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Novel Approach for Industrial Noise Cancellation in Speech Using ICA-EMD with PSO

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Abstract

Speech Signals have high range of variation in amplitudes and frequency. These acoustic signals with diverse properties are hard to recognize and filter if mixed with noise. To separate noise from original signal, the artifact peaks are separated from original signal and discarded. In this paper, the ICA method of signal denoising is used to differentiate the speech signal from periodic noise and Empirical Mode Decomposition method is proposed to generate the components of signal. The IMF(s) of signal is the non-linear descending order of frequency components that have been filtered for better SNR. Filtering with wiener filter has amended output but also results in loss of information. The selection of IMF(s) for signal regeneration when optimized using objective function of PSO, the information of original signal was dramatically preserved with suppressed noise. The system is tested on 4 example signals and proposed technique illustrates lower mean square error and higher SNR compared to wiener and ICA.

Keywords: *Speech Signals, EMD, Wiener filter, PSO, SNR*

1. Introduction

Speech Signals belongs to the family of acoustic signals and due to their digital representation are generally studied in digital signals processing. The speech signals and noise signals originate from two different sources that add up in channel (ex: air) before being propagated to user's ears (Figure 1).

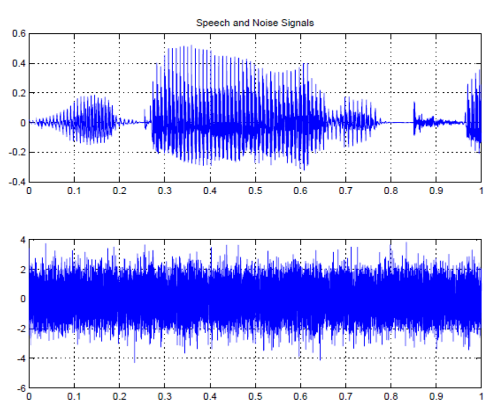

Figure 1. Original Speech Signal and Noise Signal to be added

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In digital transmission, the noise can add up in signals due to finite precision of coded transmission waveform (quantization noise). The spectral quality index [1] and Signal-to-Noise ratio [2, 3, 4] of signals are directly proportional to noise present in signal. The first attempt for signal denoising was performed by Weiner *et al.* [5] who suppressed the noise from the source signal. However, for filtering the assumption is made that both noise and signal should be stationary and their statistic information is available priori. These conditions in present era communication are impossible to withstand. In past few decades the wireless channels have become too noisy in nature. The acoustic problems due to these have gained considerable amount of exponential growth with increase in technology and systems.

The source of noise can be any object or activity such as: machines, wind, engines and myriad noises and are often loud and irritating. Some noises could not be heard as they range outside the frequency audible to human ears but can corrupt the signal. Based on their nature of frequencies noises are scaled in two categories:

Broadband Noise: the energy of noise is distributed uniformly across all frequency bands (sound of jet plane)

Narrowband Noise: the noise is concentrated at specific frequencies (Rotating machinery)

The noise besides degrading the signal quality has its own adverse effects on human health [6] .The noise cancellation techniques are either passive or active in nature [7, 8]. The passive noise control techniques use absorbing and reflecting materials to deflect the noise from its path towards the receiver [9, 10]. Active noise cancellation techniques use computational algorithms that defend the original signal through process of filtering [11]. During the past decade considerable progress has been made in the advancement of low bit-rate speech-coders for both civilian, military communications and computer based voice applications.

