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Enhancing Noise Reduction with Bionic Wavelet and Adaptive Filtering

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Abstract Speech signals often contain different forms of background and environmental noise. For the development of an efficient speech recognition system, it is essential to preprocess noisy speech signals to reduce the impact of these disturbances. Notably, prior research has paid limited attention to pink and babble noises. This gap in knowledge inspired us to develop and implement hybrid algorithms tailored to handle these specific noise types. We introduce a hybrid method that combines the Bionic Wavelet transform with Adaptive Filtering to enhance signal strength. The performance of this method is assessed using various metrics, including Mean Squared Error, Signal-to-Noise Ratio, and Peak Signal-to-Noise Ratio. Notably, our findings indicate that SNR and PSNR metrics are especially effective in enhancing the handling of pink and babble noises.

Keywords: Empirical Mode Decomposition, Lease Mean Square, Bionic Wavelet Transform, Noise Reduction, Normalized Least Mean Square.

1. Introduction

Speech recognition is the capability of a machine or programme to identify words and phrases in spoken language that utilise algorithms acoustic and linguistic modelling techniques. The performance of recognition systems deteriorates when the spoken signal is contaminated by unwanted signals [1]. Distinguishing noisy segments by retaining critical minimal speech features presents a formidable challenge in applications related to speech processing [2]. In speech signals, various forms of noise can be introduced, whether occurring naturally or through artificial means, either in an additive or convolutive manner. This paper centres its attention on diminishing the presence of coloured and environmental noise by employing wavelet and adaptive filtering methods. The integration of these techniques is employed to mitigate the impact of coloured noises (pink and white) and environmental noises (babble and street) at various sound levels. Considering the scarcity of research on addressing pink and babble noises, our moto was to explore and improve signal quality by reducing these specific noise sources. Tables 1, 2, and 3 illustrate a range of noise types and their inherent characteristics that can occur naturally alongside the speech signal, as detailed in reference [3].

Numerous researchers tackle the challenges associated with noise reduction by presenting a variety of techniques. Among these, some commonly employed methods include Continuous Bionic Wavelet, Normalized

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Least Mean Square, and Recursive Least Mean Square filtering techniques. This paper introduces a hybrid approach that combines the techniques to enhance the signal strength of noisy speech signals.

The study comprises six sections structured as follows: Section 1 contains the introduction, followed by a summary of related work in Section 2. Section 3 outlines the methodology, while Section 4 presents the experimental results and compares them to the baseline approach. Finally, Section 5 encompasses the conclusion and discusses potential future enhancements 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.

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. explored the application of the EMD technique with threshold parameters for white Gaussian noise at positive decibels [4]. Authors Haifa Touati et al. investigated the adaptive Least Mean Squares (LMS) filter technique in conjunction with EMD for white Gaussian noise at positive decibel levels [5]. Wahbi Nabi et al. focused on hybrid techniques, utilizing bionic wavelet transform combined with Kalman filtering to address babble noise at positive decibel levels. Norezmi Jamal et al. also discussed their approach, using Deep Neural Network with Harmonic Regeneration to reduce babble noise exclusively at positive decibels [6] [7]. Additionally, the authors combined the normalized least mean square filter with the Morlet wavelet to mitigate additive white Gaussian noise [8]. Anil Garg et al. proposed a hybrid method to reduce both babble and street noise, employing BWT-Butterworth filters applied to signals at positive decibel levels [9].

The literature provided highlights a notable gap in noise reduction research. Specifically, it's evident that pink noise has not been addressed by any of the mentioned authors. Furthermore, the research on babble and street noises has been limited to situations with positive decibel levels. This observation underscores the need for further investigation and the development of noise reduction techniques targeting these specific noise types and situations. Therefore, in this paper, we combine the adaptive filter NLMS with BWT to evaluate and assess the effectiveness of the NLMS filter in reducing pink and babble noise.

3. Methodology

Figure 1 below illustrates the flow diagram of the system architecture, which aims to diminish unwanted noise through the integration of EMD, wavelet, and filtering techniques. A succinct description is provided for each approach, along with a discussion of the mathematical principles and algorithms employed in crafting noise reduction solutions.

