International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Noise Reduction using Modified Central Frequency BWT and RLS filter

Shraddha C. *[1], Chayadevi M. L.[2], M. A. Anusuya[2], Vani H. Y.[3]

Submitted: 02/11/2023 **Revised**: 21/12/2023 **Accepted**: 04/01/2024

Abstract: Speech signals are majorly mixed with different types of noises namely background noise, environmental noise, white noise, colored noise and so on. To have an efficient speech recognition system, it is necessary to have noisy speech signals preprocessed to reduce their noise levels. Very few works are addressed to handle pink and babble noises. Hence, we were motivated to design and apply hybrid algorithms to handle these types of noises. A new hybrid Modified Central Frequency Bionic Wavelet transform using Recursive Adaptive Filter is proposed as a novel method to increase the signal strength. This method is evaluated using MSE, SNR and PSNR parameters. Among these SNR and PSNR metrics has been observed to yield better results for pink and babble noises.

Keywords: *Empirical Mode Decomposition, Lease Mean Square, Modified Central Frequency Bionic Wavelet Transform, Noise Reduction, Normalized Least Mean Square, Recursive Least Square*

1. Introduction

Speech recognition refers to a machine or a program ability to recognize words and phrases in spoken language using algorithms through acoustic and language modelling algorithms. Recognition systems performance degrades if speech signal is contaminated with unwanted signals [1]. Identifying the noisy segments by preserving high minimal speech features is a challenging task in speech related applications [2]. Various types of noises get induced to speech signal either naturally or artificially in additive or convolutive modes. This paper addresses colored and environmental noise reduction techniques using wavelets and adaptive filtering techniques. The amalgamation of these techniques is applied to handle pink, white(colored), babble & street(environment) noises at various decibels. Since very few research works were identified in handling pink and babble noises, we were motivated to observe and work towards increasing the signal strength by reducing the noise. table 1, table 2 and table 3 depict various noise types and their characteristics that can be naturally induced along with the speech signal [3].

Challenges to reduce noise are addressed by many researchers by proposing various techniques. A few commonly adopted techniques are Continuous Bionic Wavelet, Normalized Least Mean Square and Recursive Least Mean Square filtering techniques. In this paper hybrid technique has been proposed using the above techniques to increase the signal strength of the noisy speech signal.

The study is comprised of six sections, which are structured as follows, an introduction is found in section 1, followed by a summary of related work in section 2. The methodology is stated in section 3. Section 4 includes the experimental results and compares the results with the baseline approach. Lastly, section 5 consists of the conclusion and future enhancement of the work.

Table 1. Different forms of noise based on statistical properties.

Noise Type	Description
Additive	Noise which gets added to unintended signal.
White	Signals with equal intensity at different frequencies
Black	Noise which contains silence.
Gaussian	Noise having probability density function equal to normal distribution
Pink/ flicker	Noise whose power spectral density is inversely proportional to frequency of the signal.

[1]*Vidyavardhaka College of Engineering, Mysuru, affiliated to Visvesvaraya Technological University, Belagavi, INDIA*
ORCID ID : 0000-0003-3539-8744
[1,2]*B.N.M. Institute of Technology, Bangalore, affiliated to Visvesvaraya Technological University, Belagavi, INDIA*
ORCID ID : 0000-0002-0312-4530
[2]*JSS Science and Technology University, Mysuru, INDIA*
ORCID ID : 0000-0002-5236-8400
[3]*JSS Science and Technology University, Mysuru, INDIA*
ORCID ID : 0000-0002-3735-3104
** Corresponding Author Email: shraddha.sunilkumar@gmail.com*

Table 2. Different forms of noise based on different frequency.

Noise Type	Description
White	Noise which is indeterminist and can't be predicted in natural way. frequencies with even strength
Narrowband	Noise generated from electricity supply of 60 Hz frequency
Colored	Noise with uneven frequency distribution
Impulsive	Signal which is spontaneous and generates for short duration
Transient	Signal, which is spontaneous, generates for short duration and where noise pulse is broad in nature

Table 3. Different forms of noise when coupled with external environment.

Noise Type	Description
Intermodulation	When signal of different frequencies shares the same non-linear medium
Cross talk	Process in which in a signal transmitted in channel of a transmission systems creates undesired interference onto a signal in another channel
Interference	Modification or disruption of a signal travelling along a medium
Atmospheric	It's also called static noise and it is the natural source of disturbance caused by lightning discharge in thunderstorm and the natural (electrical) disturbances occurring in nature
Industrial	Noise created through automobiles, aircraft, and ignition electric motors and switching gear

2. Background Study

Author Yannis Kopsinis et al. has addressed EMD technique using threshold parameters applied to white gaussian noise at positive decibel [4]. Authors Haifa Touati et al. has addressed adaptive Least Mean Squares (LMS) filter technique with EMD for white gaussian noise for positive decibels [5]. Wahbi Nabi et al. has worked on hybrid techniques using bionic wavelet transform with Kalman filtering for babble noise at positive decibels and Norezmi Jamal et al. has also discussed their applications, Deep Neural Network with Harmonic Regeneration to reduce babble noise at positive decibels only [6] [7]. Authors has combined normalized least mean square filter with morlet wavelet to reduce additive white gaussian noise [8]. Anil Garg et al. proposed hybrid method to reduce babble and street noise using BWT-Butterworth filter applied on positive decibels [9]. Swathi Kotte, MbachuC suggested the recursive least square filter performs well in denoising the environmental noisy speech signal [10][11].