For the active cancellation techniques most of the authors prefer conversion of space-time domain speech signal to frequency domain signal. The easiest method so far for this is Fast-Fourier Transform. However, the limitations of this method are recognized over the time. The use of wavelet transform [13] for filtering of noise signals achieves a better response if compared only with FFT method [14, 15]. The efficiency of wavelet transform is given by the number of decomposition levels and the method to choose threshold. Soft thresholding is better than hard thresholding [13] and HAAR and Daubechies soft wavelet thresholding techniques have mixed response for signal in range 8-20 dB [16]. The optimization of wavelets such as adaptive [17, 18], robust wavelet denoising [19] are modifications performed in attempt to elevate the performance. In Bayesian denoising method [20, 21], optimal signal estimated for generation of minimum mean square estimators for specific features of speech signal. In addition with wavelet [22] assumes a minimal local regularity translates into constraints on the multifractal spectrum of the signal. The theoretical approach for this is based on Holder exponent [23] in a stochastic frame. ICA method for speech enhancement has rich literature due to its efficiency and nature of segmenting speech signals from periodic database. Speech enhancement with missing TF was based on ICA [24] as ICA can be data-driven, adaptive and linear representation in nature. The combination of ICA with wiener filter [25] was used to minimize mean square error, constrained ICA with Bessel Features [26] to extract subsets of desired independent source signals from a set of mixture of source signals. ICA with adaptive filters [27] was used for speech enhancement exploiting the properties of ICA and filtering the components before reconstruction. Liang Hong [28] tested Bayesian algorithm with ICA for maximum a posteriori (MAP) estimator and transformation of learned speech data via ICA. For periodic noise ICA seems to be an indispensible method. However, singular application of ICA is not a healthy effort hence wavelets were introduced for denoising [29, 30, 31]. EMD is intuitive and adaptive, and data driven thus computation of

EMD does not require any previously known value of the signal. EMD generates the IMF(s) that are similar to independent components but with additional property of decreasing nature. Thus the separation of noise becomes easier in this respect. The EMD is studied by many researchers for white noise [32], adaptive noise [33], EEMD with adaptive noise [34], and Arrhythmia ECG Noise [35] cases. These all are the non-periodic noise and thus performance of EMD was comparable and standard against ICA. The methods in literature are though efficient on their part, but none of these is presented as the combined approach in case of both periodic and non-periodic signals. Since, the noise source cannot be predicted in real applications, hence the algorithm must be robust enough to compensate any case and filter the speech signals.

The property of Independent Component that it assumes two signals originated from different sources and separates them. This method is ideal to some extent for speech signals as the speech and noise originates from different sources. Hence, this method is extensively researched for speech processing. We used this property of ICA to separate the speech signal in domain of periodic noise. The organization of paper is as follows: in second section the proposal is present and subsequent sections describe their models and the filtering of signal in relation with these. The fitness function from EMD is fed to PSO for generation of gbest which is considered as the selective parameter for number of IMF(s) to be considered. The results section witness the accuracy and superiority of proposed method over conventional methods. A conclusion is present at the end.

2. Proposed method

Before the detailed formulation of proposed work, block models (Figure 2(a) and Figure 2(b)) for processing of signals (periodic and non-periodic) are presented to understand the flow of structure. The speech signal and noise source arise from two different sources that are mixed to generate an input signal. The mixing instead of acquiring the noise contained signal has additional benefit of comparing the signal quality index (SQI) and Mean Square Error (MSE) of received signal. The optimization of EMD using objective function from PSO eliminates the high frequency components while saving considerable amount of information. The EMD cannot filter the noise components and signal if the noise is periodic in nature. Hence, in this scenario ICA is implemented to determine the nature of noise and gather the information about nature of speech. The next steps are same as of non-periodic signals for final regeneration of output.

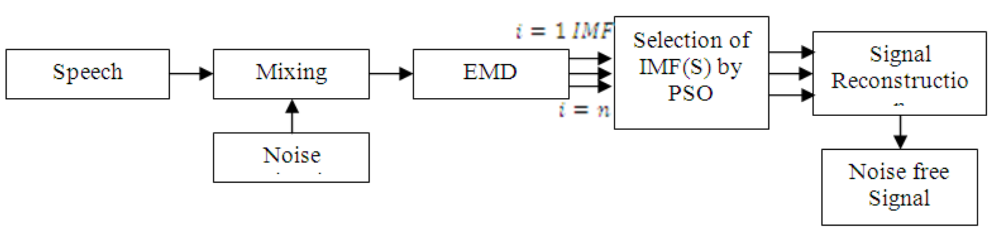


Figure 2(a). Noise Elimination approach for a non-periodic signal

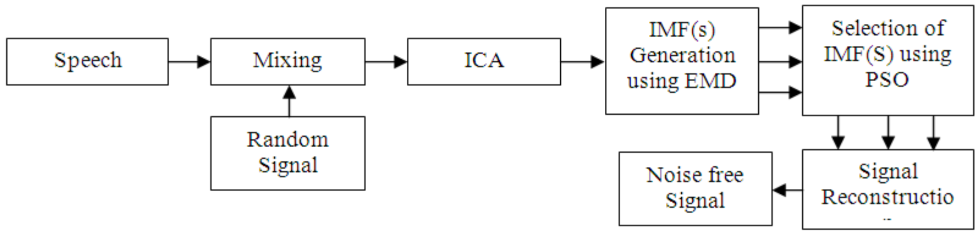


Figure 2(b). Noise elimination approach for a periodic signal

Let $y(t)$ is the input signal given by the original signal $x(t)$ and presence of noise $n(t)$ in it.

