The proposed work transforms the each frame of the signal through the best suited optimized wavelet and obtained the approximation and detail coefficients. Most of these coefficients have very low amplitudes when compared to the maximum coefficients [11]. Also, due to transformation techniques used for audio compression results tonal coefficients in the process of decomposition. To eliminate the undesired tonal effect masking of those coefficients is the preliminary task. In the proposed method to exploit the audio components of the current frame under linear extrapolation the data from the previous two successive windows are considered. Then tonal masking threshold is to be estimated from the successive frames to eliminate those coefficients, as if the difference between the magnitudes of successive coefficients is more than 7dB. In fact it is intended to employ a sub-band noise masking to resemble the perceptual entropy as efficient as possible. Hence both tonal and noise masking thresholds need be calculated from the neighborhood and should eliminate them for improving the quality of the input speech signal (low SNR audio). A global threshold is obtained by calculating the threshold of the signal based on irrelevance and redundancy [2] even in the silence part and is represented as:

$$G_{th}(i) = 10log_{10}\left(\textstyle\sum_j 10^{0.1M_{tm}(i+j)} + 10^{0.1M_{nm}(i+j)} + 10^{0.1T_j}\right) \tag{5}$$

Where T_j represents the threshold in silence at a particular frequency, M_{tm}, M_{nm} are tonal and noise masking curves respectively and are represented by equations (6) and (7).

$$M_{tm}(i+j) = X_{TM}(i) + MF(i,j) - 0.275z(j) - 6.025 \tag{6}$$

$$M_{nm}(i+j) = X_{NM}(i) + MF(i,j) - 0.275z(j) - 2.025 \tag{7}$$

Where $X_{TM}(i)$, $X_{NM}(i)$ are the sound pressure levels of tonal and noise maskers at the spectral component index i, $MF(i,j)$ is the masking function defined based on the bark distance [2], Z(j) represents the position on the masking entropy. The perceptual entropy signifies the extent to which speech signal could be compressed with minimum perception distortion by reducing the Reconstruction Distortion Length (RDL).

D. Quantization and Coding:

The proposed work transforms the each frame of the signal through the best suited optimized wavelet and obtained the approximation and detail coefficients. Most of these coefficients have very low amplitudes when compared to the maximum coefficients [11]. There are two types of setting a threshold – Soft Decision Making Threshold and Hard Decision Making Threshold. Here a global threshold is set based on the noise and tonal masking so that all the minimum valued coefficients can be ignored and a better compression can be achieved, then quantized forming a codebook by selecting the minimum and maximum coefficients of each frame can increase the compression ratio further. Quantization is an irreversible process of valuing the data set. The codebook is thus formed by Level Optimized Wavelet Coefficient Quantization (LOWCQ) by reducing the slope – overload distortion. Adaptive Wavelet Selection (AWS) based on the BMEF and quantizing the wavelet coefficients (LOWCQ) are the key contributions in coding and quantizing with less distortion. Hence a Dynamic Dictionary Scheme (DDS) is developed and operated to preserve the quality and intelligibility of each speech sample. Basically, the information loss is due to the distortion caused by quantization in the compression schemes, but in the proposed method due to optimal quantization forming codebook in addition with DDS prevents the signal information with lower distortion.

E. Logarithmic Compander Assisted Quantization (LCAQ):

It is inevitable to develop a coding technique for compression after transformation. LCAQ is a compressor-expander scheme that could work under low SNR conditions by maintaining a adaptive step size in accordance with the speech signal for a variable quantization levels. Even though, the signal is having sufficient energy when it is influenced by noise it becomes imperceptible for the human ear. In the applications like under water surveillance or in Cockpit Voice Recorders in aircrafts experiences the effect of noise is more than the signal energy and is inevitably difficult for human perception. Hence, in digitizing the speech signal initial SNR of the signal plays a vital role in design and develop of the algorithms used for speech processing purpose. Therefore, the coded speech requires varying quantization levels with the step size proportional to short term stationary signals. This eventually increases the coding efficiency by employing fewer bits.

