International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2015): 78.96 | Impact Factor (2015): 6.391

Speech Enhancement Based on ICA and Adaptive Wavelet Thresholding in Stationary and Non Stationary Noise Environment

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Abstract: ***This paper presents a new approach to speech signal Enhancement in case of white Gaussian noise as well as in highly Non-Stationary Environment. Human ear mostly perceives mixture of various speech sources, but they are intended to interpret desired single speech signal. The proposed system is based on fundamental blind source separation technique known as Independent Component Analysis along with adaptive wavelet Thresholding scheme which enhances signal. An Independent Component Analysis is technique which effectively separates various statistically independent components from input mixture speech signal vectors. An Independent component analysis produces mostly accurate estimates of original speech sources; this basic phenomenon is incorporated to separate out speech signal and noise signal from a mixture of individual sources. Furthermore, Adaptive wavelet domain Thresholding is implied on estimated source signal to improve quality and intelligibility. Threshold value is adaptively estimated for different input signal with noise estimation method. The Time as well as frequency domain Objective Quality Measures such as Log-Likelihood Ratio (LLR), Frequency weighted segmental SNR (fwSNRseg), Weighted Spectral Slope (WSS), Perceptual Evaluation of speech Quality (PESQ), Itakura-Saito (IS) Ratio are then evaluated for resultant Enhanced speech signal with respect to the original desired signal.***

Keywords: Independent Component Analysis, Non Stationary Noise, Wavelet Transform, Adaptive Thresholding

1. INTRODUCTION

Speech enhancement is an important problem in the field of speech signal processing, with great impact on most of the speech recognition, cellular communication and speech coding applications. The goal of speech enhancement is to improve the quality and intelligibility of the signal, so as to reduce background additive noise and fatigue perceived by human listeners. In a real world system; we have multiple speakers in a closed environment. The audio system has different microphones for independent speakers, but in actual scenario, each of the microphones picks up speech signals from all the speakers, which results in noisy perceived signal. Blind source separation (BSS) is signal processing technique is essential to distinguish each of the speakers and to perform required controlling operations on the individual source signal. Another requirement is, speech enhancement algorithm should effectively separate the speech signals in presence of white noise as well as non stationary noise. Hongyan Li & Huakui Wang proposed technique of combining wavelet threshold de-noising and independent component analysis to separate Additive noise from mixed speech signals [1]. This method may reduce the affect of noise and improve the signal-noise ratio (SNR) of separated signal. Li Hongyan & Ren Guanglong, reported work to independent component analysis (ICA) when the measured signals are contaminated by additive noise, a method based on single channel ICA speech enhancement algorithm and FASTICA algorithm is proposed to separate noisy mixed speech signals [2]. Petr Tichavsky and Erkki Oja proposed an improved version of the FastICA algorithm which is asymptotically efficient, i.e., its accuracy given by the residual error variance attains the Cramér–Rao lower bound [12]. Mark D. Plumbley and Erkki Oja proposed the use of a nonnegative principal component analysis (nonnegative PCA) algorithm, which is a special case of the nonlinear PCA algorithm, but with rectification nonlinearity, and they conjecture that this algorithm will find such nonnegative well-grounded independent sources, under reasonable initial conditions [13,16]. Lateron, De-Shuang Huang and Jian-Xun Mi proposed general framework to incorporate a priori information from problem into the negentropy contrast function as constrained terms to form an augmented Lagrangian function. In this algorirhm a new improved algorithm for cICA is presented through the investigation of the inequality constraints, in which different closeness measurements are compared [14,16]. Xin Zou, Peter Jan covic, Ju Liu, and Münevver Köküer, presented a novel maximum a posteriori (MAP) denoising algorithm based on the independent component analysis and demonstrated that the employment of individual ICA transformations for signal and noise can provide the best estimate within the linear framework. The signal enhancement problem is categorized based on the distribution of signal and noise being Gaussian or non-Gaussian and the estimation rule is derived for each of the categories [15]. Alok Sharma, Kuldip K. Paliwal, proposed an algorithm in which vector kurtosis is utilized in the subspace ICA algorithm to estimate subspace independent components. One of the main advantages of the presented approach is its computational simplicity but it is prone to small non linearity's in input signal [16, 17, 18]. Specific Literature survey has been carried out on wavelet transform. Huan Zhao, Xiujuan Peng, Lian Hu, Gangjin Wang proposed speech enhancement algorithm based on distribution characteristic of noise and clean speech signal in the frequency domain, a new speech enhancement method based on teager energy operator (TEO) and perceptual wavelet packet decomposition (PWPD)[19]. This approach proposed by Manikandan, is very efficient it is cascaded by other noise reducing methods. As can be seen from the results, that when this method was cascaded by wavelet de-noising method it overall was very much improved the efficiency of the combination was better than when either of the techniques were used individually. Thus the combination of this method with some general known other methods, gives the advantage of transmitting signals with low power [20].