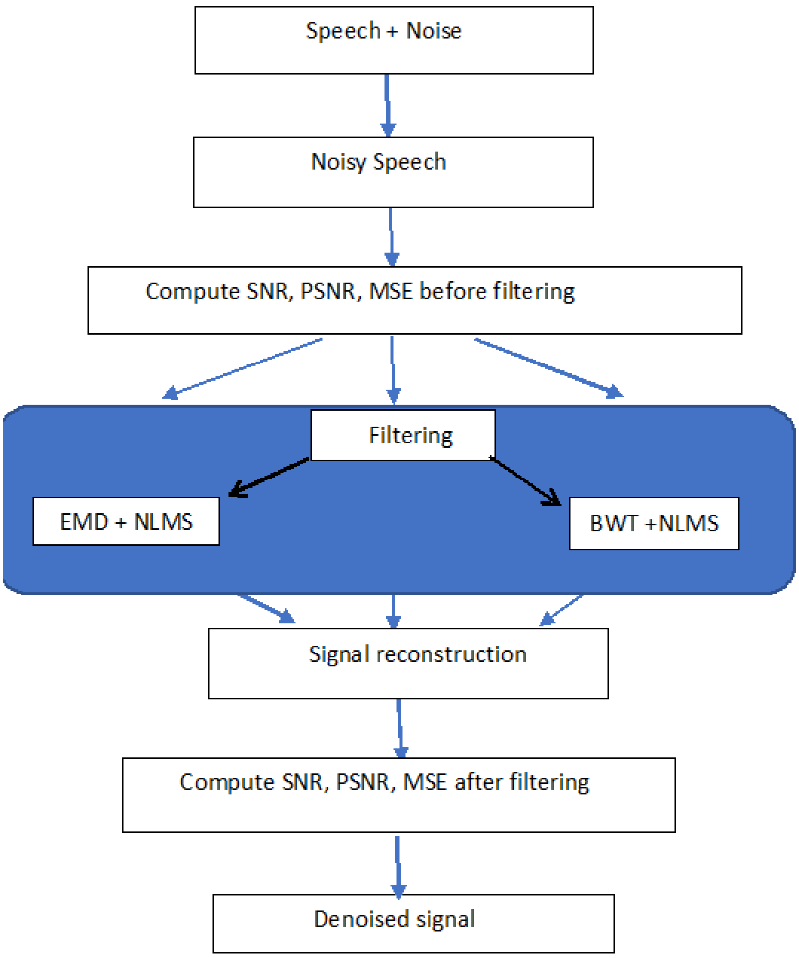


Figure. 1. Flow diagram proposed for Noise Reduction

3.1 Empirical Mode Decomposition [EMD]

Empirical Mode Decomposition (EMD) serves as a valuable instrument in the examination of speech signals. This method dissects the signal into distinct amplitudes and frequencies, referred to as Intrinsic Mode Functions (IMFs). Each IMF is subjected to a thresholding process designed to remove sections with low energy that are notably affected by noise. Equation 1 is employed to calculate EMD interval thresholding. When the signal is not present, the absolute value of the extrema remains below the threshold; otherwise, it surpasses the threshold.

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

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

3.2 Bionic Wavelet Transformation [BWT]

The Bionic Wavelet Transformation is a speech analysis method rooted in auditory modelling principles. It dynamically adapts the frequency and instantaneous amplitude of the speech signal. A mother wavelet is employed to fine-tune the active control mechanism, mirroring the human auditory model's approach to signal analysis. This model accomplishes adaptive adjustments to cochlear filters by modifying the acoustic resistance (R_{eq}) and compliance (C_{eq}) of the basilar membrane (BM) with the introduction of a flexible new quality factor, as expressed in Equation 2.

$$Q_{eq} = R_{eq}^{-1}\sqrt{L / C_{eq}} \tag{2}$$

where L is acoustic mass,Ceq and Req is computed

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

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

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 (w_n) by updating the squared norm of the regressor. The filter step plays a prominent role, and its step size(μ) is normalized according to Equation 5, where x(n) is the input signal vector, μ(n) is the step size of input vector and β is normalized step size in the range of 0< β<1. Since filter is adaptive, the obtained filter coefficients are less sensitive to the variations of the input power of the signal (x(n)) [10][11]. Hence NLMS filters are the better choice for processing noisy speech data [12].

