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Enhancing the Noise Immunity in Speech Signal by Using Combined Filtering Technique

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Abstract

Improving the noise reduction and improving voice signal efficiency in speech processing is one of the most significant considerations in today's studies. The key to real-time signal processing is the reduction in speech signals by noise. Due to the complexity of the identification of speakers and the specific feature of a public channel, noise decrease in the voice signal processing community has always been a challenge. To solve this problem, we proposed a new technique of noise reduction for speech signalling established on complete empirical ensemble mode decomposition with adaptive noise (CEEMDAN) and least mean square adaptive filter (LMSAF). This technique of sound reductions, known as CEEMDAN -LMSAF, has three main advantages, including enhanced algorithms for the decomposition of the empirical mode (EMD) and the EMD ensemble (EEMD), which can reduce mixing and prevent the loss of vibrational mode decomposition (VMD). LMSAF also overcomes the range of the decomposition amount and the basis for reducing wavelet noise with regard to noise reduction in bright IMFs. First, the original signal is broken down into IMFs, which can be distributed into bright IMFs and actual IMFs. LMSAF is then used to sense noisy IMFs and to remove modules of noisy IMFs. Finally, there is a reconstruction of both denounced noisy IMFs and real IMFs, and the last signal denounced. Through comparing simulation signals and noise signals, which have a greater impact on noises reduction and a convenient implementation, the validity of CEEMDAN-LMSAF can be shown relative to other noise reduction approaches. CEEMDAN-LMSAF also provides the accurate basis from which speech signals are detected, extracted, categorised and recognised.

Keyword: ACEEMDAN, Least Mean Square Adaptive Filter, Empirical Mode Decomposition, Speech signal and Noise decline.

1 INTRODUCTION

Recent cellular phones include voice memoranda and a verbal communication function, and have speak-recognition and recording systems. Significant background noise problems should be resolved to efficiently use these systems. In order to resolve such problems, many noise reduction methods were suggested. Multi-channel noise lessening ways like those based on beam forming and beam-shaping [1], as well as source separation, require many microphones. The spatial features of every microphone source, causing systems instability, must also be processed inverted matrix calculation. Methods for reduction of noise from single-channel microphone [2] are however low costs, small and of low computational complexity. This is why it is vital for the communication or recording of a message using a minor device to shrink the noise of a single channel microphone. The output speech signal of these methods leads to two key problems, namely distortion of speech and other audio noise [2-4]. Disorders of speech make it difficult to listen and reduce speech accuracy by unduly suppressing the target signal.

There are certain voice signals that have certain non-linear, non-Gussian and non-stationary models. The Fourier Analysis is based on outdated signal analysis and processing systems, which cannot express local signal performance at the time frequency. Wavelet transformation can be used to refine the signal in multi-scales through the calculation of a flex and transition that solves the problem of the frequency change of the Fourier transform. However, based on the analysis of Fouriertransform and restricted by the selection of the base and decomposition layer for wavelets inputs. For speech signals, we hope we will not only obtain frequency information about the signal, but will also be able to change the frequency law over time. Empirical mode decomposition (EMD) as an empirical signal analysis scheme overcomes the limitations of Fourier's transformation and can decay any signal in theory into IMFs scheme [4].

In a few researchers, better EMD algorithms have been developed to solve EMD mode mixes. These include the more universal and efficient EMD (EEMD) [5] and complete EEMD algorithms with adaptive noise. In several fields of signal processing noise reduction practices were used using EMD, improved EMD procedures and VMD.

Wavelet denoising providing the improveddemonisingpractise, which comprises three basic phases:

- wavelet transform of high noised signal
- Inverse wavelet transform to attain the noise free signal.
- wavelet coefficients thresholding scheme

However, the finest wavelet base function, breakdown flat and threshold rule is difficult to select. An effective denoising technique is also the least significant square adaptive filter. [6] The LMSAF criterion is to minimise the MSE rate, which means to minimise the variance among the estimated signal and the actual filter output by mathematically expectations and to change the tap-weight vector conferring to this principle. It has low computer difficulty, robuststability and a variety of applications. Though, only by using LMSAF is the noise reduction effect limited.