$$y(t) = x(t) + n(t) \tag{1}$$

The frequency spectrum of the signal is given by the fast Fourier transform:

$$s(f) = \sum_{n=0}^{N-1} y(t).e^{-i2\pi k(n/N)} \tag{2}$$

The presence of noise in signal causes high frequency spectral power which elevates Sound Quality Index (SQI) of signal (W):

$$W = \log\left\{\frac{e^{\int df \log(s(f))}}{\int df s(f)}\right\} \tag{3}$$

Here, $s(f)$ is frequency spectrum of $y(t)$. Equation 1 states the presence of high frequency random noise is responsible for rise in value of W.

3. Empirical mode decomposition

For n number of data points, the maximum number of components is given by its log value with base 2. The intrinsic mode functions obtained via Hilbert transform satisfies every condition for being meaningful instantaneous frequencies. EMD uses an iterative sifting approach for decomposing a signal into IMF sets []. The original signal for suppose $x(t)$ is a speech signal to be decomposed. Local maxima of signal for positive amplitude portion are generated and saved as envelop $E_u(t)$, where E_u stands for envelop for maxima of upper level. Similarly, for amplitudes of lower extremes another envelop $E_l(t)$ is generated. The mean of upper and lower envelop (m_1) is calculated ($m_1 = (E_l(t) + E_l(t))/2$). The first component ($h_1$) is given as the difference of mean m_1 and signal [15] [16] $x(t)$.

$$h_1 = x(t) - m_1 \tag{4}$$

From equation (4) h_1 is the new data set for further steps of iteration. The new couple of envelop is generated based on data set value and mean m_{11} is generated. This mean is and data set in place of original signal and first mean generates second component of signal. For k^{th} component the generalized form of above equation is written as:

$$h_{1k} = h_{1(k-1)} - m_{1k} \tag{5}$$

This iteration is repeated till the Intrinsic Mode Function(s) (IMF) is generated. The h_{1k} component is selected as IMF based on following criteria:

i. The number of extrema is equal or a unit greater than total number of zero crossings in a given dataset.

ii. The mean of local minima and maxima at any point in a dataset is zero.

In another case, the h_{1k} can be treated as IMF beside the above criteria if the standard difference of two consecutive components falls in pre-defined range. The standard difference (SD) in a generalized manner is given by:

$$SD = \sum_{n=0}^{N} \frac{|h_{i-1}[n] - h_i[n]|^2}{h_{i-1}{}^2[n]} \tag{6}$$

The first intrinsic mode function is represented as c_1 against h_{1k} for sake of convenience. This component when subtracted with original signal $x(t)$ provides the residual value of signal. The process of IMF calculation on this signal is repeated till the signal attains a constant value or becomes monotonic in nature (Figure 2). The signal thus is a function of residuals (r) and IMFs and can be reconstructed by their summation

$$x[n] = \sum_{i=1}^{N-1} c_i[n] + r_N[n] \tag{7}$$

The property of EMD to decompose a signal into respective IMF(s) by finding the peak of signal leads initial IMF(s) with high frequency data and Sound Quality Index (SQI). These IMF(s) can be manipulated and a transmute signal can be generated with inconsistent spectrum for better SNR. However, if extra IMF(s) are eliminated, the result may lead to loss of information. Hence, the number of IMF(s) with minimum spectral flatness can be optimized using an objective function:

$$\hat{y}(t) = \sum_{i=k+1}^{n} IMF_i + r(t) \tag{8}$$

Where, $\hat{y}(t)$ is reconstructed signal and k is the number of initial IMF(s) to be eliminated. If $\hat{y}(t)$ is signal filtered from high frequency noise components, the value in denominator term of equation 6 will shrink. The geometric mean of spectrum (numerator of equation 6) will be much lesser as the central tendency of spectrum shifts towards low frequency. Hence, the difference in values of W before (equation 1) and after modification ($\hat{W}$: obtained from equation 6) of input signal will be greater than zero ($W - \hat{W} > 0$). Fig 3 is the output of EMD having 8 IMF(s) from a given signal (function).

