

A Hybrid Approach for Speech Signal Denoising using ICA-DWT

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Abstract – In this paper problem considered is noise cancellation in speech signal corrupted by industrial noise. A Hybrid denoising method is presented as combination of Independent Component Analysis (ICA) and Discrete Wavelet Transform (DWT) for speech signal denoising. Independent component analysis is a computational method for separating a multivariate signal into additive subcomponents by assuming that the subcomponents are non-Gaussian signals and that they are all statistically independent of each other. Spatial features in ICA is transformed into time and frequency domain with help of DWT. The experimental results shown that proposed hybrid algorithm has better performance on signal to noise ratio(SNR) and signal quality index(SQI) compared to FAST ICA algorithm.

Keywords – Speech Signal, Independent Component Analysis, Discrete Wavelet Transform, SNR, SQI.

I. INTRODUCTION

In all practical situations, the received speech waveform contains some form of noise component. The noise may be a result of the finite precision involved in coding the transmitted waveform (quantization noise), or due to the addition of acoustically coupled background noise. Depending on the amount and type of noise, the quality of the received waveform can range from being slightly degraded to being annoying to listen to, and finally to being totally unintelligible[1-3]. The problem of removing the unwanted noise component from a received signal has been the subject of numerous investigations.

There are two different approaches for electrical noise reduction. The first approach is passive electrical noise reduction techniques, such as those applied in hearing aids, cochlear implants, etc. where the signal and ambient noise are recorded using a microphone, noise reduction techniques such as spectral subtraction, the LMS algorithm, etc. are applied and the listener hears only the clean signal. One of the important assumptions of this technique is that the listener is acoustically isolated from the environment[4-5]. This assumption is however not valid in a large particularly those number of situations where the ambient noise has a very large amplitude. In such situations, the second approach of Active Noise Cancellation (ANC) is applicable.

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 [6] as ICA can be data-driven, adaptive and linear representation in nature. For periodic noise ICA seems to be an indispensable method. However, singular application of ICA is not a healthy

effort hence wavelets were introduced for denoising [7] [8] [9]. The use of wavelet transform [10] for filtering of noise signals achieves a better response if compared only with FFT method [11][12]. Thus for speech denoising in industrial noise a hybrid algorithm is proposed based on ICA and DWT.

II. PROPOSED HYBRID MODEL

The noise cancellation for speech signals using adaptive wavelet thresholding algorithm is developed and implemented. The developed hybrid system model is shown in figure.1.

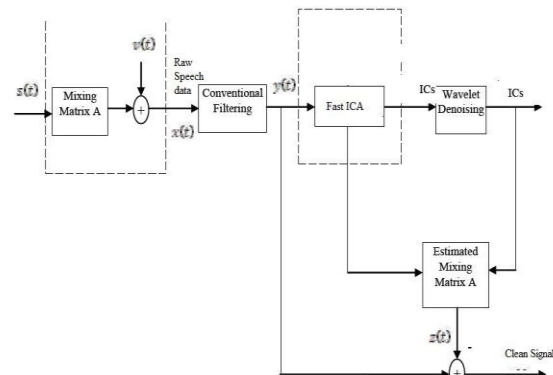


Fig.1. Block diagram of ICA-DWT Denoising model

The hybrid model for ICA with DWT

- The original audio signals are mixed with noise signals to create the source.
- These noise signals are filtered using ICA to separate them as noise signal and original signal. Use ICA to obtain Independent components (ICs) representing noise signal in speech signal data.
- The original signal is segmented using wavelet transform to generate the high frequency and low frequency amplitudes. Use Daubechies level 3 wavelet to separate any informative content leaked in the ICs.
- The original signal is compared with output of ICA to test the accuracy of proposed system.

III. INDEPENDENT COMPONENT ANALYSIS

In signal processing, independent component analysis (ICA) is a computational method for separating a multivariate signal into additive subcomponents by assuming that the subcomponents are non-Gaussian signals and that they are all statistically independent of each other. ICA is a special case of blind source separation.

The Fast ICA technique aims to maximize the statistical independence of the unconstrained sources and at the same time reducing the divergence among the spatially constrained source sensor projections and their corresponding reference topographies. A deflationary technique is implemented to take out only desired components, and therefore the output of the FastICA technique is ICs (which are noise signals in our case), and an estimate of corresponding mixing matrix. This results in fast computational time, as compared with if all ICs are extracted.