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

The updated filter co-efficient are computed from Equation 6, by replacing μ in the LMS weight vector update equation given by,

$w_{n+1} = w_n + \mu e(n)x*(n)$, with μ(n) which leads to the Normalized LMS algorithm.

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

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

The standard bionic wavelet is determined by applying Equation 8. To compute the T function of the mother wavelet, ψ(t), Equation 7 is utilized.

$$\psi(t) = \frac{1}{T\sqrt{a}}\hat{\psi}\left(\frac{t}{T}\right)exp(j\omega_0 t) \tag{7}$$

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(f_0) =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.

$$BwT(a,\tau) = \frac{1}{T}\sqrt{a}\int f(t)\tilde{\Psi}^{*}\left(\frac{t-\tau}{aT}\right)exp\left(-j\omega_0\left(\frac{t-\tau}{a}\right)\right)dt \tag{8}$$

3.5 Algorithms

This section provides hybrid algorithms applied to evaluate the noise reduction methods using LMS, NLMS 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.

4. Data Analysis and Findings

4.1. Data Collection and Preprocessing

A corpus is a substantial dataset categorized into two distinct forms, depending on the type of signals it contains: speech and noisy corpus. There are numerous established speech and noise corpuses available. The creation of the noisy speech corpus [13] involves combining speech and noise corpuses to suit the specific needs of a particular application. In our simulation work, we generate the noisy speech corpus by merging the TIDigit speech [14] with the Noisex-92 [15] noise corpus at the word level. This balanced database comprises over 25,000-digit sequences and involves a total of 326 speakers, including 111 men, 114 women, 50 boys, and 51 girls, each pronouncing 77-digit sequences.

In this corpus, we consider both white and pink noises as colored noise, while babble and street noises represent environmental noises. These noisy signals are initially sampled at 16kHz. However, for our experimentation, they are down sampled to 16 kHz to match the sampling frequencies of the TIDigit speech signals.

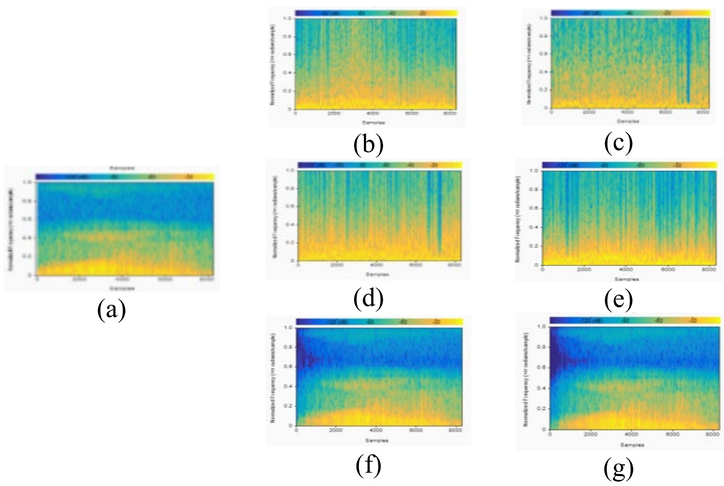
4.2 Comparison Analysis with proposed techniques

4.2.1 Method 1: EMD with NLMS

When the EMD-NLMS technique is applied to a noisy speech signal, a significant enhancement of 19dB in Signal-to-Noise Ratio (SNR) is evident, as demonstrated in Figure 2. Notably, the suggested method excels in improving SNR, with a remarkable 21.96dB enhancement for pink noise and an even more impressive 22.08dB improvement for babble noise at 10dB. Specifically, Figures 2(b), 2(d), and 2(f) depict the spectrograms for pink noise, while Figures 2(c), 2(e), and 2(g) represent spectrograms for babble noise at 10dB when the EMD-NLMS hybrid algorithm is applied.

Since the EMD-NLMS approach consistently delivers improved SNR results at 10dB compared to 5dB. This phenomenon is attributed to the fact that the local mean and the first-level Intrinsic Mode Functions (IMFs) are in close proximity to zero across all frame-level IMFs, thereby reducing the number of extrema in the noise segments.