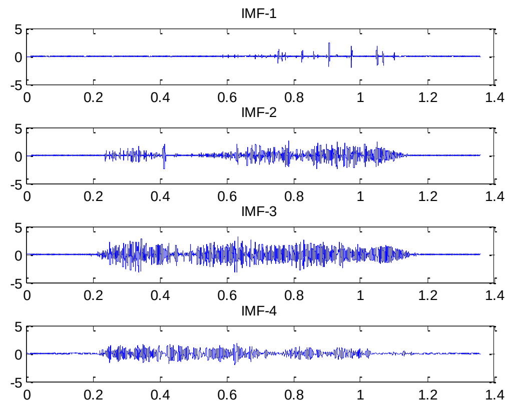


Figure 3(a). IMFs of speech signal mixed with noise

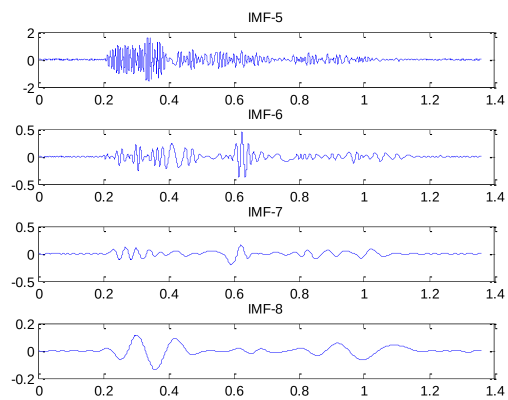


Figure 3(b). IMFs of speech signal mixed with noise

Figure 3: The speech signal and noise signal from Figure 1 are decomposed using Empirical Mode Decomposition. The Intrinsic functions are accounted till the signal becomes monotonic in nature. The 8th IMF from EMD decomposition is the end of decomposition process in the test input considered for experiments. The IMFs obtained are in frequency time domain and signal can be reconstructed by conversion to space-time domain and summing all components.

4. Particle swarm optimization

Particle Swarm Optimization is a heuristic approach originally proposed by James Kennedy and Russell C. Eberhart (1995) [36]. This iterative process (Figure 4) evaluates the candidate solution of current search space. The candidate solution lies in the fitness landscape and determines minimum and maximum of objective function and hence from equation 3 and equation 8.The fitness function is

$$(Maximize\ f(k) = W - \widehat{W}) \tag{9}$$

can be solved using PSO with constraints of voice quality. The PSO generates the random value of k as the initial solution. Using fitness function PSO will generate $f(k)$ equal to the number of k. These candidates are referred as the individual best position and individual best solution for given problem. PSO keeps a record of the best fitness value as the individual best fitness. This best fitness value of every individual ($f(k)$) is compared and global fitness value is generated. As the information about objective function is not acceptable in inputs of PSO algorithm, hence the distance of solution from local and global maximum and minimum is random and not known to user. The values of gbest are sourced to the equation of velocity (equation 7) and position (equation 8) and the candidate solution maintains their position and velocity and the fitness value is updated at every stage of iteration.

$$v_i(t+1) = Wv_i(t) + c_1 r_1[\hat{x}_i(t) - x_i(t)] + c_2 r_2[g(t) - x_i(t)] \tag{10}$$

Here, $v_i(t+1)$ is the velocity of i^{th} particle at $t+1$ iteration, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are elements of a sequence in the range (0, 1) uniform and random in nature. The position of particle is calculated as [12]:

$$p_i(g+1) = p_i(g) + v_i(g+1) \tag{11}$$

The individual and global best fitness are updated and even replace global and local best fitness values if necessary. The velocity and position update step is responsible for the optimization ability of the PSO algorithm. This process is iterated for 100 times and the value of gbest at 100th iteration is the output of PSO.