This Paper mainly focuses on an enhancement technique based on Independent Component Analysis which deals with blind source separation problem and leads to generate statistically independent sources. Moreover, the individual sources processed through Adaptive Wavelet Thresholding block to further reduce Non-stationary Noisy and alternatively produces enhanced speech signal. The rest of the paper is organized as follows. Section II describes the Independent component analysis. Section III describes Noise estimation technique. Section IV describes the Wavelet Thresholding. Section V describes Proposed System. Section VI describes an Experiments and Results.

2. Independent Component Analysis

Independent component analysis (ICA) is an efficient mechanism for multiple applications such as blind source separation (BSS), unsupervised learning, as well as in speech signal feature extraction. ICA is concept related to higher order statistics in which the former estimates a least-squares linear transformation which extracts the uncorrelated statistically independent components. Independent component analysis was originally developed to deal with problems that are closely related to the cocktail-party problem. Since the recent increase of interest ICA has become popular, it has other interesting applications as well. A general ICA model is the given by:

$$x(t) = As(t) + v(t) \quad (1)$$

x(t) is observed mixture vector of original signal s(t) and additive noise signal v(t).The basic purpose of ICA is then to estimate the realizations of the original signals using only observation of the mixture $\mathbf{x}(t)$, let us denote **W**, and obtain the independent component simply by:

$$\hat{S}(t) = W\, x(t) \quad (2)$$

Where W denotes demixing matrix which estimates source signals $\hat{S}(t)$.

A.Preprocessing For ICA

ICA is mostly performed on a mixture of data; such data contain less number of latent components which may lead to poor results. Hence, preprocessing techniques that is carried prior to ICA to reduce of the dimensionality of the input signal.

i. Centering: It is easier to estimate an Un-mixing Matrix 'W' if the measured signals have a mean of zero, a variance of one and zero correlation. That is then we obtain the centered observation vector, *Xc*, as follows:

$$Xc = X - m \quad (3)$$

This step simplifies ICA algorithms by allowing us to assume a zero mean.

ii. Whitening: Whitening is a process which produces new random vector having unit covariance matrix with zero mean, thus reduces the number of parameters to be estimated. Instead of having to estimate the n^2 elements of the original matrix '*A*', we only need to estimate the new orthogonal mixing matrix, where an orthogonal matrix has $n(n-1)/2$ degrees of freedom. This procedure is also called sphereing since it normalizes the eigenvalues of the covariance matrix.

B.The FASTICA Algorithm:

The FASTICA algorithm is proposed by Hyvanrinen is based on a fixed-point iteration scheme. Here we adopted kurtosis as the estimation rule of independence. Kurtosis has widely used as a measure of non-Gaussianity in ICA and related fields, which can be estimated simply by using the fourth moment about mean of the sample data. Kurtosis is defined as follows:

$$\mathrm{Kurt}(S_i) = E[S_i^4] - 3(E[S_i^2])^2 \quad (4)$$

We erect adjective function:

$$\mathrm{Kurt}\,(w^T\tilde{x}i) = E[(w^T\tilde{x}i)] - 3[E\{(w^T\tilde{x}i)^2\}]^2 \quad (5)$$

Since the observation signal has been pre-whitening, thus equation (8) can be simplified as:

$$\mathrm{Kurt}\,(w^T\tilde{x}i) = E[(w^T\tilde{x}i)^4] - 3\|w\|^4 \quad (6)$$

Seeking the gradient of equation (9), we get the following:

$$\Delta w \alpha\, E\,[\tilde{x}i\,(w_i(k)^T\tilde{x}i)^3] - 3\|wi(k)\|^2\, w_i(k) \quad (7)$$