Noise and speech signals exhibit variations in the number of zero-crossings within their interval thresholding values. The IMFs extracted from the noisy signal are effectively filtered using the Normalized Least Mean Squares (NLMS) filter. The resulting filter coefficients demonstrate enhanced signal strength. This optimization is achieved by setting the filter's step size to 1. However, determining the precise step size involves a trial-and-error process because it needs to adapt to the distinct characteristics of different noise types.



(a) (b) (c) (d) (e) (f) (g)

Figure. 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 Modified Central Bandwidth Transformation (MCBWT) was introduced as an alternative to traditional EMD to further improve the signal quality. The key parameters for MCBWT are initially established in Section 2.2. Figure. 6 illustrates that the suggested method notably excels at 10dB, yielding a remarkable 23dB improvement for pink noise and a substantial 22.8dB enhancement for babble noise. Furthermore, additional performance metrics, including Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), are depicted in Figure 7 and Figure 8.

In Figure 3, specifically 3(b), 3(d), and 3(f), you can see spectrographic representations of pink noise, while Figures 3(c), 3(e), and 3(f) illustrate spectrographic representations of babble noise when applying the Modified Central frequency Bandwidth Transformation (MCBWT) with an NLMS filter at 10dB. This achievement is realized by modifying the T function of the wavelet, and the NLMS filter plays a crucial role in minimizing the mean square error between the speech and noisy signals. Notably, the filter coefficients are fine-tuned by adjusting the step size within the range of 1 to 1.37, with smaller step sizes resulting in better performance and vice versa.

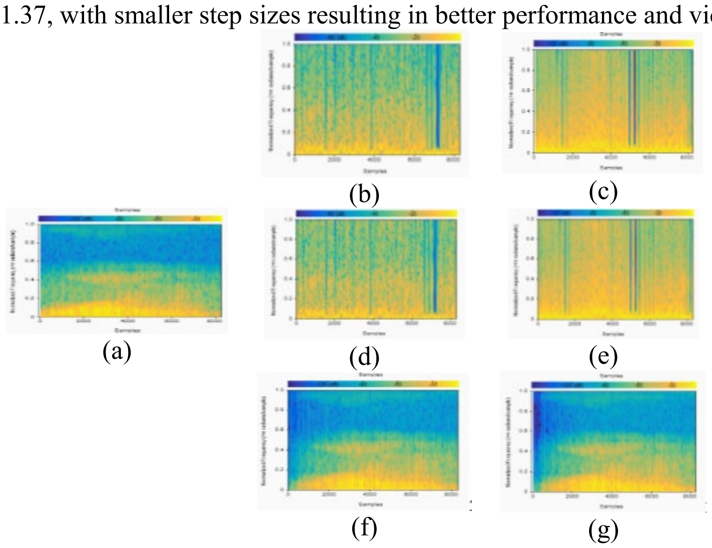


Figure. 3. Spectrogram of (a) clean speech (b) & (c) speech signal corrupted by pink noise and babble noise at 10dB(d) & (e) first level of denoised speech signal from MCBWT(f) & (g) final denoised speech signal after combing MCBWT with NLMS filter.

4.3 Comparative Analysis with Existing Techniques

The performance of the proposed methodologies is evaluated by assessing the Signal-to-Noise Ratio (SNR) between the input noisy signal (input SNR) and the output de-noised signal (output SNR) across all the methods, considering various decibel levels for white, pink, babble, and street noises. The specific numerical values for the SNR parameter are organized and presented in Table 5 for reference and analysis.

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)
White	-5	8	-	21.5513	20.2181
	-10	4	-	21.3231	19.9519
	-15	-	-	21.2194	19.8554