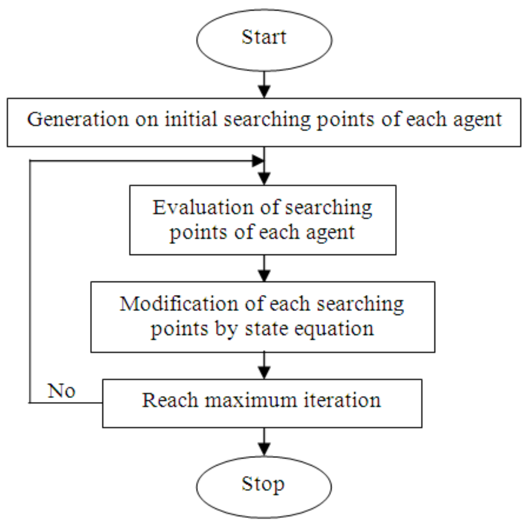


Figure 4. Flow Process of Particle Swarm Optimization

5. Experimental Setup

5.1 Evaluation Parameters

Out of many, we have selected two parameters to acknowledge the efficiency of proposed work. These parameters are selected considering the fact that they are available in most of parallel researches and thus are standard tool if anyone wants to compare the novelty of proposed work with existing methods.

5.1.1 Signal Quality Index: Signal quality index is the spectral flatness of a signal given by standard difference in equation 3.

5.1.2 Signal to Noise Ratio: The function SNR measures the response of a weakly nonlinear system stimulated by a sinusoid. When given time-domain input, SNR performs a periodogram using a Kaiser window with large side lobe attenuation. To find the fundamental frequency, the algorithm searches the periodogram for the largest nonzero spectral component. It then computes the central moment of all adjacent bins that decrease monotonically away from the maximum. To be detectable, the fundamental should be at least in the second frequency bin. Higher harmonics are at integer multiples of the fundamental frequency. If a harmonic lies within the monotonically decreasing region in the neighborhood of another, its power is considered to belong to the larger harmonic. This larger harmonic may or may not be the fundamental.

The function estimates a noise level using the median power in the regions containing only noise. The DC component is excluded from the calculation. The noise at each point is the estimated level or the ordinate of the point, whichever is smaller. The noise is then subtracted from the values of the signal and the harmonics.

SNR fails if the fundamental is not the highest spectral component in the signal.

5.2 Test Inputs

5.2.1 Periodic Noise: Periodic noise is continuous noise with repetitive waveforms of a specific length. The epochs of these waveforms are the disturbances created due to repetitive activity of a machine. The frequency of this wave is the number of epochs generated per unit time. The noise is commonly expressed in 'Hertz' and if the noise is audible it lies in the range 20-20,000 Hz. Studying in terms of speech signal following noise and speech signals are considered for experimentation- Noise: a) Diesel Engine b) Machinery

Speech Signals: a) Welcome b) Hello Girl c) Lalala

5.2.2 Non-periodic Noise: Every single noise that doesn't replicate itself in same fashion and same interval of time is classified as non-periodic noise. The nature of this noise is random and the waveform persist high unsymmetrical amplitudes. The source of these signals could be anything including the mixture of 3 or more periodic noises.

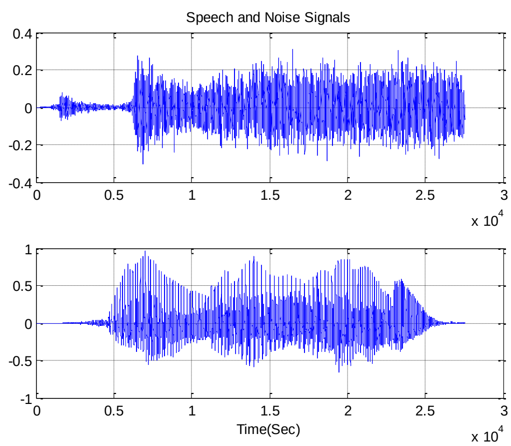
6. Results

Table 1. A comparative Table of ICA and Proposed Method in terms of SNR for Periodic noise (Diesel Noise) and 3 Speech Signals