The positive feature that popularized this method is its ability to cope with diverse artifacts that are mixed with the original signal. ICA belongs to the blind source separation category that differentiates the original source waveforms with maximal independence against each other [13]. Specific patterns in the ICA components are found for the artifacts of signal. In original signals these artifacts overlap with original source signal and thus ICA tends to distinguish and measure the overlapping projection.

ICA exploits higher-order statistical dependencies among data and discovers a generative model for the observed multidimensional data. In the ICA model, observed data variables are assumed to be linear mixtures of some unknown independent sources (independent components). A mixing system is also assumed to be unknown [14]. Independent components are assumed to be non-Gaussian and mutually statistically independent. ICA can be applied to feature extraction from data patterns representing time series, images or other media.

The input signal of ICA is $z(t)$, which is nothing but the sum of considered speech signal $x(t)$ and noise $y(t)$ of environment.

$$Z(t) = x(t) + y(t) \quad (1)$$

The input signal $z(t)$ is a mixed speech and noise signal and intensity and proportion of noise in this signal are random factors. To suite this context, the blind source separation technique seems feasible as the mixing process of signals cannot be elaborated. Independent Component Analysis considers the input signal as the $z(t)$ original signal $x(t)x(t)$ multiplied by a mixing matrix A [15].

$$Z = AX \quad (2)$$

Here, Z and X are the matrix representation of input signal and speech signals respectively. ICA tends to determine the speech signal from input signal via inverting the mixing coefficient W ($W=A^{-1}$) in equation 5

$$S = WZ \quad (3)$$

IV. WAVELET TRANSFORM

The signals separated from ICA are now independent noise signals and independent source signals. The independent source signals are fed to DWT for filtration. The principle under which the wavelet thresholding operates is similar to the subspace concept, which relies on the fact that for many real life signals, a limited number of wavelet coefficients in the lower bands are sufficient to reconstruct a good estimate of the original signal. Usually these coefficients are relatively large compared to other coefficients or to any other signal (especially noise) that

has its energy spread over a large number of coefficients [16].

A. Discrete Wavelet Transform

The denoising of speech signal is dependent on the fact that noise artifacts are present in form of abrupt peaks in original signal. As the name indicates the signal is sampled into wavelets in discrete manner and has key advantage of temporal resolution over Fourier transform. The Daubechies wavelet method based on the use of recurrence relations samples the mother wavelet into finer samples with each sample having resolution double that of mother wavelet. The components of a wavelet are divided precisely half of previous component and are arranged in upper half (Detailed Coefficients) and lower half (Approximate Coefficients).

$$S_i = \frac{1}{\sqrt{M}} \sum_n s(t) \varphi_i(n) \quad (4)$$

$$S_j = \frac{1}{\sqrt{M}} \sum_n s(t) \psi(n) \quad (5)$$

Here, $i \geq j$ $s(t)$ is the output of ICA and $\varphi_i(n), s(t)\psi(n)$ are the functions of discrete variables. Equation 6 represents the approximate coefficients.

The AC of present wavelet is further scaled in 2nd level AC and DC (See figure 2). The removal of noise in DWT is performed by soft thresholding method considering its benefits over hard one. In this method the denoising of a DC is given by [17]:

$$S_j = \sigma \sqrt{2 \log N} \quad (6)$$

The i^{th} level of DC is an orthonormal function against the noise function having standard deviation σ . N is the frequency values in DC component and this estimation.

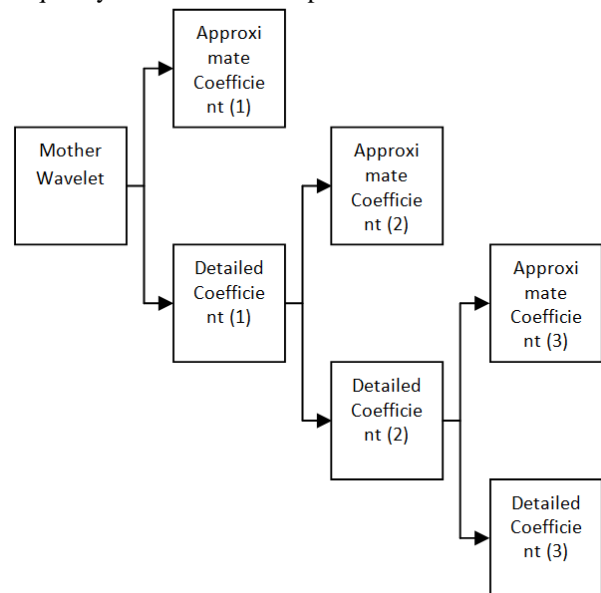


Fig.2. 3-Level Discrete Wavelet Transform for speech signal cascading into various frequency components

V. EVALUATION PARAMETER

Out of many, we have selected three 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.