	5	14	-	22.1828	21.8482
	10	18	-	22.0617	22.9491
	15	-	-	20.7906	22.1657

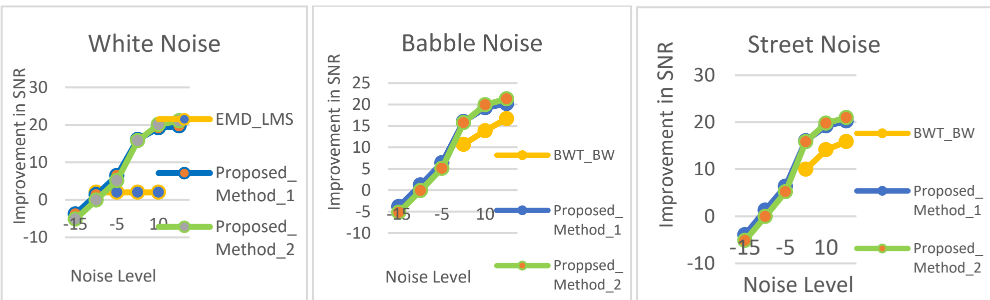
Pink	-5	-	-	21.3162	20.2340
	-10	-	-	21.1578	19.9411
	-15	-	-	21.1745	19.8418
	5	-	-	22.1890	21.9435
	10	-	-	21.9617	23.0024
	15	-	-	21.1373	22.3360

Babble	-5	-	-	21.4756	20.2002
	-10	-	-	21.2342	19.9302
	-15	-	-	21.1799	19.8335
	5	-	7.85	22.0833	21.8269
	10	-	3.93	22.0942	22.8000
	15	-	1.54	21.2876	22.4050

Street	-5	-	-	21.4620	20.2804
	-10	-	-	21.3509	19.9931
	-15	-	-	21.0930	19.8745
	5	-	7.75	22.1444	21.9432
	10	-	3.98	22.0887	22.6892
	15	-	1.55	21.3421	22.0791

In Figure 5, the rationale behind the proposed methodology and the existing denoising techniques of EMD_LMS and BWT_BW is illustrated. The values under consideration are represented in decibels, spanning from -5 to -15, encompassing various noise types such as white noise, pink noise, babble noise, and street noise. Figure 5 illustrates the difference between the signal-to-noise ratio (SNR) at the input and the SNR at the output. Graphically, we can observe a 10% enhancement in SNR. Consequently, it can be concluded that the suggested approach, MCBWT in conjunction with the NLMS filter, outperforms the other methods discussed earlier in noise reduction, a fact corroborated by the data presented in Table 5.

Figure 9 illustrates the most effective noise reduction technique for mitigating pink and babble noise, and the specific values for each technique have been organized.



(a) (b) (c)

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

4.4 Evaluation metrics

The evaluation metrics outlined below are employed to assess the performance of hybrid algorithms and identify enhancements in noisy signals.

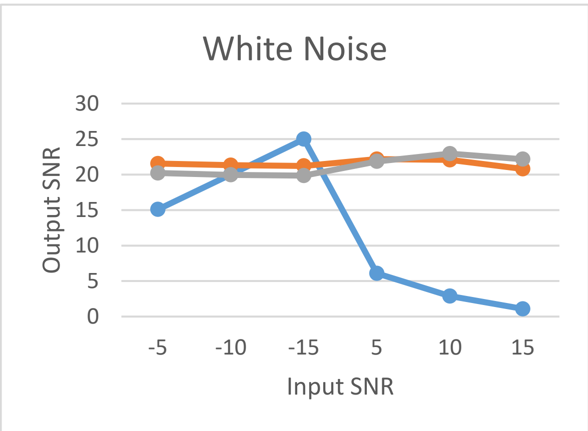
4.4.1 Signal to Noise Ratio (SNR)

This measure is used to calculate the signal-to-noise ratio of the speech signal, representing the ratio of the desired signal level to the noise level and it is computed using Equation 10.

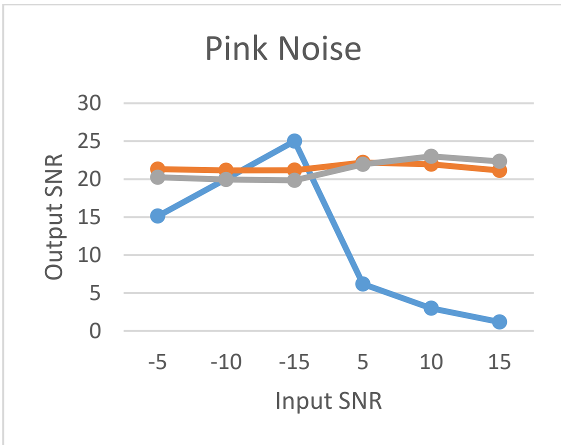
$$\mathrm{SNR} = 10 * \log_{10} \frac{\Sigma\big(s(n)\big)^2}{\Sigma\big(s(n) - e(n)\big)^2} \tag{10}$$