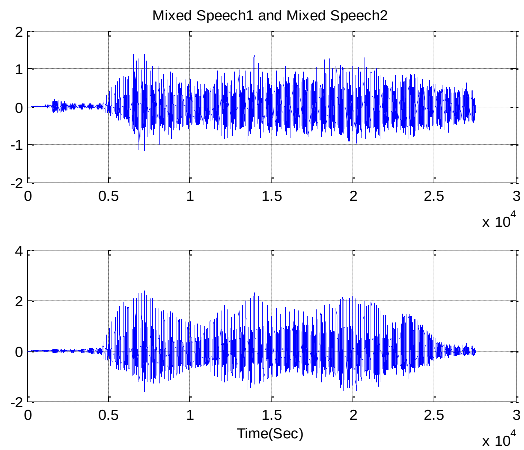
Periodic Noise/Speech Signal	ICA SNR (dB)	ICA+EMD+PSO SNR (dB)
Diesel Engine/Welcome	6.949	7.4379
Diesel Engine/Hello Girl	13.009	13.139
Diesel Engine/lalala	15.879	17.232

Table 2. A comparative Table of ICA and Proposed Method in terms of SQI for Periodic noise (Diesel Noise) and 3 Speech Signals

Periodic Noise/Speech Signal	ICA (SQI)	ICA+EMD+PSO (SQI)
Diesel Engine/Welcome	0.9994	0.99936
Diesel Engine/Hello Girl	0.99962	0.99961
Diesel Engine/lalala	0.9997	0.99965



(a)



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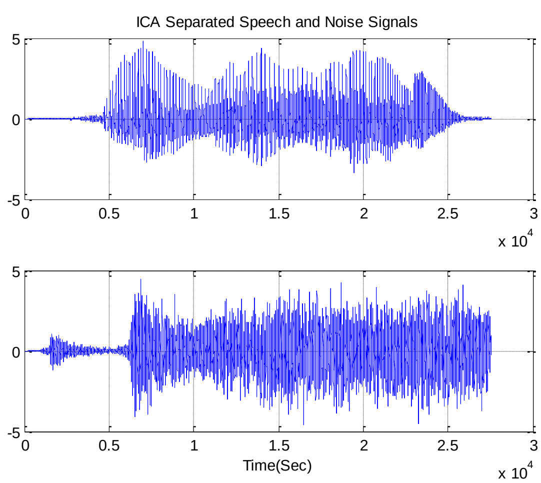
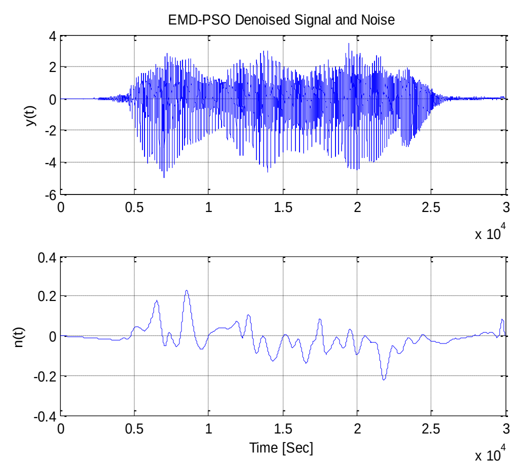


(c)



(d)

Figure 5. Are the representation of test input signals i.e. a speech signals and diesel noise mixing and separation through ICA and proposed algorithm. (a) is the original noise and source and the mixture is given in (b). The separation through ICA in noise and speech signals (c) is clearly visible to be inferior against EMD+PSO method (d).

Table 3. A comparative Table of ICA and Proposed Method in terms of SNR for Periodic noise (Machine Noise) and 3 Speech Signals

Periodic Noise/Speech Signal	ICA SNR (dB)	ICA+EMD+PSO SNR (dB)
Machinery/Welcome	16.587	17.575
Machinery/Hello Girl	19.7593	19.761
Machinery/lalala	13.254	14.6547

Table 4. A comparative Table of ICA and Proposed Method in terms of SQI for Periodic noise (Machine Noise) and 3 Speech Signals

Periodic Noise/Speech Signal	ICA (SQI)	ICA+EMD+PSO (SQI)
Machinery/Welcome	0.99975	0.99971
Machinery/Hello Girl	0.99982	0.99978
Machinery/lalala	0.99988	0.99983