B. Signal Quality Index

Signal quality index is the spectral flatness of a signal given by standard difference in following equation.

$$W = \log \left\{ \frac{e^{\int df \log(s(f))}}{\int dfs(f)} \right\} \quad (7)$$

C. Signal to Noise Ratio

The SNR is a measure of low magnitude waves stimulated by some sinusoid approach. The input wave in space-time domain is studied via periodogram optimized with Kaiser Window to attenuate large side lobes. The algorithm looks for the non-zero spectral component to result fundamental frequency. The central moment of each subject is computed for all adjacent bins in a decreasing order (i.e. from maximum to minimum). These frequencies are detectable in second bin and further frequencies are the replica of these steps. The power of a signal is selected as the larger harmonic in case if the signal shows the monotonically decreasing behavior compared with neighboring signal. The function is the ratio of noise intensity in noise contaminated region derived via median power. To calculate the performance, DC component is rejected and noise at every step could be either ordinate of a point or estimated level. This noise is eliminated for an artifact free signal.

VI. SIMULATION RESULTS

The results of periodic noise are subsequently arranged for diesel engine, machinery and factory noise respectively. The tables below after figures are comparative analysis for three speech signals in each noise domain. The input parameters of each test are same hence the explanation is limited only to figure 3 and figure 4. Similarly the tables against them will indicate the respective SNR and SQI for each speech signal in domain of respective noise. The comparative remark is made at conclusion.

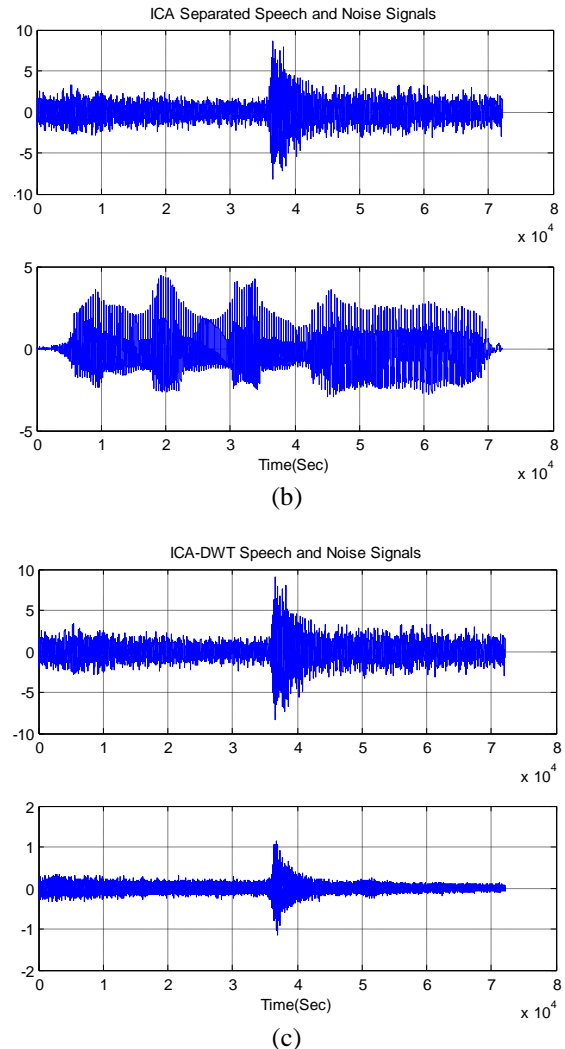
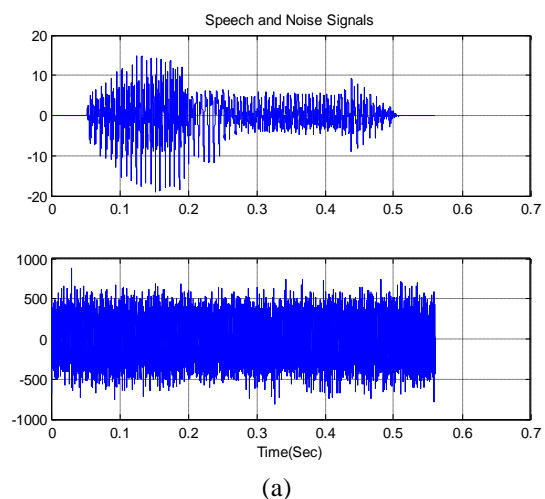
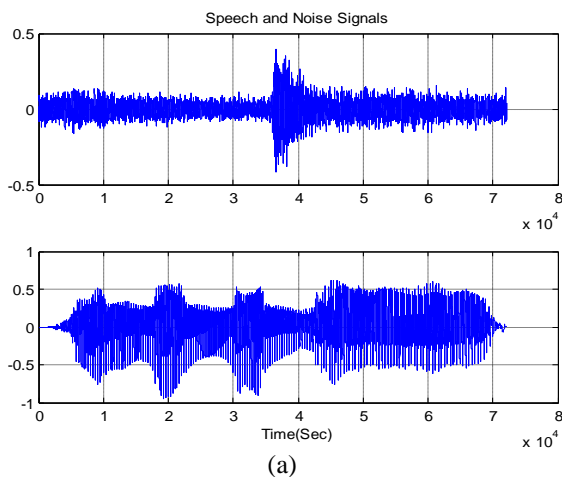