In order to identify noisy IMFs, various types of entropy processing are used [7]; wavelet denotation thresholds are usually employed to procedure noisy IMFs [8]. However, the above-mentioned methodologies of noise decomposition have certain restrictions: (I) VMD needspredetermined quantities of decomposition and balance parameters; (ii) a threshold should be set in order for noisy IMFs to be identified using the correlation coefficient, reciprocal info and diverse types of permutation entropies.

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2 PROPOSED METHODOLOGY

In this study, a new noise reducing technique is proposed to overcome this problem by using CEEMDAN and LMSAF for underwater acoustic signals. First, parameter selection difficulties can be overcome with the use of CEEMDAN. Second, denotation of noisy IMFs through the use of LMSAF threshold selections are resolved. Finally, the technique proposed in denoising is more efficient than other similar techniques.

This research work introduces a novel noise-reduction filtering technique as CEEMDAN and LMSAF to reduce and eliminate the speaker's noise signals during converastion. The flow chart of proposed scheme is shown in Figure 1 as is a new noise reduction system. The following are the experimental steps:

(1) CEEMDAN decomposes noisy speech signals into a number of IMFs.
(2) Calculate average modifications of two adjacent IMFs and recognise loud IMFs and actual IMFs.
(3) LMSAF on bruised IMFs, denoted bruised IMFs obtained.
(4) The re-construction of denoted noisy IMFs and genuine IMFs can produce denounced noisy signals.

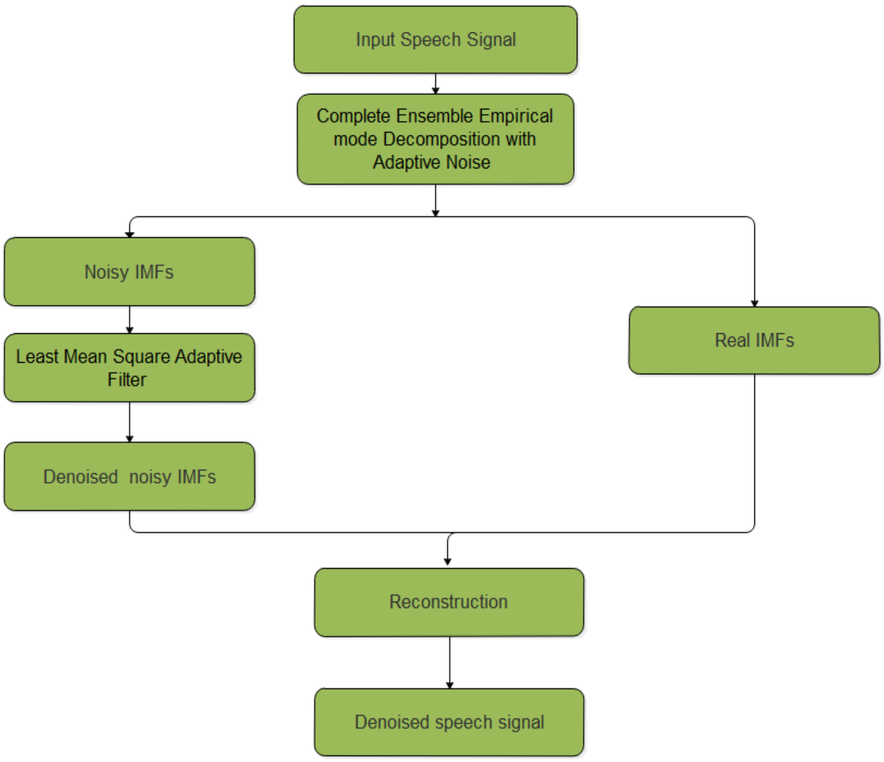

Figure 1: The flow chart of proposed scheme.