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

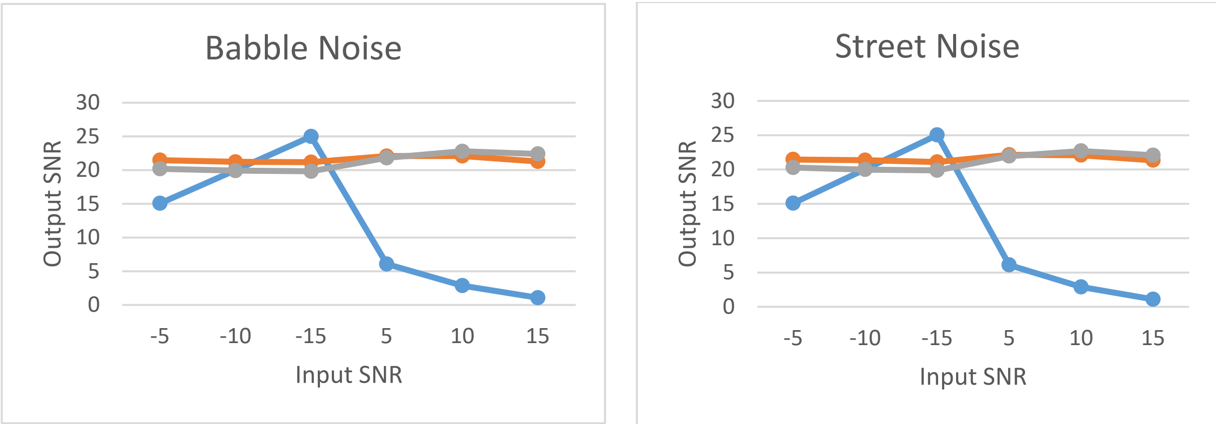
Figure 6 below illustrates the performance of the signal-to-noise ratio (SNR) metric across all the currently available methods and the newly proposed techniques for various types of noise. Graph represented in colour indicates SNR before applying filter technique, color indicates SNR value after applying the proposed method-1(EMD-NLMS technique), and color indicates SNR value after applying the proposed method-2 (MCBWT-NLMS).



(a)



(b)



(c) (d)

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

Observations: MCBWT combined with the NLMS hybrid approach demonstrates a consistent improvement in signal-to-noise ratio (SNR) for positive decibel values. On average, MCBWT-NLMS exhibits a 10dB improvement for positive decibels.

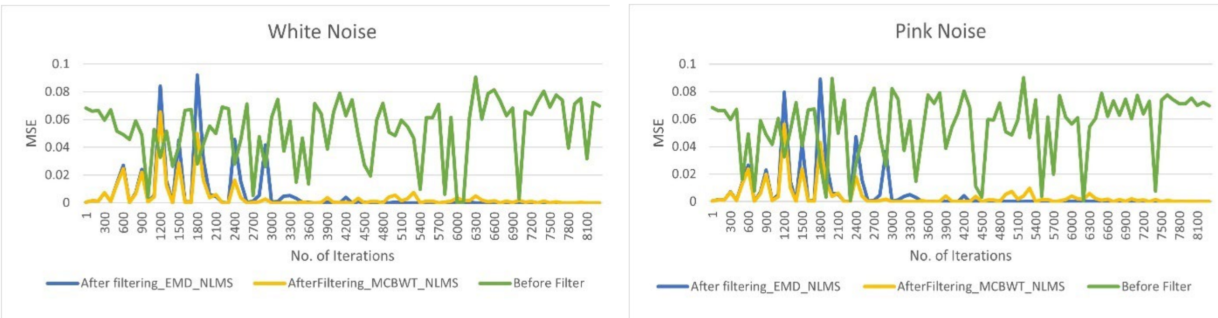
4.4.2 Mean Square Error (MSE)

This metric is employed to determine the dissimilarity between the noisy input speech signal, denoted as s(n), and the reconstructed output speech signal, denoted as e(n). It is computed according to Equation 11.