Using the fixed point algorithm, the iteration of fixed point algorithm can be expressed:

$$w_i(k) = E[\tilde{x}i\,(w_i(k\text{-}1)^T\,\tilde{x}i)^3] - 3w_i\,(k\text{-}1) \quad (8)$$

Thus we obtain the FASTICA algorithm as follows:
(1)Center the data to make its mean zero.
(2)Whiten the data to get $\tilde{x}i$ (t)
(3)Make i=1;
(4)Choose an initial orthogonal matrix foe W and make k=1;
(5)Make $w_i(k) = E\,[\tilde{x}i\,(w_i(k\text{-}1)^T\,\tilde{x}i)^3] - 3w_i\,(k\text{-}1)$
(6)Make $w_i(k) = \dfrac{w_i(k)}{||\,w_i(k)||}$
(7)If not converged, make k=k+1 and go back to step (5)
(8)Make i=i+1
(9)When i<number of original signals, go back to step (4)

Until $|w_i(k)^T\, w_i(k\text{-}1)|$ is equal or close to 1, the iteration finish and results in estimation of individual speech sources with small amount of residual noise. The next crucial part is to estimate noise level for each individual source with noise estimation technique for effective noise cancellation.

3. Noise Estimation

Noise power estimation is an important component of speech enhancement as well as speech recognition systems. The efficiency and robustness of such systems, under low signal-to noise ratio (SNR) conditions and non-stationary noise environments, is highly affected by the capability to track fast variations in the statistics of the noise [9]. Traditional noise estimation methods, which are based on voice activity detectors, VAD's are difficult to tune and their reliability greatly degrades for weak speech components having low input SNR. In the Minimum Statistics method [3], the variance of estimated noise is about twice as large as the variance of a conventional noise estimator. Minima Controlled Recursive Averaging (MCRA) [4] that combines the robustness of the minimum tracking with the simplicity of the recursive averaging. The performance of basic MCRA algorithm is improved [5] based on some additional aspects as follows: Speech presence and absence probability estimation, Minimum tracking during only speech activity period which are fundamental techniques introduced with procedure of two iterations for smoothing of noisy power spectrum and minimum tracking. First iteration accomplishes voice activity detection in each frequency band. The smoothing procedure in second iteration provides relatively strong speech components; this facilitates decreased variance of the minima values. Let x (n) and d (n) denotes speech and uncorrelated additive noise signals, respectively. The observed noisy signal y (n) is divided into overlapping frames and it is analyzed using the short-time Fourier transform (STFT)

$$Y(k,l) = X(k,l) + D(k,l) \quad (9)$$

Where, k= Frequency Bin index
l= Frame Index

1) Initialize variables at the first frame for all frequency bins k.
2) For all time frames 'l' For all frequency bins k, Compute posteriori SNR and Conditional gain as follows:
Posteriori is defined by $\gamma(k,l)$

$$\gamma(k,l) \triangleq \frac{|Y(k,l)|^2}{\lambda_d(k,l)} \quad (10)$$

Where, $\lambda_d(k,l) \triangleq E\{|D(k,l)|^2\}$ denotes short term spectrum of speech and noise signal.

Priori SNR is estimated by, $\hat{\xi}(k,l)$

$$\hat{\xi}(k,l) = \alpha G_{H1}^2(k,l-1)\gamma(k,l-1) + (1-\alpha)\max\{\gamma(k,l-1,0)\} \quad (11)$$

Where, α is weighting Factor which controls tradeoff between signal distortion and noise reduction.

$$G_{H1}(k,l) \triangleq \frac{\xi(k,l)}{1+\xi(k,l)}\, exp\left(\frac{1}{2\int_{\upsilon(k,l)}^{\infty}\frac{e^{-t}}{t}}dt\right) \quad (12)$$

$G_{H1}(k,l)$ Is the spectral gain function of the Log-Spectral Amplitude (LSA) estimator in a case when speech is present.