From the above literature it is observed that pink noise is not addressed by any authors and babble/street noises are addressed only for positive decibels. The author has suggested applying RLS filter for noise reduction applications [12]. Hence in this paper the RLS filter is combined with MCBWT to analyze and observe the performance of RLS filter in pink and babble noise reduction.

3. Methodology

The below Fig. 1 depicts the system architecture flow diagram to reduce the noises by combing EMD, wavelet and filtering techniques. Each method is briefly explained with their mathematical concepts and algorithms applied to design the noise reduction algorithms.

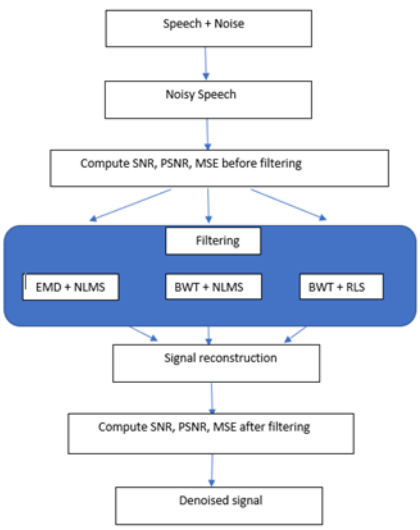


Fig. 1. Flow diagram proposed for Noise Reduction

3.1 Empirical Mode Decomposition [EMD]

The Empirical mode decomposition (EMD)is a tool used for the analysis of speech signal. It breaks the signal into various amplitudes and frequencies called Intrinsic Mode Functions (IMFs). Each IMF is applied with a thresholding technique to eliminate low-energy IMF parts that are significantly corrupted by noise. EMD interval thresholding is computed by Equation (1). The absolute value of the extrema will be below the threshold when the signal is absent else it will be above the threshold.

$$\tilde{h}(\mathrm{i})\left(z_j^{(i)}\right) = \begin{cases} h^{(\mathrm{i})}\left(z_j^{(i)}\right)\frac{\left|h^{(\mathrm{i})}\left(r_j^{(i)}\right)\right|-T_i}{\left|h^{(\mathrm{i})}\left(r_j^{(i)}\right)\right|}, & \left|h^{(\mathrm{i})}\left(r_j^{(i)}\right)\right| > T_i \\ 0, & \left|h^{(\mathrm{i})}\left(r_j^{(i)}\right)\right| \leq T_i \end{cases} \quad (1)$$

for j = 1, 2, . . ., n(i), where $h^{(\mathrm{i})}\left(z_j^{(i)}\right)$ indicates the samples from instant $z_j^{(i)}$ to $z_{j+1}^{(i)}$ of the ith IMF.

3.2 Bionic Wavelet Transformation [BWT]

BWT is a time frequency speech analysis technique based on an auditory model. This adjusts the speech signal frequency and instantaneous amplitude adaptively. The mother wavelet adjusts the active control mechanism of the human auditory model for the signal analysis. The model employs adaptive modification of cochlear filter by the adjustment of acoustic resistance (Req) and compliance (Ceq) of the basilar membrane (BM) with adaptable new quality factor, given by Equation (2).

$$\mathrm{Q_{eq}} = \mathrm{R_{eq}^{-1}}\sqrt{\mathrm{L} / \mathrm{C_{eq}}} \quad (2)$$

where L is acoustic mass, Ceq and Req is computed.

$$\mathrm{C_{eq}} = \left(1 + \mathrm{G_2(x)}\left|\frac{\partial[\mathrm{d(x,t)}]}{\partial \mathrm{t}}\right|\right)^2 \mathrm{c(x)} \quad (3)$$

$$\mathrm{Req} = \mathrm{R(x)} - \mathrm{G_1(x)}\frac{\mathrm{d}_{\frac{1}{2}}}{\mathrm{d}_{\frac{1}{2}} + |\mathrm{d(x,t)}|}\mathrm{R(x)} \quad (4)$$

where d (x, t) is the displacement of the BM at position x at time t. (∂ [d (x, t)]/∂t) is the first-order differential.

R(x) and C(x) are passive BM acoustic resistance with compliance. This adaptive mother wavelet transforms and modifies the target signal's frequency, and its amplitude.

3.3. Normalized Least Mean Square [NLMS]

The extended version of Least Mean Square [16] is NLMS adaptive filter [1]. It normalizes the weight vector by updating the squared norm of the regressor. Since the filter is adaptive, obtained coefficients results are less sensitive to the variations of the input power. NLMS filters are the better choice for processing noisy speech data. The filter step plays a prominent role, and its step size is normalized according to the Equation (5).

$$\mu(n) = \frac{\beta}{\|x(n)^2\|} \quad (5)$$

The updated filter co-efficients are computed from Equation (6).

$$w_{n+1} = w_n + \beta\frac{x(n)}{\|x(n)^2\|} \quad (6)$$

3.4 Recursive Least Square [RLS]

The Recursive Least Squares (RLS) filter is based on the least square method. The RLS filter step size has a high convergence in speed and rate between 0 and 1, regardless of the eigenvalue [8]. The filter is defined by Equation (7)

$$w(n) = w(n) + \mathrm{e}(n) \cdot k(n) \quad (7)$$

where $w(n)$ is the filter coefficients vector. $k(n)$ *is* gain vector given by, $k(n) = \frac{p(n)\cdot u(n)}{m+u^T\cdot p(n)} \cdot u(n)$, where m is the forgetting factor and $p(n)$ is input signals inverse correlation matrix.