III. PERFORMANCE MEASURES:

The performance of the proposed method can be measured in terms of compression ratio (CR), RDL, short-term objective intelligibility (STOI), PSNR, Performance Evaluation of Speech Quality (PESQ). CR can be obtained as the ratio of the size of input signal to that of the size of compressed signal, i.e.

$$CR = \frac{length(S(n))}{length(compressed\ signal)} \quad (8)$$

RDL is the parameter used to measure the distortion caused during the signal processing and can be expressed as average of squared difference between the input and reconstructed signals. STOI is the intelligibility measure of the reconstructed signal that to which extent the listener can be able to identify the content of the signal. The intelligibility measured greater than 0.7 is giving a good Mean Opinion Score (MOS) for the reconstructed signal. Peak Signal-to-Noise Ratio (PSNR) is the quality measure of the reconstructed signal. Higher the PSNR indicates higher the quality of the signal.

PESQ is the international standard important measure of the quality of the signal. Perceptual speech quality plays a crucial role in the hearing impaired. Quality improvement need not necessarily improve the intelligibility of the signal. Also quality can be improved at a compensation of intelligibility. PESQ can be expressed as in equation (9):

$$PESQ = a_0 + a_1 D_{avg} + a_2 A_{avg} \quad (9)$$

Where a_0 =4.5, $a_1 = -0.1$, $a_2 = -0.0309$, D_{avg} is the average disturbance value and A_{avg} is the average asymmetrical disturbance.

IV. RESULTS AND DISCUSSION:

The proposed method is implemented on the voiced and unvoiced speech signals in .wav form taken from NOIZEUS database which is developed from AURORA set of signals, TIMIT database which consists of 30 speech signal samples with a combination of male and female speakers. The algorithm is also implemented on noisy signals which are corrupted with babble, airport, station, car, and train noises at different noise energy levels so that the their initial SNR represented as 0dB, 5 dB, 10 dB, 15 dB. The noisy speech signals are processed through the adaptive optimized wavelet transformation followed by masking, thresholding, quantization and coding to represent the recorded speech data in compact form for transmission and storage purposes and also maintaining its intelligibility and improving the quality of the reconstructed signals. The compressed signal undergoes the process of decompression while retrieving the signal at the decoder. The decompressed output is compared with the original signal without any noise interference for measuring the performance of proposed method in terms of STOI and PESQ. Different parametric comparisons are made in table 4.1 to 4.5 for various noisy signals considered from NOIZEUS. The noises chosen are having high impact on the speech signals in mobile applications. In all the cases the proposed method is quoting a variable compression ratio as DWT is used.

TABLE 4.1 PERFORMANCE MEASURE OF PROPOSED METHOD FOR TRAIN NOISE AT VARIOUS INITIAL SNR SIGNAL

Noisy speech signal	Parameter				
	Compression Ratio	**STOI**	**RDL**	**PSNR (dB)**	**PESQ**
0 dB	2.2958	0.84137	0.00394	24.05	2.352656
5 dB	2.2674	0.88734	0.00273	25.65	2.557477
10 dB	2.1829	0.92988	0.00224	26.49	2.971080
15 dB	2.1503	0.94546	0.00193	28.56	3.585561

TABLE 4.2 PERFORMANCE MEASURE OF PROPOSED METHOD FOR STATION NOISE AT VARIOUS INITIAL SNR SIGNAL

Noisy speech signal	Parameter				
	Compression Ratio	**STOI**	**RDL**	**PSNR (dB)**	**PESQ**
0 dB	2.3201	0.79637	0.00456	23.42	2.331371
5 dB	2.2499	0.84268	0.00259	25.93	2.544640
10 dB	2.1988	0.93792	0.00192	27.17	2.938545
15 dB	2.1773	0.95931	0.00177	28.55	3.385958

The average compression ratio for initial 0 dB SNR voiced and unvoiced signals is found be 2.31336, which is greater than 50% with an average intelligibility of 0.84936. With the increase of noise energy, distortion increases and the quality and intelligibility is found to be less when compared to the signals with higher energy. The average compression ratio for initial 5 dB, 10 dB, 15 dB SNR voiced and unvoiced signals is found be 2.23657, 2.18945, 2.16453 which is greater than 50% in all the cases with an average intelligibility of 0.89854, 0.93249, 095628 respectively. It is observed to maintain the intelligibility of the compressed signal, the compression levels are varied from 4.1 to 1.99 in the entire data set considered.