3) Compute first iteration of smoothed power spectrum $S(k,l)$ in time domain.

$$S(k,l) = \alpha S(k,l-1) + (1-\alpha)Sf(k,l) \quad (13)$$

Where, $sf(k,l)$ is frequency smoothing of noisy power spectrum in each frame.

$$Sf(k,l) = \sum_{i=-w}^{w} b(i)|Y(k-i,l)|^2 \quad (14)$$

$b(i)$ is normalized window function over period $2w+1$.
Next task is to update minimum value of $S(k,l)$ by following equation:

$$S_{min}(k,l) = \min\{S_{min}(k,l-1), S(k,l)\} \quad (15)$$

4) Compute the indicator function $I(k,l)$ for speech presence time period.

$$I(k,l) = \begin{cases} 1 & if\ \ \gamma_{min}(k,l) < \gamma_0 |\ H_0(k,l)) < \varepsilon \\ 0 & Otherwise \end{cases} \quad (16)$$

5) Calculate Speech presence probability $p(k,l)$

$$p(k,l) = \left\{1 + \frac{q(k,l)}{1+q(k,l)}(1 + \xi(k,l))\exp(-\upsilon(k,l))\right\}^{-1} \quad (17)$$

$q(k,l)$ Is speech absence probability.

6) Update Noise spectrum estimate, $\hat{\lambda}_d(k,l+1)$

$$\hat{\lambda}_d(k,l+1) = \tilde{\alpha}_d(k,l)\bar{\lambda}_d(k,l) + [1-\tilde{\alpha}_d(k,l)]|Y(k,l)|^2 \quad (18)$$

Where, $\tilde{\alpha}_d(k,l) \triangleq \alpha_d + (1-\alpha_d)p(k,l)$ is a time varying frequency dependent smoothing parameter.

$\hat{\lambda}_d$ is updated estimate of noise which is further processed to decide threshold value for elimination of noise.

4. Adaptive Wavelet Thresholding

Wavelet transform, because of its joint time frequency signal representation with a high degree of sparseness and its excellent localization property, has rapidly become popular signal processing tool for a variety of applications. In effect, wavelet denoising attempts to reduce the noise presented in the speech while preserving the speech characteristics regardless of its frequency content [8].It involves the following three steps: 1) a linear discrete wavelet transforms 2) nonlinear Thresholding 3) a linear inverse discrete wavelet transform. A well-known wavelet Thresholding (shrinking) algorithm, named Wave Shrink, was introduced by Donoho [11] as a powerful tool in denoising signals degraded by additive white noise. Usually, the numerical values of signal wavelet coefficients are relatively large compared to noise coefficients. Therefore, we can achieve noise reduction by eliminating (shrinking) coefficients that are smaller than a specific value estimated by noise estimation algorithm called threshold, while preserving important attributes such as formants, pitch of original speech signal [7].

5. Proposed System

The Proposed system incorporates an Independent Component Analysis to decompose mixture input signal with various non stationary noise signals into individual speech signals, this accomplishes first technique which separate out the major quantity of color noise from mixture. After separating out clean and noise signal, there is possibility of small amount of noise which remains in separated clean signal, so in order to estimate residual noise value; separated signals are processed through noise estimation block. Meanwhile, the noise signal is discarded from discrete wavelet transform process, whereas extracted clean speech signal is converted to discrete wavelet domain for further processing. We have incorporated adaptive wavelet domain Thresholding technique which is very efficient for denoising small amount of residual noise in speech signals. This block is provided with input threshold value which adaptively estimated for every input speech signal.

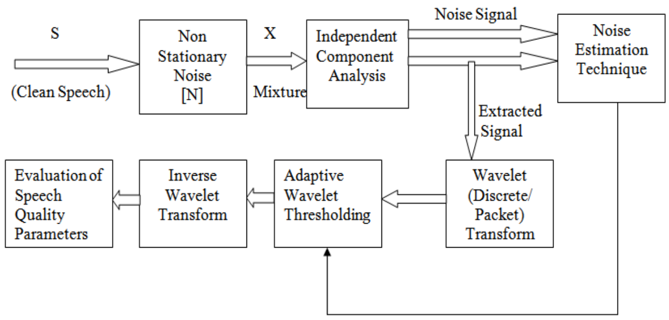

Figure 1: Proposed Speech Enhancement System

The wavelet coefficients lying below threshold are set to zero or eliminated from signal. In order to reconstruct denoised signal from wavelet domain, we need to take inverse discrete wavelet transform, which finally produces enhanced speech signal. The quality parameters of enhanced speech signal should be measured with respect to parameters of input noisy observation signal. Yi Hu and Philipos C. Loizou worked on various objective and subjective evaluation parameters [6], among those, we have evaluated Log-likelihood ratio (LLR), Weighted Spectral slope (WSS), Frequency weighted segmental SNR (FwSegsnr), Itakura Saito ratio (IS ratio), Perceptual evaluation of speech quality (PESQ).