3.5 Proposed Method- Modified Central Frequency Bionic Wavelet Transformation [MCBWT]

The standard bionic wavelet is computed using Equation (9). The T function of the mother wavelet $\psi(\mathrm{t})$ is computed using the Eqn. (8).

$$\psi(t) = \frac{1}{T\sqrt{a}}\hat{\psi}\left(\frac{t}{T}\right)exp(j\omega_0 t) \quad (8)$$

The parameter values of T function are varied in the proposed MCBWT over the standard values of T function of basic mother wavelet transformation. These values are set by trial-and-error method to identify the thresholding sensitivity of the parameters to reduce the noise.

The following parameter values are modified over the standard parameter values for our simulation, with scale(a)=13, base frequency(f0)=5/(6*π), central frequency(ω_0) = 5024 Hz and wider support length(t) = [−8,8]). Since the parametric values of T function is modified it is coined as MCBWT.

$$BwT(a,\tau) = \frac{1}{T}\sqrt{a}\int f(t)\tilde{\Psi}^*\left(\frac{t-\tau}{aT}\right)exp\left(-j\omega_0\left(\frac{t-\tau}{a}\right)\right)\mathrm{d}t \quad (9)$$

3.6 Algorithms

This section provides hybrid algorithms applied to evaluate the noise reduction methods using LMS, NLMS, RLS and Bionic wavelet functions.

- **EMD with NLMS Algorithm**

Input: Clean and Noisy signal are used to generate, noisy speech signal

Output: Noise Reduced Speech Signal

Step1: compute the 1st level IMFs of noisy speech segment for various intervals.

Step2: Perform the EMD-Interval thresholding, to obtain denoised version of the original signal using Equation (1) by setting the thresholding value of 0.7.

Step3: Iterate steps 2, over the speech segments.

Step4: Frames above the threshold value are retained and the average is computed.

Step5: NLMS filter is applied for the signal obtained in step 4, by setting step size as 1.37 and minimum filter length as 1 to obtain final denoised signal.

- **Modified Central Frequency BWT with NLMS Algorithm**

Input: Clean and Noisy signal are used to generate, noisy speech signal

Output: Noise Reduced Speech Signal

Step1: Apply modified central frequency bionic wavelet transformation to the input signal.

Step 2: Parameters of MCBWT are set as, a=13, t = [-8,8] and f0=5/(6*π) and ω_0= 5024 Hz to morlet wavelet

Step3: Apply inverse BWT.

Step4: Reduced noise signal is fed to NLMS by varying the filter step size from 1 to 1.37 with filter length as 1 to reduce noise further.

- **Modified Central Frequency BWT and RLS Algorithm**

Input: Clean and Noisy signal are used to generate, noisy speech signal
Output: Noise Reduced Speech Signal

Step1: Apply modified central frequency bionic wavelet transformation to the input signal.

Step2: Parameters of MCBWT are set as, a=13, t = [-8,8] and f0=5/(6*π) and ω_0= 5024 Hz to morlet wavelet

Step 3: Apply inverse BWT.

Step4: RLS filtering is applied for the resultant signal obtained in the step3 by setting filter step size to 0.0026, forgetting factor as 1 and filter length to 1, to obtain final noise reduced signal.

4. Data Analysis and Findings

4.1. Data Collection and Preprocessing

Corpus is a large collection of data, classified into two different forms based on the type of signals namely speech and noisy corpus. There exist many standard noise and speech corpuses. The noisy speech corpus [13] is tailored by merging the speech and noise corpus according to the requirement of the application for our work. For our simulation work the noisy speech corpus is generated by combining TIDigit speech [14] and Noisex-92 [15] noise corpus at word level. This dialectically balanced database consists of more than 25-thousand-digit sequences. There are total of 326 speakers, out of which 111 men, 114 women, 50 boys and 51 girls each pronouncing 77digit sequences. White, pink noises are considered for colored noises. Babble and street noises are considered environmental noises. This noisy corpus is collected from Noisex-92 database. These noisy signals are sampled at 16kHz. For our experimentation, it is further down sampled to 16 kHz to match with the TIDigit speech signal sampling frequencies.

4.2 Comparison Analysis with proposed techniques

4.2.1 Method 1: EMD with NLMS

When noisy speech signal is applied to EMD-NLMS technique, an improvement of 19dB in SNR is observed as shown in below Fig. 2. The SNR of the suggested method is observed to be higher for pink noise, yielding a 21.96dB improvement and 22.08dB improvement for babble noise at 10dB. Fig. 2(b), 2(d), 2(f) represents spectrograms for pink noise and Fig. 2(c), 2(e), 2(g) represents spectrograms for babble noise at 10db when EMD-NLMS hybrid algorithm is applied. The EMD-NLMS approach finds still improved results for SNR at 10dB over 5dB.This is due to the fact that the local mean and its first level IMFs are very close to zero for all the frame level IMFs to the number of extrema of the noise segments.

Noise and speech signals differ in number of zero-crossings with their interval thresholding values. The obtained IMFs of noisy signal will be efficiently filtered by the NLMS filter. Obtained coefficients have better signal strength. This could be achieved by varying the filters step size as 1. The step size is set by trial and error procedure due to the varying characteristics of different noise types.