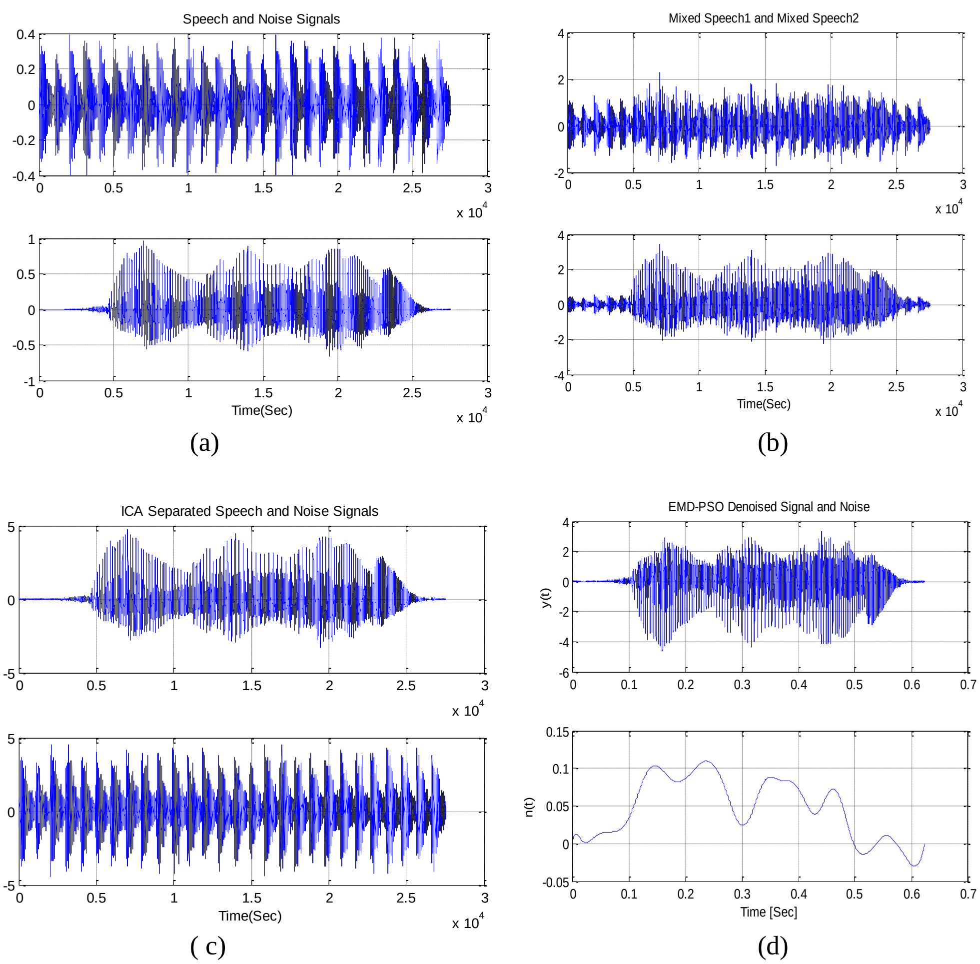


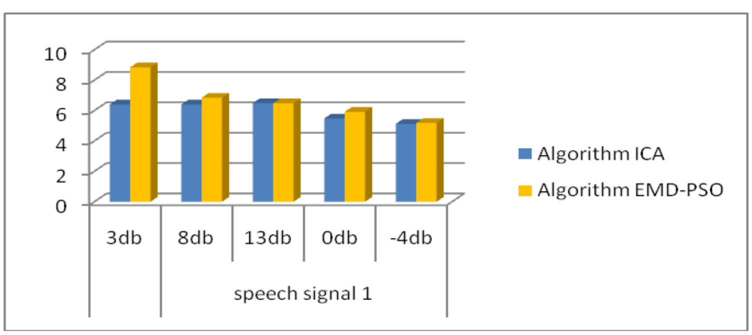
Figure 6. (a) Machine noise and speech signal (b) Mixed signal (c) ICA separated (d) Separated Speech and Noise Signal

Figure 6 is the representation of test input signals, *i.e.*, a speech signals and machinery noise mixing and separation through ICA and proposed algorithm. (a) is the original noise and source and the mixture is given in (b). The separation through ICA in noise and speech signals (c) is clearly visible to be inferior against EMD+PSO method (d).