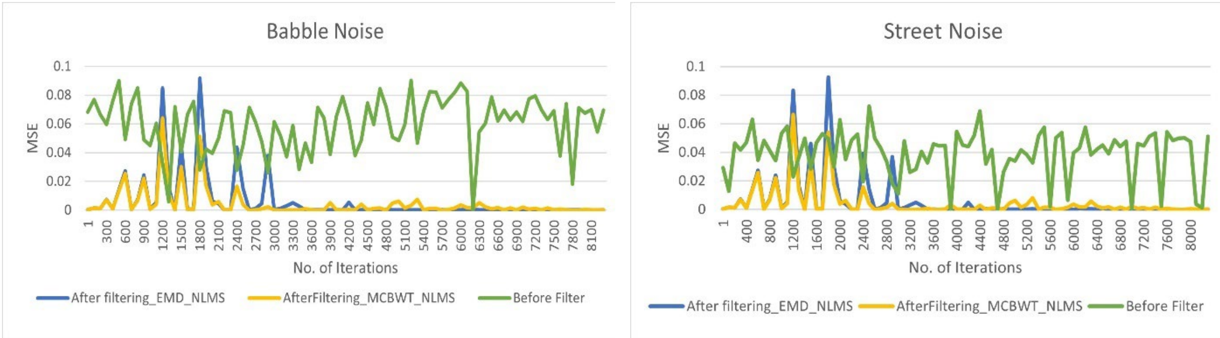
$$MSE=E(s(n)-e(n))^2 \tag{11}$$

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

Figure 7 below illustrates the performance of Mean Squared Error (MSE) values for various types of noises.



(a) (b)



(c) (d)

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

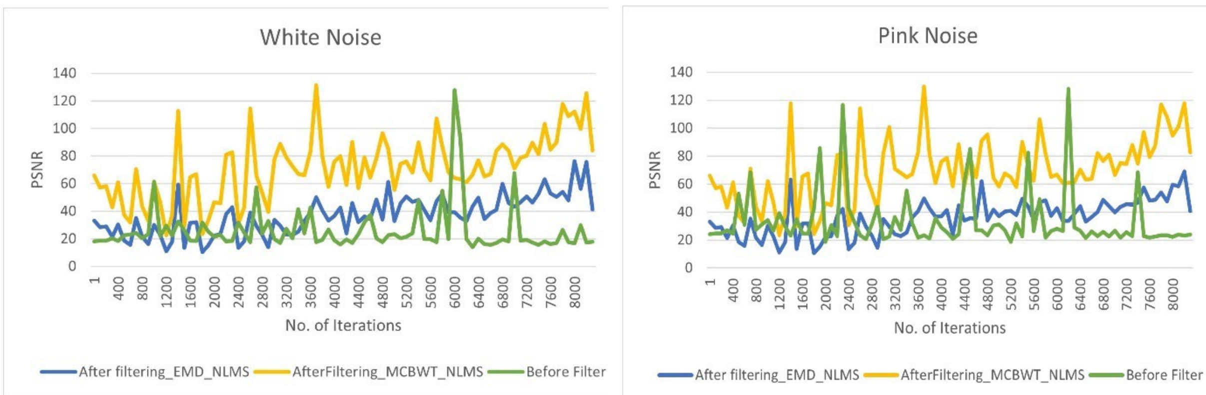
Observations: On average, there is a reduction of 0.75 dB in noise across all the methods. Looking at Figure 8 above, it becomes evident that the Mean Squared Error (MSE) decreases with an increase in the optimal step size (0.01), regularization parameter of 13, and a minimum filter length of 3. Among the techniques, the NLMS filter consistently yields lower MSE values compared to others. On average, this results in a 0.6 dB improvement for positive decibel values.