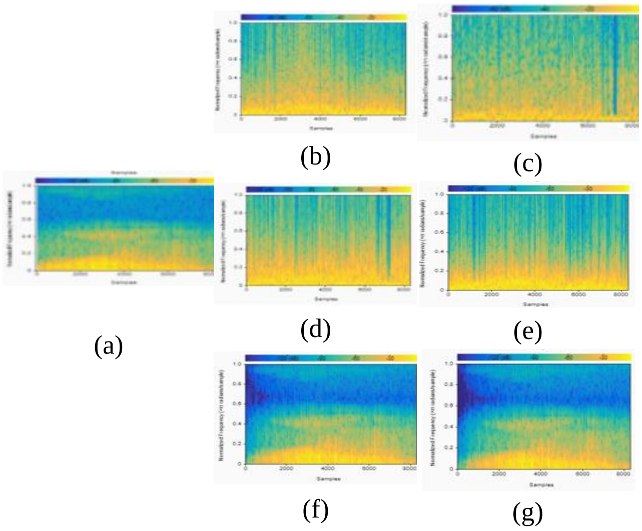
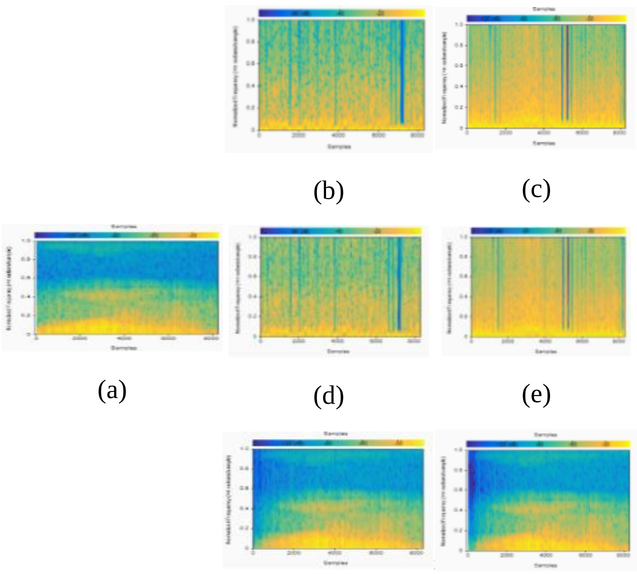


Fig. 2. Spectrogram of (a) clean speech (b) & (c) speech signal corrupted by pink noise and babble noise at 5dB(d) & (e) first level of denoised speech signal from EMD (f) & (g) final denoised speech signal after combing EMD with NLMS filter.

4.2.2 Method 2: MCBWT with NLMS

The MCBWT was proposed to replace the traditional EMD, to further enhance the signal ratio. The base values of the parameters proposed are as discussed in MCBWT of section 2.2. From Fig. 6, it is observed, the SNR of the suggested method is higher at 10dB yielding 23dB improvement for pink noise and 22.8dB for babble noise. Results for another performance metric (MSE and PSNR) are represented in Fig. 7 and Fig. 8. In Fig. 3, 3(b), 3(d), 3(f)are spectrographic representation of pink noise and Fig. 3(c), 3(e), 3(f) are spectrographic representation of babble noise when Modified Central frequency BWT(MCBWT) with NLMS filter is applied at 10dB. This is achieved by modifying the T function of the wavelet. The NLMS filter reduces the mean square error between the speech and the noisy signal. The filter coefficients are adjusted by varying the step size between 1 to 1.37. Lower the SNR step size is more and vice versa.



(b) (c)

(a) (d) (e)

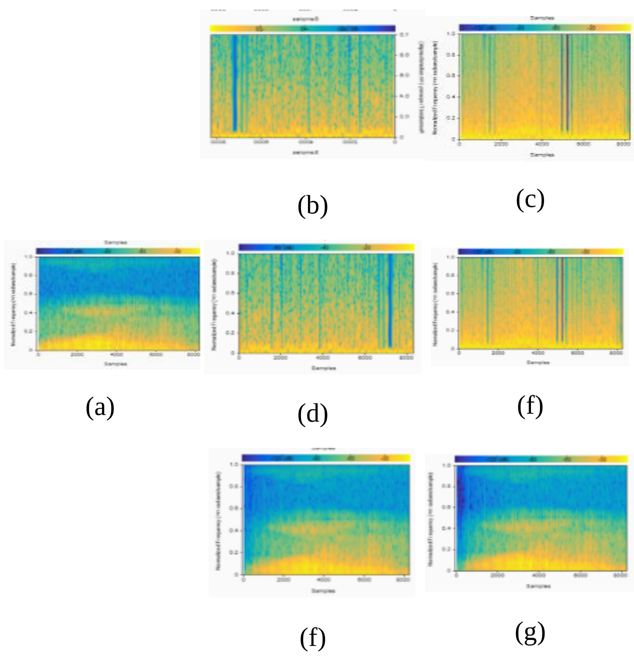
(f) (g)

Fig. 3. Spectrogram of (a) clean speech (b) & (c) speech signal corrupted by pink noise and babble noise at 10dB(d) & (e) first level of denoised speech signal from MCBWT(f) & (g) final denoised speech signal after combing MCBWT with NLMS filter.