Fig. 3. The mixing and denoising of periodic noise and speech signal. (a) are the speech and noise signals that underwent mixing, (b) represents the ICA separated ICA and noise (c) filtering of signal using ICA and DW



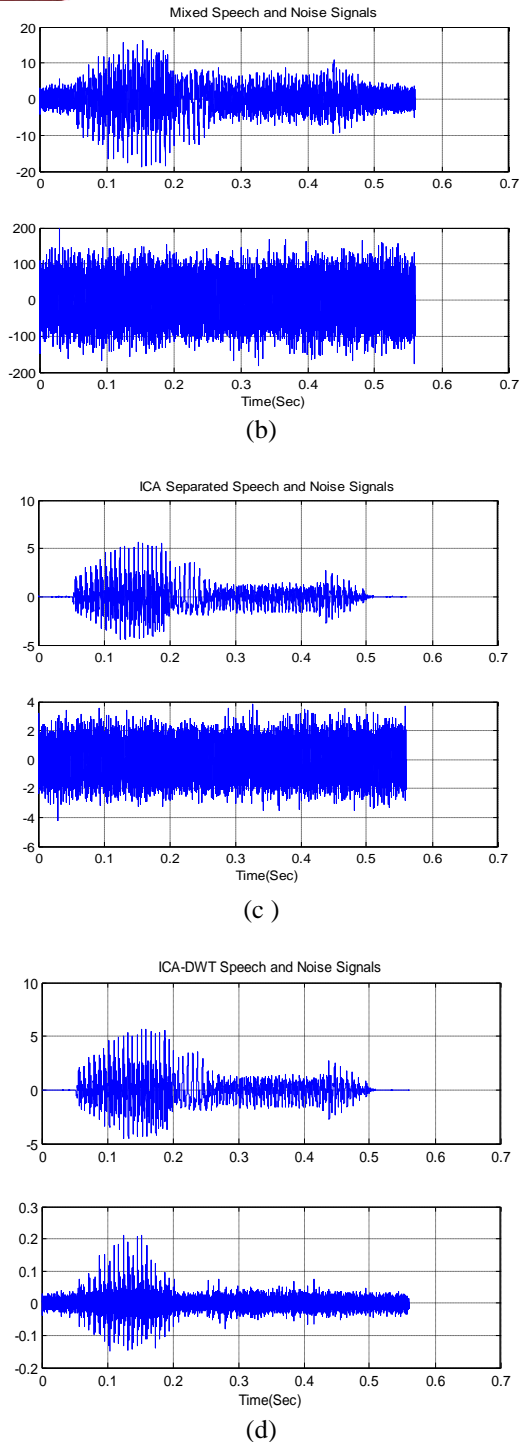


Fig.4. The mixing and denoising of noise and speech signal. (a) are the speech and noise signals that underwent mixing, (b) mixing of speech and noise signal (c) represents the ICA separated ICA and noise (d) filtering of signal using ICA and DWT

Table I: Comparison of different algorithms in 'diesel Engine' domain

Input signal	Method	SNR (dB)	SQI
lalala	ICA	15.879	0.99982
	ICA-DWT	16.177	0.99966
Hello girl	ICA	13.009	0.99962
	ICA-DWT	13.362	0.99885