2.1 Principle of CEEMDAN

In this paper, we utilise CEEMDAN's benefits with better decomposition presentation and without current parameters to course acoustic signals underwater. CEEMDAN's aim is to disassemble acoustic signals in underwater into IMF with various oscillation approachesappear randomly [9 and 10]. There are two steps therefore in the decomposition process of CEEMDAN, there are follows as,

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Step 1: to get initial IMF

The input signal $x_i(t)$can be conveyed as:

$$x_i(t) = x(t) + N_i(t) \quad i = 1,2, \dots . K \tag{1}$$

where $x(t)$and $N_i(t)$ are the input speech signal and the ith Gaussian white noise sequences.

Decompose every input signal $x_i(t)$ into $D_i(t)$and $res_i(t)$ as follows:

$$x_k(t) \rightarrow c_{k1}(t)res_k(t) \tag{2}$$

Calculate the mean of$D_{i1}(t)$:

$$D_1(t) = \frac{1}{K}\sum_{i=1}^{K} D_{i1}(t) \tag{3}$$

Where $D_1(t)$ is the initial IMF of x(t), is termed as IMF1

$$initial\ IMF \rightarrow IMF1$$

Step 2: Get the other IMFs.

Compute the residual item $res_1(t)$:

$$Res_1(t) \rightarrow x(t) - D_1(t) \tag{4}$$

Decompose total input signal $N_i(t)$ into $D_i(t)$and $res_N(t)$ as follows:

$$N_k(t) \rightarrow D_{NK\,1}(t)res_{Nk}(t) \tag{5}$$

$$D_2(t) = \frac{1}{K}\sum_{i=1}^{K} D_{Res\,1}N_{i1}(t) \tag{6}$$

Where N and Rest (t) signifies the sum of $D_i(t)$ and residual item of $x(t)$

2.3 Principle of LMSAF

Solid performance and simple structure and easy deployment have the advantages of LMSAF. Its principle of fundamental importance is to cancel the noise signal and the input signal reference so that noise in the noisy signal can be removed [11],[14-15]. The noise signal reference is related to the signal noisy, but not to the LMSAF real signal.

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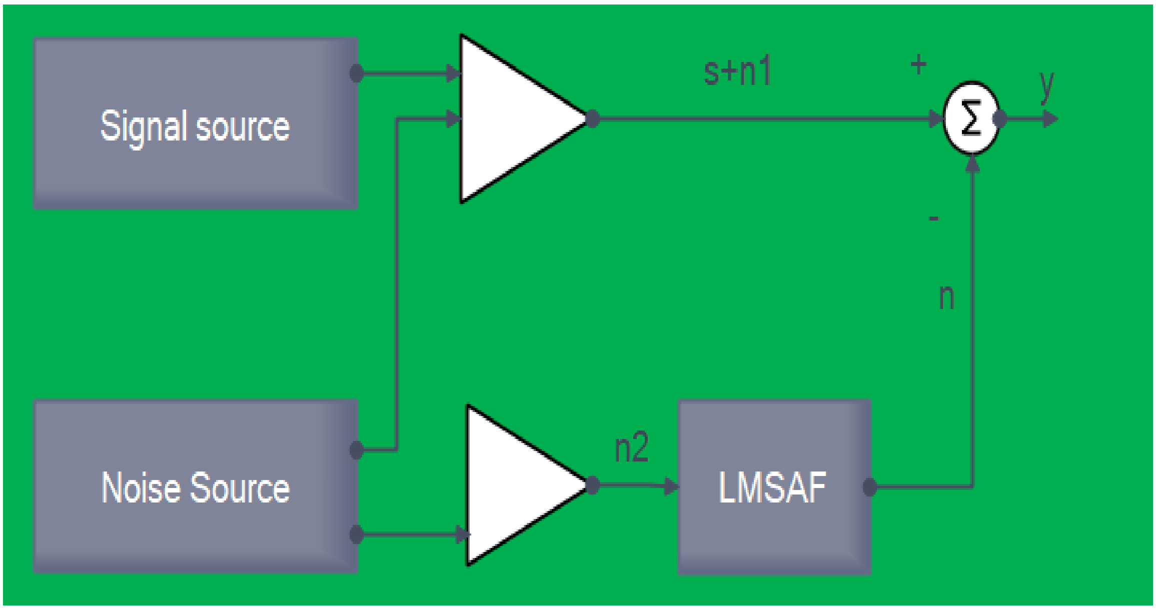

Figure 2: Illustration diagram of LMSAF

Figure. 2displayed the circuit design of LMSAF. Input of LMSAF comprises noisy signal $s + n1$ and input noise signal, $n2, n1$ and are $n2$ correlated, and the correlation between real and noise signal is slightly in minor form, the output y of LMSAF can be conveyed as:

$$y = s + n1 - n \tag{7}$$

where,n is the estimate of n2 through LMSAF. The detailedprocedures of LMSAF are as trails:

(1) Prime the amount of taps of filterM,weight vector $W(0)$, step factor μ.