TABLE 4.3 PERFORMANCE MEASURE OF PROPOSED METHOD FOR CAR NOISE AT VARIOUS INITIAL SNR SIGNAL

Noisy speech signal	Parameter				
	Compression Ratio	STOI	RDL	PSNR (dB)	PESQ
0 dB	2.2752	0.82997	0.00410	23.88	2.339777
5 dB	2.2137	0.87166	0.00231	26.37	2.549954
10 dB	2.1838	0.93339	0.00208	26.82	2.976454
15 dB	2.1542	0.94948	0.00192	27.20	3.548655

TABLE 4.4 PERFORMANCE MEASURE OF PROPOSED METHOD FOR BABBLE NOISE AT VARIOUS INITIAL SNR SIGNAL

Noisy speech signal	Parameter				
	Compression Ratio	STOI	RDL	PSNR (dB)	PESQ
0 dB	2.3560	0.88056	0.00399	25.02	2.383866
5 dB	2.2231	0.91607	0.00203	26.26	2.567653
10 dB	2.2078	0.95781	0.00192	27.20	2.991968
15 dB	2.2027	0.99374	0.00188	27.50	3.573755

TABLE 4.5 PERFORMANCE MEASURE OF PROPOSED METHOD FOR AIRPORT NOISE AT VARIOUS INITIAL SNR SIGNAL

Noisy speech signal	Parameter				
	Compression Ratio	STOI	RDL	PSNR (dB)	PESQ
0 dB	2.3487	0.90126	0.00348	24.79	2.342759
5 dB	2.2170	0.92334	0.00246	26.06	2.583679
10 dB	2.1814	0.93001	0.00230	26.39	2.959631
15 dB	2.1157	0.96806	0.00192	27.12	3.554656

By the observation it is found to be the effect of station noise is more and the effect of airport noise is less on voiced/unvoiced signals in the database. Table 4.6 compares the proposed method with Contourlet Transformation (CT) [8] in terms of PESQ and shows proposed technique quotes good PESQ compared to the existing at low SNR conditions. Table 4.7 represents the performance evaluation of ADWT-TCBA for clean speech signals taken from three different sets of database and an average PESQ 3.654723 at compression ratio of 2.6547.

TABLE 4.6 PERFORMANCE COMPARISON OF PESQ FOR VOICED/UNVOICED SIGNALS AT DIFFERENT INITIAL CONDITIONS

Compression ratio (%)	Contourlet Transform[8]	Proposed Method
40-50	0	2.578956
50-60	0.156	3.556988

TABLE 4.7 PERFORMANCE MEASURE OF PROPOSED METHOD FOR CLEAN VOICED/UNVOICED SIGNALS

Noisy speech signal	Parameter				
	Compression Ratio	STOI	RDL	PSNR (dB)	PESQ
S1-S30 Timit	1.9985	0.98126	0.00038	36.79	3.742759
L1-L30 Timit	3.4170	0.96334	0.00046	36.06	3.753679
Noizeus	2.1366	0.94769	0.00188	28.42	3.222221

TABLE 4.8 PERFORMANCE COMPARISON OF SNR FOR VOICED/UNVOICED CLEAN SIGNALS

Compression ratio (%)	CT [8]	DWT [1]	proposed Method
30-40	--	28.623	35.37245
40-50	11.881	36.961	36.58236
50-60	28.646	31.5338	38.89936

TABLE 4.9 PERFORMANCE COMPARISON OF PESQ FOR VOICED/UNVOICED CLEAN SIGNALS

Compression ratio (%)	Compressed sensing using Haar [6]	Compressed sensing using Hadamard [6]	Compressed sensing using Random Gaussian [6]	Compressive sensing [5]	Contourlet Transform [8]	Proposed Method
30-40					--	3.0568
40-50	---	---	---	---	3.171	3.5432
50-60	2.52	2.35	3.11	3.593	3.741	3.7826