4.2.3 Method 3: MCBWT with RLS

Noise is reduced further by replacing NLMS with RLS filter, this improves signal ratio up to 24.23dB for pink and 24dB for babble noise at 10dB. The modified T function with the covariance matrix coefficients of RLS filter are used to measure the linear coupling between the noise and speech signal. This is achieved by setting the RLS weighted vector filter coefficients to 0.026. The initial value of the weighted vector is set to 0, with the filter step varying from 0.99 to 1.39 with the order of the filter varying from 2 to 5. The covariance convergence is more in RLS than in LMS filter. This increases the signal strength by reducing the noise. The scale parameter of T function and the step size value of RLS filter helps in yielding better result than NLMS filter.

In Fig. 4, 4(b), 4(d), 4(f) depicts the spectrogram of pink noise and Fig. 4, 4(c), 4(f), 4(g) depicts the spectrogram of babble noise at 10dB when MCBWT with RLS filter is applied.



(b) (c)

(a) (d) (f)

(f) (g)

Fig. 4. Spectrogram of(a) clean speech (b) & (c) speech signal corrupted by pink noise and babble noise at 10dB (d) & (e) first level of denoised speech signal from MCBWT (f) & (g) final denoised speech signal after combing MCBWT with RLS filter.

The major parameters contributed to the proposed methods of MCBWT-RLS are briefed in table 4. A description of the method (MCBWT) explained to improve speech is explained as shown in the below table 4.

Table 4: Summary of the method Proposed

Method	Features, Benefits, Findings and Performance Accuracy of Proposed Method
MCBWT_RLS	Along with other parametric variations of T function in Bionic wavelet (MCBWT), quality of speech is further improved with proper selection of step size in RLS filter. Due to recursive update of filter coefficients in RLS filter, error is reduced with a high convergence between the noisy filtered coefficients and the clean speech coefficients. This method is observed with average increase in SNR by 11dB, average decrease in mean square error by 0.8 and average increase in PSNR by 23dB

for pink and babble noise at 10dB.The scale parameter of Wavelet function and the step size parameter of RLS filter plays the major role in increasing the signal strength.

The suggested methodologies performance is examined by considering the SNR ratio between input noisy signal (input SNR) and output de-noised signal (output SNR) for all above methods for white, pink, babble and street noises for varied decibels. The numerical values obtained for SNR parameter are tabulated in table 5.

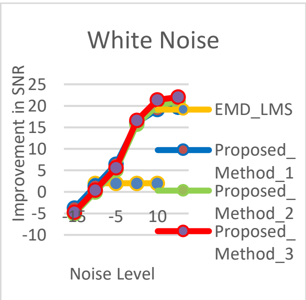
4.3 Comparative Analysis with Existing Techniques

Table 5: Justification of suggested methodology with the prevailing techniques

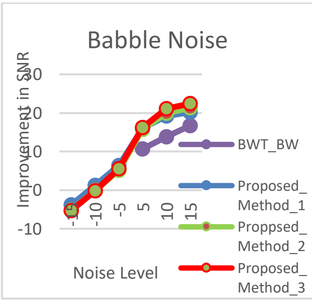
Noise Type	Noise Level (dB)	Existing Technique		Proposed Technique		
		EMD_ LMS (dB)	BWT_BW (dB)	EMD_NLMS (dB)	MCBWT_NLMS (dB)	MCBWT_RLS (dB)
White	-5	8	-	21.5513	20.2181	20.7055
	-10	4	-	21.3231	19.9519	20.3889
	-15	-	-	21.2194	19.8554	20.2737
	5	14	-	22.1828	21.8482	22.7393
	10	18	-	22.0617	22.9491	24.2398
	15	-	-	20.7906	22.1657	23.1156
Pink	-5	-	-	21.3162	20.2340	20.6895
	-10	-	-	21.1578	19.9411	20.3617
	-15	-	-	21.1745	19.8418	20.2513
	5	-	-	22.1890	21.9435	22.8876
	10	-	-	21.9617	23.0024	24.4320
	15	-	-	21.1373	22.3360	23.3960
Babble	-5	-	-	21.4756	20.2002	20.6577
	-10	-	-	21.2342	19.9302	19.8554
	-15	-	-	21.1799	19.8335	19.7444
	5	-	7.85	22.0833	21.8269	22.3427
	10	-	3.93	22.0942	22.8000	24.0000
	15	-	1.54	21.2876	22.4050	23.4833
Street	-5	-	-	21.4620	20.2804	20.7466
	-10	-	-	21.3509	19.9931	20.4192
	-15	-	-	21.0930	19.8745	20.2884
	5	-	7.75	22.1444	21.9432	22.7418
	10	-	3.98	22.0887	22.6892	23.9890

15	-	1.55	21.3421	22.0791	22.9765

In the below Fig. 5, shows the justification of the suggested methodology and the prevailing de-noising techniques of EMD_LMS and BWT_BW. The values considered are in decibels varying between -5 to -15 for various noise types like white, pink, babble and street noises. The difference between the input and output SNR is depicted in Fig 5. An improvement of 10% is observed for the SNR graphically. Hence the suggested method MCBWT with RLS filter reduces the noise better when compared to the others discussed above. The below table 5 depicts that.



(a)



(b)

(c)

Fig. 5. Performance Justification of the suggested methodology using EMD-NLMS, MCBWT-NLMS and MCBWT-RLS with prevailing EMD-LMS and BWT-BW technique regarding improvement in SNR rate (a) white noise, (b) babble noise and (c) street noise.