(2) Compute the projected output signal of the present filtern conditions.

$$n = W^T(n)n1 \tag{8}$$

where,W^Trepresents the current tap-weight vector.

(3) Computeapproximation error is identified as$e(n)$.

$$e(n) = y = s + n1 - n \tag{9}$$

Where,$e(n)$ is equivalent to y

Modernise weight vector(W) is identified as$W(n + 1)$

$$W(n + 1) = W(n) + 2\mu(n)n1 \tag{10}$$

Repeat the stages until completed the output is gotten.

2.4 Noise Signals Reduction Processing

For the noisy voice signal, we use CEEMDAN-LMSAF. The picture. 3 is a signal input and a 5 dB noisy voicemail. The sampling frequency and the sampling point number are respectively 1 KHz and 4096. A noisy voice signal CEEMDAN is displayed in the Fig. 4. As the figure shows. Three and

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four input are diverted to noise, and in descending frequency order the results of the CEEMDAN are arranged.

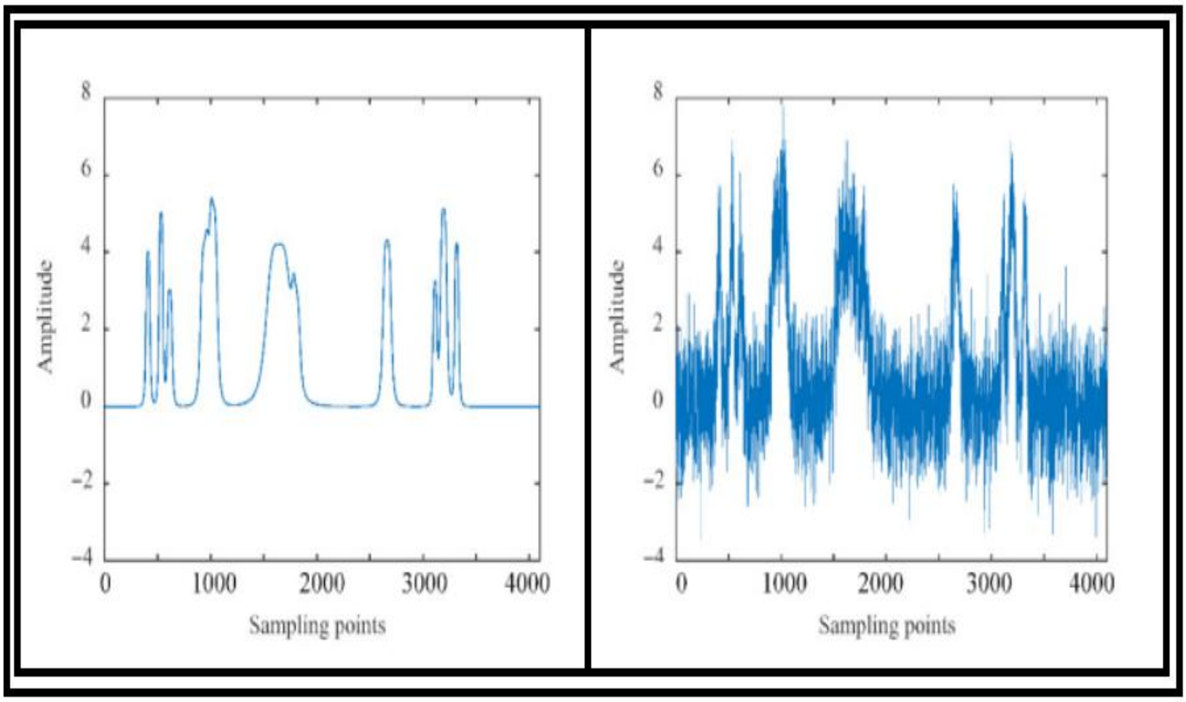

Figure 3: Graphical representation of input and noisy signal

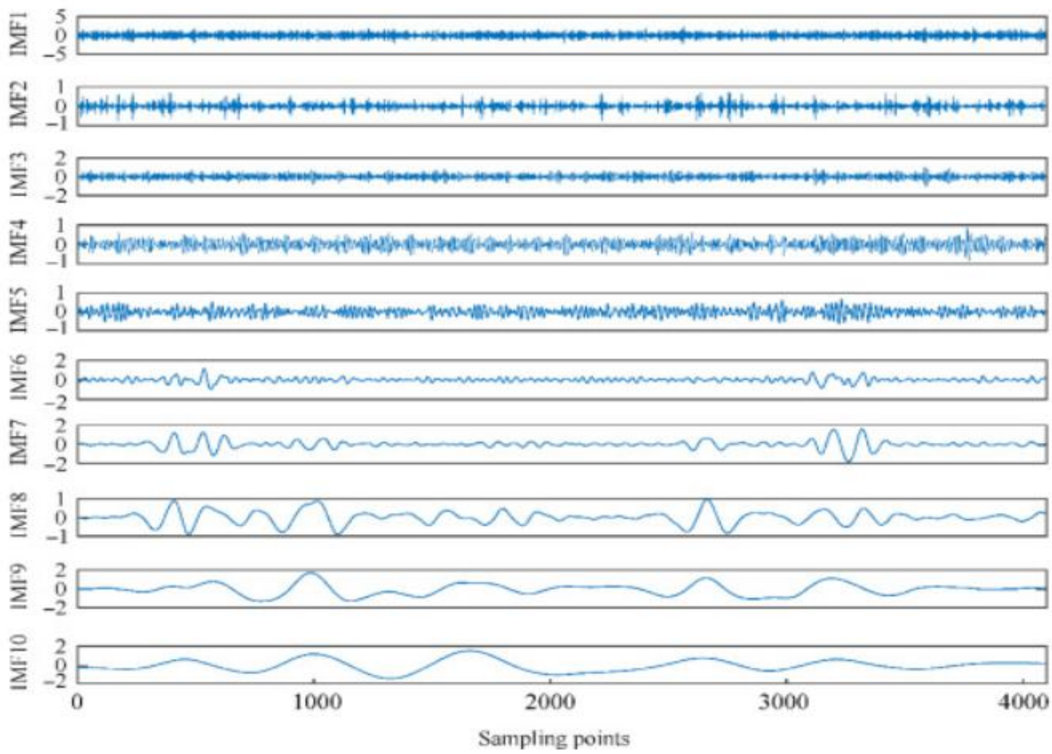

Figure. 4. CEEMDAN effect of noisy combinined signal.

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2.5 Identification of noisy IMFs

The mean variations in two adjacent IMFs are calculated and the results obtained in Table 1. The minimum mean square difference is MSV, as shown in Table 1. We can therefore be aware that the initial five IMFs and the next five IMFs are signified as the noisy IMFs and real IMFs.

Table 1. MSV oftogether IMFs

MSV-1	MSV-2	MSV-3	MSV-4	MSV-5	MSV-6	MSV-7	MSV-8	MSV-9
0.567	0.325	0.068	0.0312	0.412	0.0511	0.2032	0.1150	0.3589

3 NOISE LESSENING OF RECONSTRUCTION AND NOISY IMFS

In the processing of the first five IMFs, we use LMSF and obtain five denoted noisy IMF. Then, by reconstructing noise free IMFs and real IMFs the result of noise reduction from a noisy bumps signal is possible. The software MATLAB carries out three noise reduction experiments. Figure shows noise reduction results of 5 dB bright signals. 5. As the figure shows. 5, most noise components will be removed after comparison with clear signals, and denounced signals will be close to the original.