4.4.3 Peak Signal to Noise Ratio (PSNR)

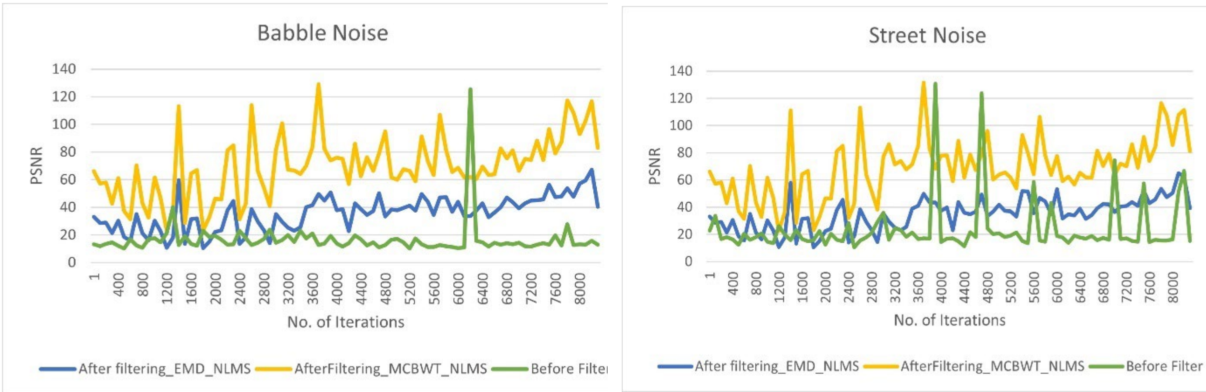
This metric is employed to evaluate the quality of the reconstructed speech. A high Peak Signal-to-Noise Ratio (PSNR) suggests high-quality reconstruction. It is calculated using Equation 12.

$$PSNR=10 * \log_{10}(1/MSE) \tag{12}$$

Figure 8 below depicts the performance of Peak Signal-to-Noise Ratio (PSNR) for all the methods across various types of noise.



(a) (b)



(c) (d)

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

Observations: An observation reveals that the signal reconstructed using the MCBWT in conjunction with the NLMS filter attains a higher PSNR value in comparison to other methods, particularly when a filter length of size 3 is employed with the NLMS filter. This suggests that shorter filters tend to yield higher PSNR values than longer ones. On average, there is an achievement of 21 dB for positive decibels across the various methods. The most effective validation metric for quantifying noise reduction, particularly for pink and babble noise, is visually presented in Figure 10.

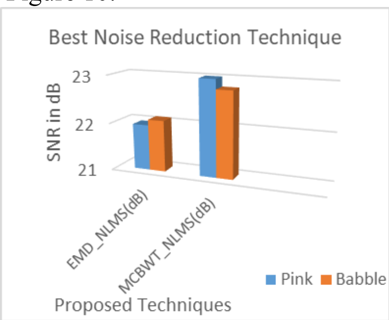


Figure. 9. Best Noise Reduction Technique for Pink and Babble Noise

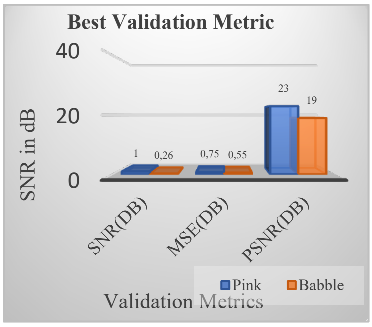


Figure. 10. Best Validation Metric for positive and negative decibels of pink and babble noise

5. Conclusion

This paper highlights that the use of an adaptive NLMS filter in conjunction with MCBWT proves to be highly effective in noise reduction, particularly for pink and babble noise at 10dB. On average, there is a substantial improvement of 10 dB, resulting in noise levels of 2.98 dB for pink noise and 2.87 dB for babble noise inputs. This success can be attributed to the similarity in signal characteristics between pink and babble noise and the parameters of the filter. Pink and babble noises are characterized by high non-stationarity and variations in peak levels, leading to the identification of numerous zero crossings in each noisy speech frame. Consequently, a slight increase in signal strength is observed compared to white and street noises. These improvements are achieved through the careful selection of MCBWT and NLMS filter parameters, which are set through a trial-and-error process. It's worth noting that these results can vary depending on the statistical properties of different noise types. For pink noise, signal power decreases at lower frequencies, while for babble noise, energy is concentrated at lower frequencies. MCBWT, being a continuous wavelet, captures both time and frequency features of the signal, and the obtained wavelet coefficients are processed using NLMS filter coefficients. Experimental results are presented across various noise types and decibel levels, with these improved values also adapting to changes in signal frequencies and sampling rates. Consequently, MCBWT with NLMS filter is proposed as an advanced hybrid technique to effectively reduce the noise levels associated with pink and babble noise. This could potentially be enhanced further by considering the replacement of recursive filters in the future.

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