6. Experiment and Results

The Proposed speech enhancement algorithm was evaluated with three different types of noise signals. Algorithm is simulated using MATLAB version 7.0. These simulation results are used to evaluate quality measures of enhanced speech. Speech quality and intelligibility reflects performance efficiency of enhancement algorithm. In the Simulation, the test speech signals are taken from NOIZEUS [10] database. The number of samples in mixture (Noisy) Signal and estimated independent sources are assumed to be fixed. Performance of proposed technique is evaluated with respect to additive white Gaussian Noise as well as various Non stationary noise environments.figure-2 indicates spectrogram of at various stages of proposed system in a particular case of additive white Gaussian noise mixed with clean speech signal (sp01.wav) at 0 dB Signal to noise ratio. Figure-2 shows spectrogram in case of enhancement stages of speech signal corrupted by babble noise at 0 dB signal to noise ratio. Figure-3 shows spectrogram of noisy speech signal corrupted by 0 dB car noise. Quality Assessment is done with the objective measure parameters which are basically mathematical evaluation of distance between enhanced and original signal.

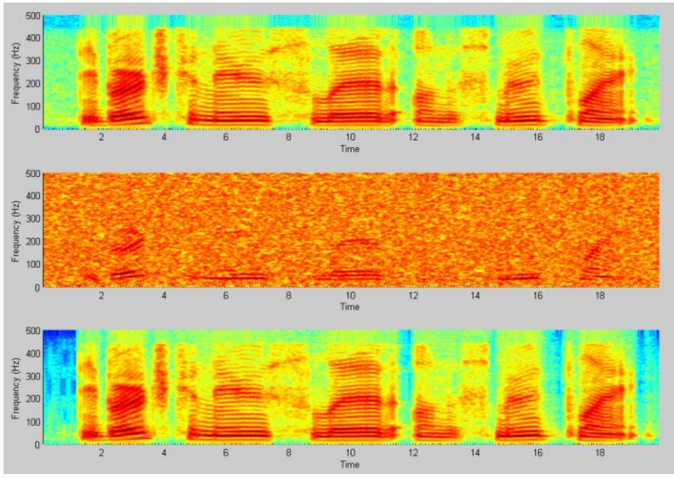

Figure 2: Enhancement of speech signal under influence of additive white Gaussian Noise (0dB) (a) Spectrogram of Clean speech (b) Noisy speech (c) enhanced speech

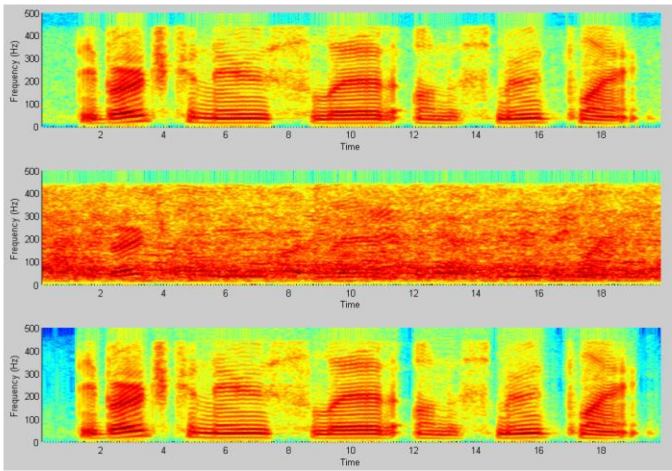

Figure 3: Enhancement of speech signal under influence of Babble Noise (0dB) (a) Spectrogram of Clean speech (b) Noisy speech (c) enhanced speech