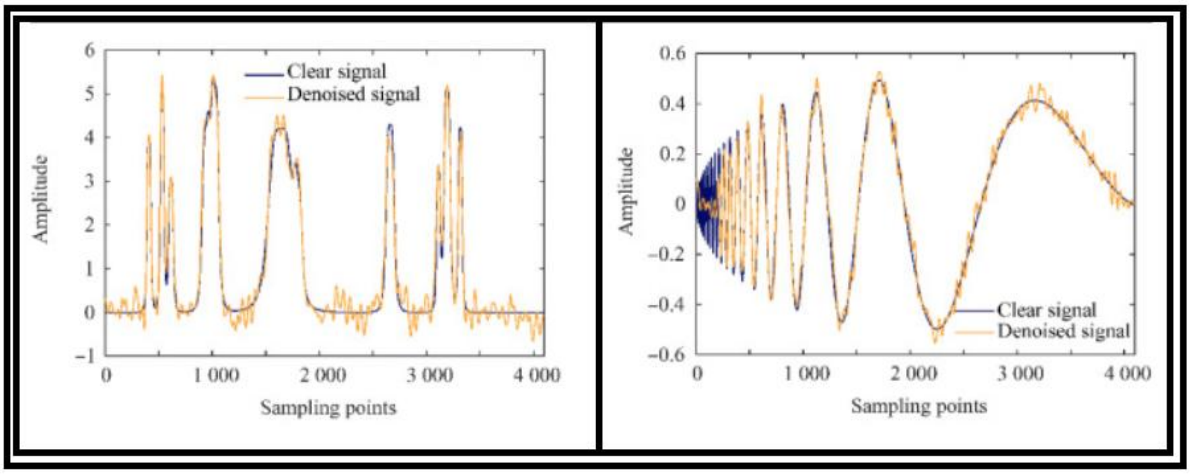

Figure. 5. Graphical Representation of Noise reduction signals.

3.1 Noise reduction effect

The theory of chaos is an important theory in the study of random non-linear signals and has chaotic characteristics. According to the attractor trajectory [12], we can therefore determine the effect of noise reduction of the acoustic speech signal. The path of the attractor is the path represented by the dynamic equation solution in the phase scheme. In general, the direction of the attractor is very smooth and frequent with a very rough and sporadic signal attraction [13]. In Figure6, the attractor trajectories for two sample frequency ranges of the signals before and after noise reduction are showed. We selected a time lag of 2 to prevent identical values between adjacent amplitudes to be better observed.

The abscissa of the pull phrases signify the amplitudes of$x(n)$, the ordenate the amplitudes of $x(n+2)$, and the range n is 1 to 1024 where n is the sampling point.

4 RESULTS AND DISCUSSION

In this section, we conducted to analysis the performance of proposed filtering technique in noise reduction of speech signal. The experimental outcome is determined by using different parametric metric, which are deliberated in following calculation. Experimentations of various noise reduction methods for diverse signals under different input SNRs are applied to prove the validity of the proposed filtering method.

$$SNR(dB) = 20\log\left(\frac{A_{out\ signal}}{A_{out\ noise}}\right) \quad (11)$$

where, $A_{out\ signal}$, and $A_{out\ noise}$ is the value of the signal amplitude and noise. The outcomes will be assessed in comparison with some given filtering methods. RMSE takes the difference for each observed and predicted value.