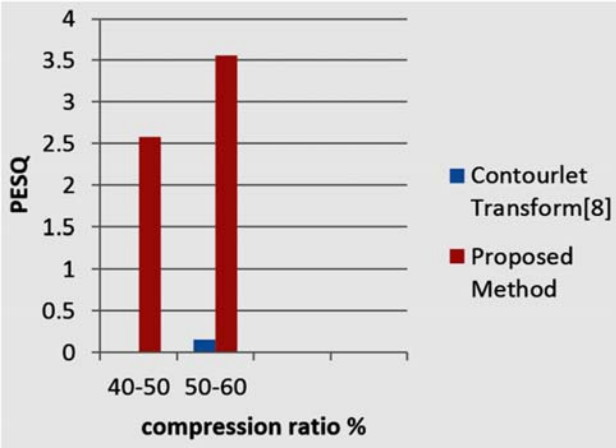

Fig. 4.1 comparison of proposed method with existing methods in terms of PESQ at initial SNR conditions

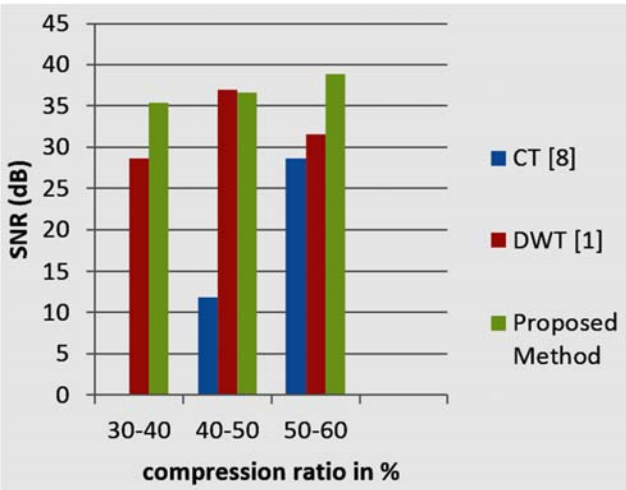

Fig. 4.2 Comparison of Proposed method with existing methods in terms of SNR (dB)

The performance of the proposed method for clean speech signals can be compared with existing methods in terms of SNR in table 4.8 and PESQ in table 4.9. The performance of the proposed algorithm is compared with existing method using bar graph as shown in Fig 4.1 for initial SNR conditions and for clean speech signals Fig 4.2 and 4.3 in terms of SNR and PESQ respectively.

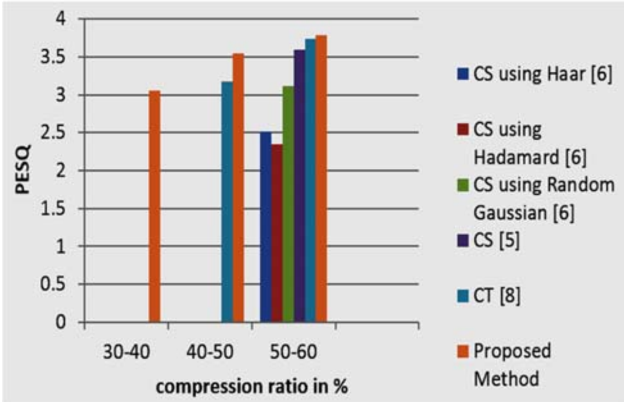

Fig. 4.3 Comparison of Proposed method with existing methods in terms of PESQ

VI. CONCLUSION

The proposed wavelet transformation technique based perceptual coding scheme can be well suited for high quality speech signal communication and transmission over wireless transmission medium under any low SNR conditions. The PESQ obtained is better compared to the existing method. In the proposed model using the optimization of the wavelet filter bank structure it provides temporal resolution, avoids aliasing and achieves maximum computational efficiency. The compression ratio of the speech signals can be varied as the compression is done through the wavelet transformation followed by coding. The compression ratio is also varied according to the effect of noise. Because of incorporating the noise masking in the proposed method, even for the low SNR voiced/unvoiced signals, the reconstruction quality can be improved a lot but at a compensation of intelligibility. At a loss of intelligibility of 5 to 10 percent the quality of the speech signal can be significantly improved by a factor of 13 to 25 percent and PESQ can be improved by more than 0.5. Better compression ratio can be achieved using the proposed transformation technique so that more number of users can be allocated a voice channel in mobile communications in busy hours. Even at typical situations where the noise effect is more (but in positive dB) the recordings can be processed using the proposed algorithm with high quality and intelligibility.

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