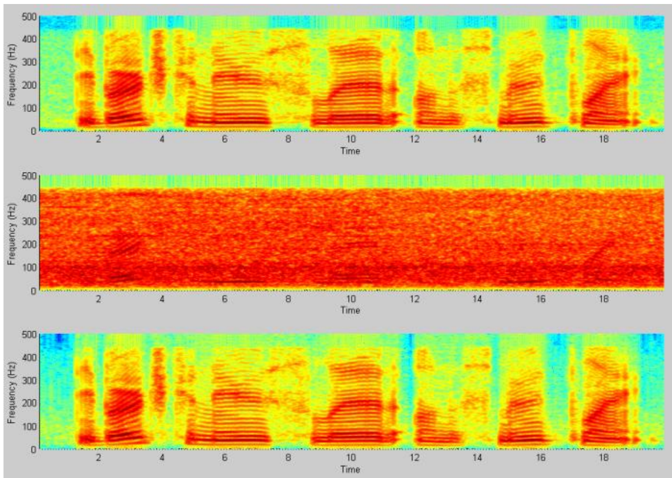

Figure 4: Enhancement of speech signal under influence of Car Noise (0dB) (a) Spectrogram of Clean speech (b) Noisy speech (c) enhanced speech

Log-Likelihood Ratio (LLR), Itakura- Saito ratio, Weighted Spectral Slope , Segmental Signal to Noise ratio are an objective quality measures corresponding to each frame of speech signal. Perceptual Evaluation of speech quality (PESQ) is subjective quality measure parameter; this is estimated with the help of various listening tests and Mean opinion score (MOS) of corresponding tests. PESQ measures suitable mainly for predicting signal distortion, noise distortion and overall speech quality. LLR provides distance between two frames by means of Log function of auto correlation ratio of corresponding clean and processed speech. The IS ratio measures distance between two frames based on various spectral levels in signal. Weighted Spectral Slope is obtained as difference between current and adjacent spectral magnitudes [6]. Small values of LLR, IS and WSS are required for better quality enhanced signal. The Table- I show numerical values of enhanced speech signal with respect to initial values in presence of AWGN noise at various levels.

Table-2 shows numerical parameter values corresponding to babble noise at various levels.

Table 1: Evaluation parameters of enhanced speech signal with respect to initial noisy speech parameters. (AWGN Noise)

	Log Likelihood Ratio (LLR)		Frequency Weighted SNR (fwSNRseg)		Weighted Spectral Slope (WSS)		Perceptual Evaluation of speech quality (PESQ)		Itakura-Saito Ratio (IS Ratio)	
SNR(dB)	Initial	Enhanced	Initial	Enhanced	Initial	Enhanced	Initial	Enhanced	Initial	Enhanced
0	1.7050	0.2210	4.4021	22.6513	60.6786	11.2179	1.5374	3.8366	3.8247	0.3687
5	1.4567	0.1483	5.4395	23.6823	53.6362	8.4059	1.5712	4.2474	3.1359	0.1953
10	1.2531	0.2992	6.9458	20.0531	46.6442	14.6955	1.6726	3.4744	2.4753	0.5666
15	1.0600	0.5711	8.1590	14.9287	41.9693	24.7499	1.9285	2.7165	2.0266	1.3094

Table 2: Evaluation parameters of enhanced speech signal with respect to initial noisy speech parameters. (Babble Noise)

	Log Likelihood Ratio (LLR)		Frequency Weighted SNR (fwSNRseg)		Weighted Spectral Slope (WSS)		Perceptual Evaluation of speech quality (PESQ)		Itakura-Saito Ratio (IS Ratio)	
SNR(dB)	Initial	Enhanced	Initial	Enhanced	Initial	Enhanced	Initial	Enhanced	Initial	Enhanced
0	1.0384	0.1171	4.9505	24.3902	67.3142	5.1138	1.3624	4.1992	3.1321	7.7178
5	0.8182	0.1140	6.0486	23.9147	55.1664	5.9384	1.8079	4.1295	2.2504	2.2524
10	0.6876	0.1283	7.3585	21.7113	47.2889	10.0826	1.9334	3.5976	2.1860	0.2201
15	0.6137	0.2277	8.3001	16.8487	41.4390	19.5780	2.1811	2.8312	2.2256	0.6350

7. Summary and Conclusion

This paper reports to blind source separation problem of multiple inputs multiple output system. It also addresses effectiveness of adaptive wavelet Thresholding along with independent component analysis which further improves quality of enhanced speech. We examine, improvement in frequency weighted signal to noise ratio, Itakura Saito ratio with respect to their corresponding input signal to noise ratio. From comparison of numerical parameter values of enhanced speech with respect to noisy speech, we concluded that, proposed algorithm performs better in stationary and non stationary noise environment. Algorithm enhances quality measure parameters at low level input signal to noise ratio, which is mostly not achieved by other competing enhancement algorithms.

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