$$RMSE = \sqrt{\sum_{i=1}^{N}(x_i - y_i)} \quad (12)$$

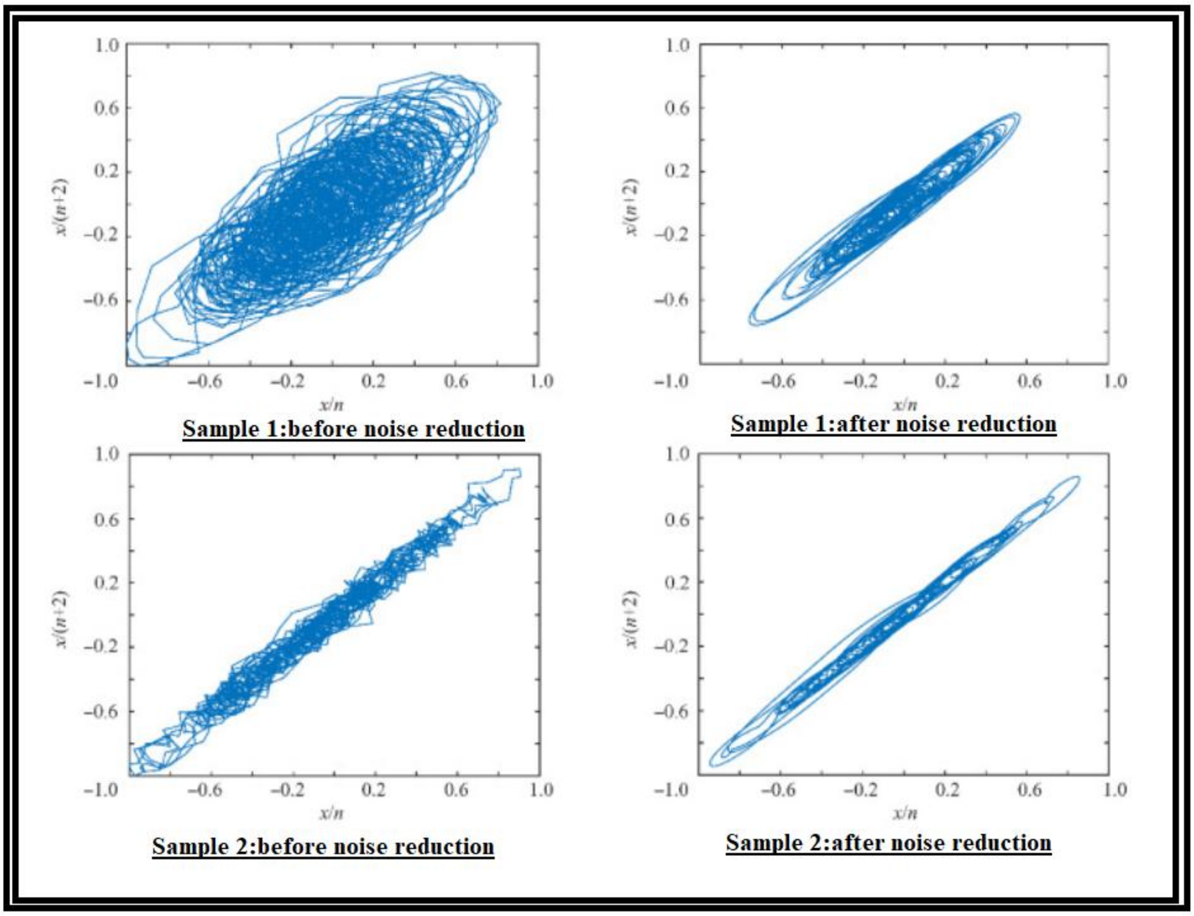

Figure 6. The graphical representation of before and after noise reduction for the speech samples.

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The criterion for evaluating the efficiency of the projected algorithm is the signal-noise value to evaluate the residual noise presence:

Table 2 displays the results of various noise reduction techniques. Input SNRs −10 dB, −5 dB, 0 dB and 5 dB are available. Techno-noise lessening EMD together with CEEMDAN, LMSAF with the proposed CEEMDAN model LMSAF.

Table 2. Outcomes of diverse noise reduction methods

Input SNR	**Output**	**Noise reduction method**		
		CEEMDAN-EMD	**LMSAF**	**CEEMDAN-LMSAF**
-10dB	SNR	2.0674	1.8682	3.1369
	RMSE	1.3785	1.3958	1.2678
-5dB	SNR	7.3568	7.0236	8.4531
	RMSE	0.76312	0.7485	0.6042
0dB	SNR	9.5635	9.2648	11.2598
	RMSE	10.9587	0.6359	0.4891
5dB	SNR	0.5136	13.365	15.6358
	RMSE	0.2859	0.3598	0.2745

The maximum SNRs and the minimum RMSE are bold as shown in Table 2 under different input SNRs. CEEMDAN is better than EMD- and LMSAF-based noise reduction techniques, CEEMDAN- LMSAF has lower RMSE and higher SNR than the three other noise lessening systems.