The best noise reduction technique to reduce pink and babble noise is illustrated in Fig. 9 and values measured for each technique are tabulated in table 6.

4.4 Evaluation metrics

The following evaluation metrics are used to evaluate the performances of hybrid algorithms to identify the improvement in the noisy signals.

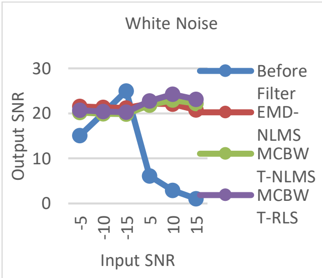
4.4.1 Signal to Noise Ratio (SNR):

This measure is used to compute the desired signal level to noise level of speech signal. It is obtained by Equation (10).

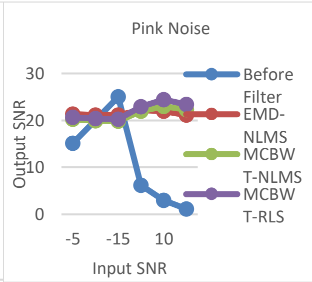
$$\mathrm{SNR} = 10 * \log_{10} \frac{\Sigma(s(n))^2}{\Sigma(s(n)-e(n))^2} \quad (10)$$

where s(n) is the desired speech signal and e(n) is the reconstructed speech signal.

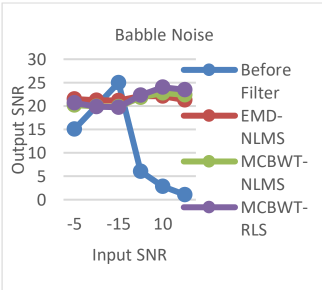
In the below Fig. 6 depicts the performance of SNR metric over all the existing and proposed methods for all types of noises.



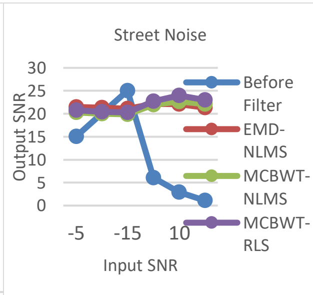
(a)



(b)



(c)



(d)

Fig. 6. Signal to Noise ratio computation of EMD-NLMS, MCBWT-NLMS and MCBWT-RLS of (a) white noise (b) pink noise (c) babble noise (d) street noise

Observations: Among all the hybrid noise reduction techniques, MCBWT with RLS hybrid technique shows an average improvement in SNR for both positive and negative decibels. An average improvement of 1dB is observed for MCBWT-RLS for positive decibels and 0.26 dB improvement for negative decibels across the methods.

4.4.2 Mean Square Error (MSE)

This metric is used to calculate the difference between noisy input speech s(n) and reconstructed output speech e(n), given by Equation (11).

$$\mathrm{MSE} = \mathrm{E}(s(n) - e(n))^2 \quad (11)$$

where s(n) is the desired speech signal and e(n) is the reconstructed speech signal.

In the below Fig. 7 depicts the performance of MSE values for all the types of noises.

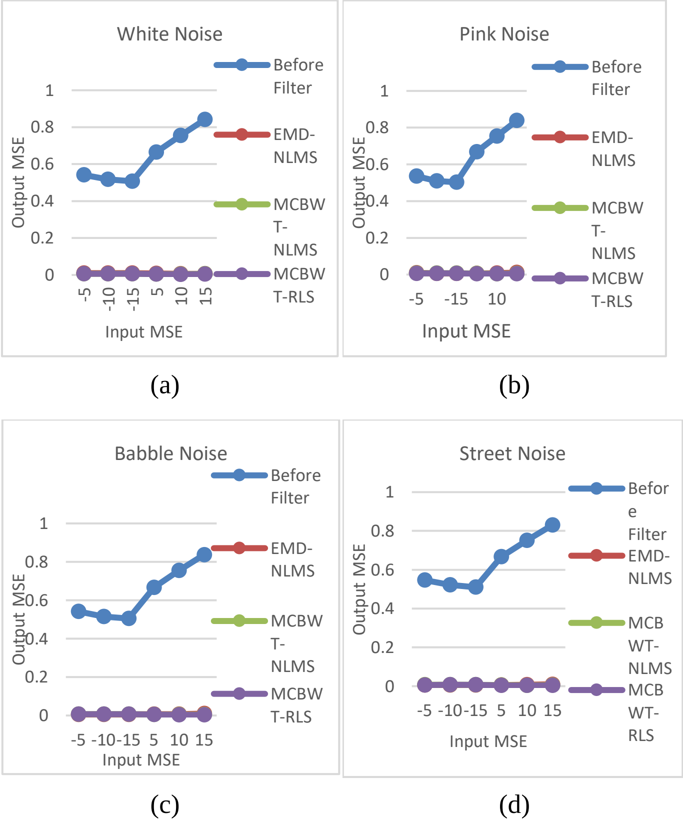


Fig. 7. Mean Square Error computation of EMD-NLMS, MCBWT-NLMS and MCBWT-RLS of (a) white noise (b) pink noise (c) babble noise (d) street noise.