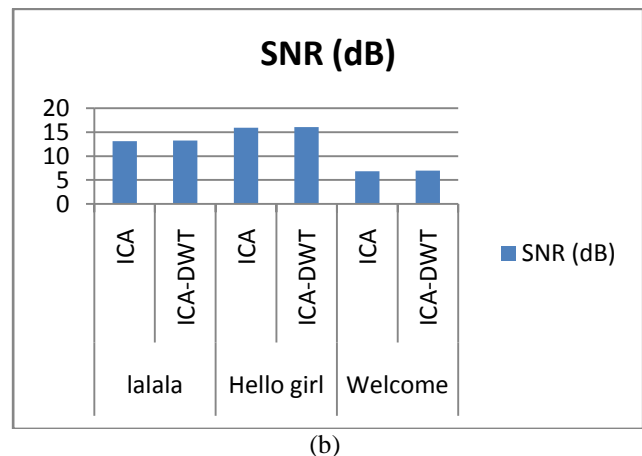
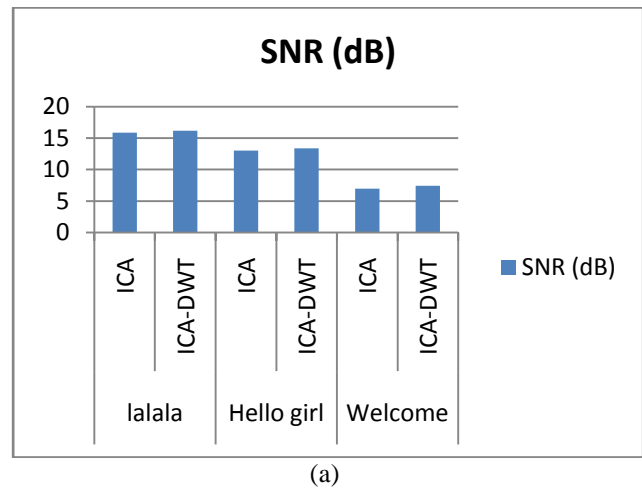
Welcome	ICA	6.949	0.99993
	ICA-DWT	7.41	0.99975

Table II: Comparison of different algorithms in 'Factory noise' domain

Input signal	Method	SNR (dB)	SQI
lalala	ICA	13.113	0.99997
	ICA-DWT	13.211	0.99989
Hello girl	ICA	15.947	0.99994
	ICA-DWT	16.022	0.9998
welcome	ICA	6.797	0.9995
	ICA-DWT	6.9273	0.99876

Table III: Comparison of different algorithms in 'Machinery noise' domain

Input signal	Method	SNR (dB)	SQI
lalala	ICA	7.7541	0.99979
	ICA-DWT	8.6987	0.99976
Hello girl	ICA	19.759	0.99938
	ICA-DWT	20.094	0.99893
Welcome	ICA	6.3219	0.87972
	ICA-DWT	8.3307	0.99828



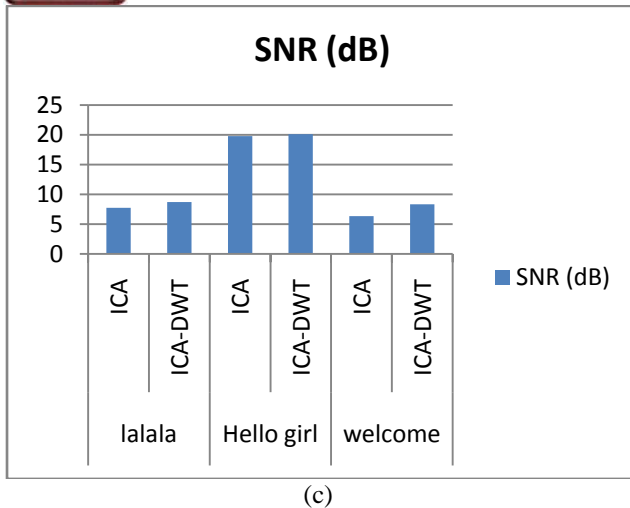


Fig.5. Comparison of performance in ICA, ICA-DWT a) Diesel engine b) factory and c) machinery noise signals. The tabular representation of results can be found in table I, II, III.

VII. CONCLUSION

In this paper a frame work for noise cancellation in Industrial ambience is developed to separate the noise from actual source with retaining the necessary information and is implemented in MATLAB 2014. Since ICA is a very popular method for blind source separation, initially ICA algorithm is implemented and found that it effectively removes noise from the speech but it does not remove all the noise from the signal because ICA's condition for separation is that signal sources should be non-Gaussian in nature but noise always has some kind of gaussianity with it and that reduces the efficiency of ICA in industrial environment. To enhance the performance of system, ICA separated signal is processed with DWT and found that SNR of signal improves. Results clearly state that the combination of ICA and DWT gives better result than the ICA.

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