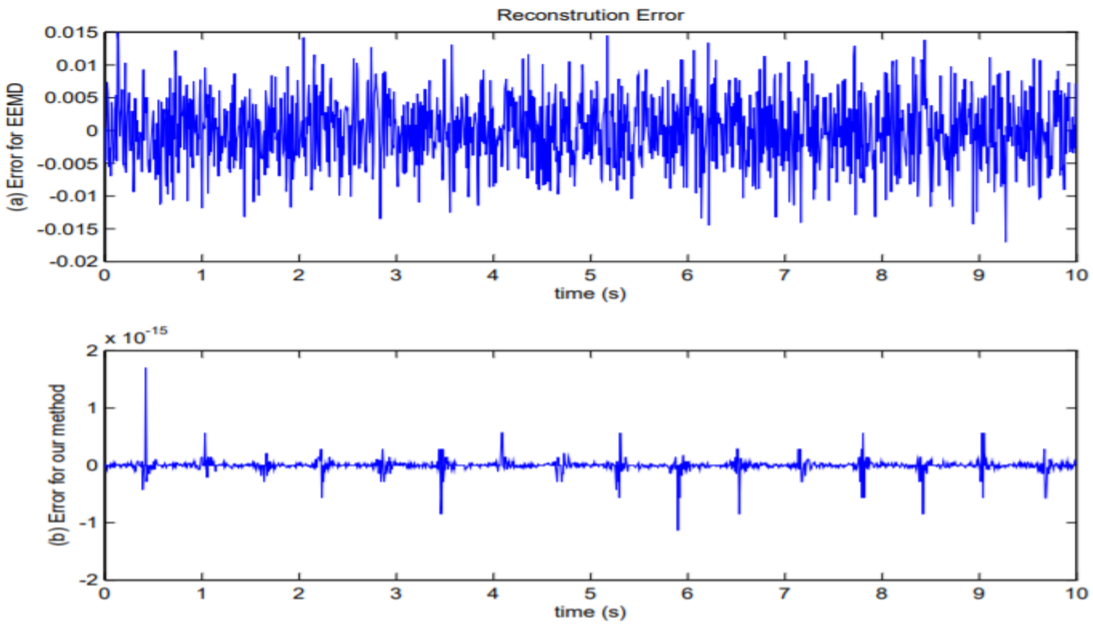

Figure 7. Reconstruction error for: (a) EEMD technique; (b) proposed technique.

And also, we compare the reconstruction error for speech signal by using proposed model with EEMD techniques, the output signal comparison results are shown in Figure 7. The maximum amplitude for the proposed model is less than 2×10^{-15}, with the normal 2×10^{-14}differential. This

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accuracy can be accomplished by EEMD, because in EEMD the procedure is extremely costly in terms of measurement costs, the amount of accomplishments needs to be increased. Theoretically the completeness of decomposition in the case of input speech signals was shown and numerically checked. This combines filtering methods for non-linear and non-stationary signals to be analysed and processed. This approach has been tested successfully for artificial and true noise cancellation signals.

5 CONCLUSION

A novel combination of filtering noise reduction method for voice signals based on CEEMDAN and LMSAF is proposed in this paper. This improves the performance of mode mingling suppression and can avoid choosing VMD parameters. This proposed filteringprocedures are effective innoise suppression can be used only for definite applications in signal processing. LMSAF can prevent the number and basis selection for the reduction of wavelet noise. In the case of the highest-SNR and lower-SNR simulation signal, the proposed noise lessening performance is higher than EMD-LMSAF, CEEMDAN and LMSAF and is amplified by about 0.5 dB by averages and declined by around 0.02, respectively, by the SNR and RMSE at various inputs. The proposed reduction of speech signals can be achieved by noise. The attractor trajectory is smoother and more regular after noise reduction than before. This demonstrates its validity. Moreover, speech signals such as detection, extraction of functionalities, classification and recognition tasks are beneficial for further processing.

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