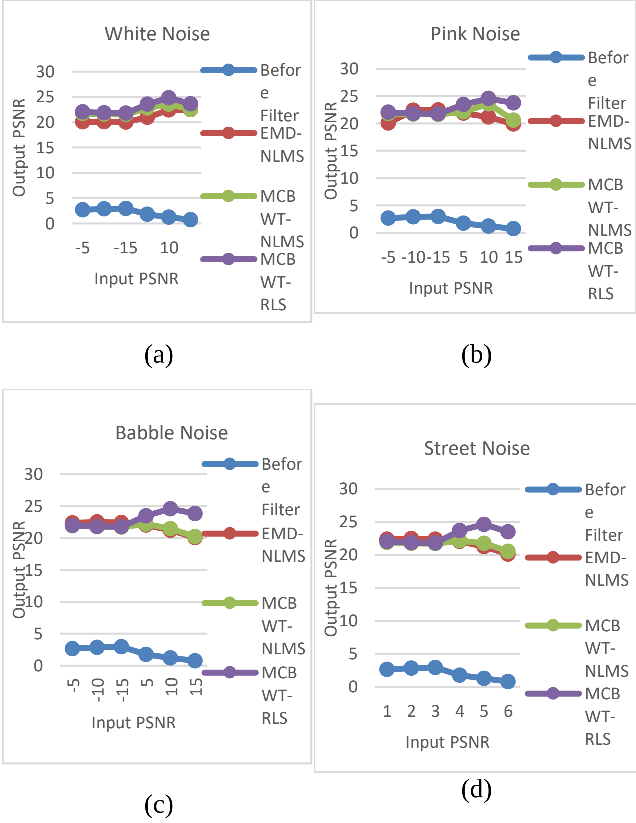


Fig. 8. Peak Signal to Noise Ratio computation of EMD-NLMS, MCBWT-NLMS and MCBWT-RLS of (a) white noise (b) pink noise (c) babble noise (d) street noise.

Observations: An average of 0.75dB noise is reduced over all the methods. From the above Fig. 8, it is observed that MSE decreases with the increase in the optimum step size as 0.0026, forgetting factor as 1 and minimum filter length as 1, the MSE obtained from RLS filter is less over the other techniques. An average improvement of 0.75dB is observed for positive decibels and an average improvement of 0.51dB for negative decibels.

4.4.3 Peak Signal to Noise Ratio (PSNR)

This is used to assess the quality of the reconstructed speech. High PSNR indicates the high quality reconstructed. It is computed by Equation (12).

$$\mathrm{PSNR} = 10 * \log_{10}\left(\frac{1}{\mathrm{MSE}}\right) \quad (12)$$

The below Fig. 8 represents the performance of PSNR of all the methods, of all types of noise.

Observations: It is observed that signal reconstructed from MCBWT with RLS filter has high PSNR value when compared to other methods, when shorter filter length of size 1 is chosen in RLS filter. Hence, it is noticed that shorter filter exhibits higher PSNR values than the longer filters. An average of 23dB and 19dB for positive and negative decibels are observed across the methods.

From the above, best validation metric to measure the noise reduction for pink and babble noise is illustrated in Fig. 10 and values measured for each is tabulated in table 7.

Table 6. Based on Noise technique for Pink and Babble Noise.

Technique	Noise Type	
	Pink	Babble
EMD_NLMS	21.96	22.08
MCBWT_NLMS	23	22.8
MCBWT_RLS	24.23	24

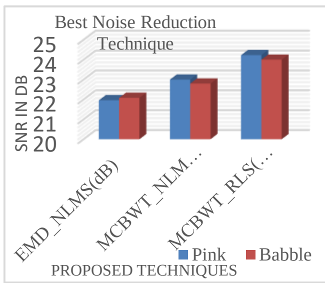


Fig. 9. Best Noise Reduction Technique for Pink and Babble Noise

Table 7. Based on validation metric for Positive and Negative decibels.

Validation Metric	Noise Type	
	Pink	Babble
SNR	1	0.26
MSE	0.75	0.55
PSNR	23	19

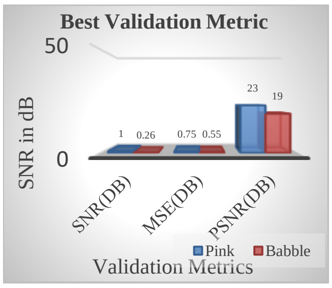


Fig. 10. Best Validation Metric for positive and negative decibels of pink and babble noise

4.5 Discussion

From this paper it is clear that an adaptive Recursive Least Square filter with MCBWT performs better in reducing the noise. For pink and babble noise at 10db. An average improvement of 5db is observed, having 2.98dB of noise for pink and 2.87 dB noise for babble noise input. This is due to the similarity existing between pink and babble noise signal characteristics with the filter parameters. 3% and 5% of improvements is observed for positive and negative decibels respectively. Since pink and babble noises are highly non-stationary varying in peaks, more zero crossings are identified in every noisy speech frame. Hence, slightly increased signal strength is observed than white and street noises. These improvements are observed when MCBWT and RLS filter parameters are used and set by trial-and-error method. The results vary as they are dependent on the statistical properties of noise types. For pink noise, power of the signal decreases at lower frequencies and for babble noise energy is high at lower frequency. This is achieved because bionic is a continuous wavelet that captures both time and frequency features of the signal. The obtained wavelet coefficients are processed with RLS filter coefficients. These improved values also subjected to variations in signal frequencies and sampling rate. Hence MCBWT with RLS filter is proposed as a new improved hybrid technique to reduce the noise levels of pink and babble noise. This is achieved by modifying the basic mother wavelet central frequency parameters.