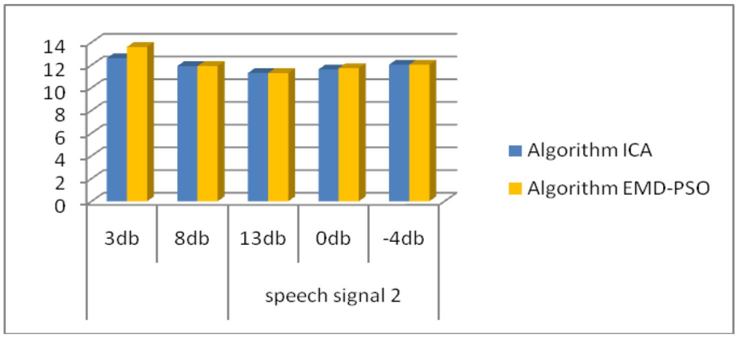
For the non-periodic noise, the mixing of signals is performed at 5 levels of sound to noise ratio. 4 such signals are aquired (column 1 of table 5) and their intial SNR are recorded (column 2). These signals after filtering with ICA and EMD-PSO, output SNR of each is signal is compared. Table 5 indicates that if EMD-PSO is selected over ICA for speech signal filtering, the output SNR will be higher than ICA for at least in all cases of input SNR greater than zero and equal or slightly less below zero SNR.

Table 5. At given Random Noise Variation Output SNR of Speech Signals

Input signal	Input SNR(db)	ICA	EMD-PSO
Speech signal 1	**3db**	6.4006	**8.8421**
	8db	6.4006	**6.8421**
	13db	6.4877	**6.4798**
	0db	5.4806	**5.9156**
	-4db	5.1267	**5.1848**
Speech signal 2	**3db**	12.595	**13.583**
	8db	11.905	**11.907**
	13db	11.292	**11.287**
	0db	11.605	**11.724**
	-4db	12.028	**12.03**
Speech signal 3	**3db**	12.19	**13.124**
	8db	14.012	**13.958**
	13db	18.065	**18.076**
	0db	9.1211	**12.14**
	-4db	14.246	**14.025**
Speech signal 4	**3db**	6.1701	**7.3886**
	8db	5.5212	**5.5154**
	13db	6.6057	**6.7166**
	0db	6.4259	**6.4199**
	-4db	6.2896	**6.2886**



(a)



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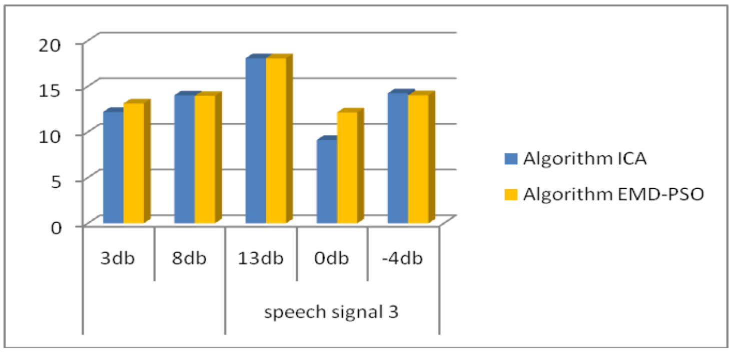

(c)

Figure 7. Comparison of performance in ICA, EMD-PSO for a) Speech Signal 1 b) Speech Signal 2 and c) Speech Signal 3

7. Conclusion

The speech signals are studied in the environment of industrial noise considering the relative security and health impacts and proposed algorithm is tested over same. The proposed method evaluated the performance on two experimental setups, *i.e.*, with periodic noise and non-periodic noise. The experiments were performed on three speech signals in the domain of industrial noise with diesel engine noise and machinery noise. It is seen that in case of periodic noise, the EMD was unable to predict the speech signal due to periodic form of nature and hence, ICA was implemented for this. The experimentation of periodic noise indicates that EMD+PSO on average has better performance (> 2dB) compared to ICA. In non-periodic noise, the SNR of EMD is greater than or equal to 100% compared with ICA. In this and else case, the fitness function of EMD optimized the PSO elevated the SNR of speech signals. The Sound Quality Index of proposed method is always a minute less than the conventional techniques. In further studies, SNR can be tested using the different adaptive technologies such as wavelet transform. However, such methods will add overhead computational cost.

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