5. Conclusion

In this study, we have proposed a hybrid MCBWT with RLS filter to enhance the signal strength of the noisy speech signals corrupted with white, pink, babble and street noise types. This Noise Reduction is employed by proposing hybrid techniques to enhance noisy speech. In this work a few hybrid works are experimented with and discussed with their performances related to noise reduction. MCBWT with RLS filter is identified to be one of the efficient methods to handle the noises particularly to pink and babble noises. The RLS filter and the central frequency of the modified bionic wavelet plays a crucial role in identifying an improved method. The experimental results are presented for various types of noises and for various decibels. An average 2db noise is reduced for Pink and babble noises. Further this method can be enhanced by considering various types of noises from various databases. The simulations can be further extended by replacing Bionic wavelets by Wavelet packets and normalized and recursive filters.

Author contributions

Shraddha C: Conceptualization, Methodology, Software, Field study **Dr. Chayadevi M L:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Dr. M A Anusuya:** Visualization, Investigation **Dr. Vani H Y**: Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Kapoor Janak, Mishra G. R., Pathak Ajita & Rai, Manish. Analysis of BSC and AWGN Channel Distortion Effect on Sound Signal in Active Noise Cancellation Application, Engineering Letters, 29(2021), 926-930.

[2] Suryawanshi I P & Manjare C A. Speech signal analysis and enhancement based on HNM synthesis. In Int conf comput commu and autom (Pune, India) 12-13 August 2016, Doi: 10.1109/ICCUBEA.2016.7860100.

[3] Shraddha. C, Chayadevi. M L and M. A. Anusuya. Noise Cancellation and Noise Reduction Techniques: A Review. In IEEE International Conference on Advances in Information Technology, Chikmagalur, India. pp. 159-166, 2019, Doi: 10.1109/ICAIT47043.2019.8987262.

[4] Y. Kopsinis and S. McLaughlin. Development of EMD-Based Denoising Methods Inspired by Wavelet Thresholding. In IEEE Transactions on Signal Processing, vol. 57, pp. 1351-1362, 2009, Doi: 10.1109/TSP.2009.2013885.

[5] H. Touati and K. Khaldi. Speech Denoising by Adaptive Filter LMS in the EMD Framework. International Multi-Conference on Systems, Signals & Devices (SSD), Yasmine Hammamet, Tunisia, pp. 1-4, 2018, Doi: 10.1109/SSD.2018.8570709.

[6] Wahbi Nabi, Mohamed Ben Nasr, Noureddine Aloui, Adnane Cherif. A dual-channel noise reduction algorithm based on the coherence function and the bionic wavelet. Journal of Applied Aoustics, pp. 186-191, 2018, Doi: 10.1016/j.apacoust.2017.11.003.

[7] Norezmi Jamal, N. Fuad and MNAH. Shaabani. A Hybrid Approach for Single Channel Speech Enhancement using Deep Neural Network and Harmonic Regeneration Noise Reduction. International Journal of Advanced Computer Science and Applications (IJACSA), vol. 11, 2020, Doi: 10.14569/IJACSA.2020.0111033.

[8] H Y Vani, M A Anusuya and M L Chayadevi. Morlet-Kernel Principal Component Analysis Features for Speech Recognition. Journal of Computational and Theoretical Nanoscience, vol.17, pp.4482-4486,2020, Doi: 10.1166/jctn.2020.9102.

[9] Anil Garg & O. P. Sahu. A hybrid approach for speech enhancement using Bionic wavelet transform and Butterworth filter. International Journal of Computers and Applications, pp. 1-10, 2019, doi: 10.1080/1206212X.2019.1614293.

[10] Mbachu C. B, Akaneme S.A. Noise Reduction in Speech Signals Using Recursive Least Square Adaptive Algorithm. International Journal of Engineering and Advanced Technology Studies, vol. 8, pp.1-7, 2020.

[11] Mowlaee P, Stahl J, Kulmer J. Iterative joint MAP single-channel speech enhancement given non-uniform phase prior. Speech Communication, pp. 85–96, 2017, Doi: 10.1016/j.specom.2016.11.008.

[12] Swathi Kotte. Performance Analysis of Adaptive Algorithms based on different parameters Implemented for Acoustic Echo Cancellation in Speech Signals. Ph D Thesis, Blekinge Institute of Technology, Sweden, 2011.

[13] Sagar Reddy Vumanthala, Bikshalu Kalagadda. Real-time speech enhancement using optimised empirical mode decomposition and non-local means estimation. Journal of Institute of Engineering Technology Computers & Digital Techniques,vol. 14, 290-298, 2020, Doi: 10.1049/iet-cdt.2020.0034.

[14] R. Gary Leonard, and George Doddington. TIDIGITS LDC93S10. Web Download. Philadelphia: Linguistic Data Consortium, 1993, doi.org/10.35111/72xz-6x59.

[15] Varga, A, Steeneken, H. Assessment for automatic speech recognition: II. NOISEX-92: a database and an experiment to study the effect of additive noise on speech recognition systems. Journal of Speech Communication, vol. 12, pp. 247–251, 1993. Doi: 10.1016/0167-6393(93)90095-3.

[16] R. Martinek, R. Jaros, J. Baros, L. Danys, A. Kawala-Sterniuk. Noise reduction in industry based on virtual instrumentation. Computers, Materials & Continua, vol. 69, pp. 1073–1096, 2021, Doi: 10.32604/cmc.2021.017568.