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An Adaptive Learning Based Speech Enhancement Technique for Communication Systems

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***Abstract** - Extraction of speech signal from contaminated signal is main task in all practical applications. While transmitting speech signal, many undesired components are added to desired speech signal and they are eliminated at destination by using adaptive algorithms. Conventional least mean square (LMS) algorithm is widely used because of its simplicity and robustness, step size is main parameter in this algorithm. If there is rapid increase in step size it will affect convergence rate and mean square error (MSE). There is a tradeoff between MSE and convergence. With variable step size, performance of algorithm is improved. Hence developed data variable, error variable, step variable and time variable based adaptive algorithms are proposed. Based on LMS, several adaptive noise elimination techniques are proposed and they are analyzed. In these algorithms step size is variable instead of constant step size and it is based on error signals at particular instant. By proposed algorithm it improves speech signal so that MSE is reduced further signal to noise ratio is also improved.*

Keywords — *Adaptive Learning, Adaptive noise cancellation, Normalization, Speech enhancement, Step size.*

I. INTRODUCTION

For speech enhancement (SE), front end speech processing system is using from many years. In speech processing signals are affected with many random noises, removal of those noise signals is a main task for speech enhancement. To improve speech signal quality in a non-stationary noise situation, pre-processing step is considered, it is generally known as SE. Main aim of speech signals to eliminate noise signal [1], [2] then quality of signal is improved in automatic recognition of speech, hearing aids and forensics of a teleconference system, mobile communications applications. Speech enhancement technique based on circular statistics [3] is considered it describes extraction of speech signal using Kalman filter with modulation domain for large spectrum noisy signals. To restore speech signals, improved speech phase posterior spectrum is used. Nonlinear Kalman filter step models are updated by considering noise and speech signals and they are updated using Fourier transform complex time. To enhance recognition rate of vehicle applications, H∞ filter technique is proposed in [4] which uses adaptive time domain and frequency domain beam formers to get noise free speech signals, further hardware system is also developed for data acquisition of audio data. For speech filtering [5], empirical mode decomposition and adaptive center-based weight average filter is considered and its mechanism is represented as frame class integration of conventional filter process by average adaptive center filter and empirical mode decompositions. Input signal is divided into frames using empirical mode decomposition, then each frame is subdivided into finite number of intrinsic mode functions. Depending on type of signal i.e., voice or unvoiced signal number of intrinsic mode functions are represented. Energy criterion is considered for recognizing voice frames whereas stationary index shows differentiation for transient sequences or unvoiced frames.

Particle filter method [6] is considered for speech enhancement, interframe dependencies and non-gaussian statistics are considered for spectral amplitudes, by incorporating properties intractable closed form solutions are obtained. Speech spectral amplitudes and Laplace distribution are modeled as autoregressive techniques in particle filter method. In practical applications, when transmitting speech signals contaminating with noise signals, so for resolution of these noise speech signals, adaptive noise elimination methods are considered for speech enhancement, then improved intelligibility and quality of speech signal with elimination of undesired speech signals, we did not predict nature of noise in this application. Further, filtering techniques are considered to reduce noise signals. Adaptive and nonadaptive filtering techniques [7] are generally considered, then noise components are eliminated by considering noise characteristics in adaptive filtering techniques. In nonadaptive filtering techniques, prior knowledge of noise is required and it is known by using notch filter, finite impulse response and infinite impulse response techniques etc., Weights of filter are fixed in non-adaptive filtering irrespective of noise contamination levels, due to this reason there is loss of information. Hence non-adaptive filter techniques are not preferred when compared to adaptive methods for various noise environment eliminations. In adaptive filtering, weights are updated for every iteration for contaminated speech signal. Various filtering techniques are studied [10]-[12] to change filter weights, in this least mean square (LMS) algorithm is

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conventional algorithm. In signal processing, adaptive solutions are provided based on conventional adaptive algorithms. Step size is main aspect in updating filter weights. Depends on step size parameter [16]-[19], steady state convergence rate is considered. Contaminated noise signal is considered as reference signal [20]-[25] in adaptive filtering techniques. Other speech processing and adaptive learning algorithms are presented in [31]–[32]. With vary of step size, developed different adaptive noise canceller techniques for eliminating noise and to improve system performance. Various parameters like minimum residual rate, computational complexity, convergence and SNRI are considered. Different techniques are considered to vary step size of adaptive filter so that we get better performance. Error variable, time variable, step variable and data variable are various step size variants, based on these method different adaptive techniques are developed. Speech enhancement unit performance is measured by considering various parameters like computational complexity, convergence and improvement in SNR.

II. ADAPTIVE LEARNING METHODOLGY FOR SPEECH ENHANCEMENT

Wavelet transform is generally used method to analyze signals, it provides temporal and spectral knowledge of signal. Frequency resolution is obtained with lower frequency signals, wavelet transforms with high frequency signals. Hence wavelet transform is used to analyze multi resolution signals, then wavelet transform for input signal represented as

$$y(t) = \sum_{m} a_{Mm} \emptyset_{Mm} + \sum_{l=1}^{M} \sum_{m} d_{lm} \emptyset_{lm}(t) \quad (1)$$

Approximate coefficient a_{Mm} and detailed coefficient d_{lm} are used in above equation, with help of these coefficients input signal is decomposed to M levels as below

$$y(t) = A_M(t) + \sum_{l=1}^{M} D_l\,(t) \quad (2)$$

By using DWT-ANE methods, reference signal is obtained. For input speech signal performed wavelet decomposition for calculating coefficients with seven decomposition levels. For last three coefficient levels, soft thresholding method is applied then obtained coefficients are used for reconstruction of wavelet signal then for ANE reference signal also generated, then this contaminated speech signal given as reference signal. Based on morphology and spectral characteristics source interest, wavelet decomposition type and levels of decomposition are selected in DWR-ANE, it is the main disadvantage of this method. Singular spectrum analysis (SSA) based ANE is proposed to overcome problems of DWT-ANE and it doesn't depend on particular type of speech signal.

A. Singular Spectrum Analysis for Reference Generation

In order to generate reference signal from the noisy signal we make use of SSA based decomposition. There are four modules in SSA namely, embedding, decomposition, grouping and reconstruction. Contaminated speech signal represents as multivariate matrix using embedding step, then obtained trajectory matrix, it is represented as follows:

$$Y = \begin{bmatrix} y\,(1) & y\,(2) & \dots & y\,(J) \\ y\,(2) & y\,(3) & \dots & y\,(J+1) \\ \vdots & \vdots & \vdots & \vdots \\ y\,(L) & y\,(L+1) & \dots & y\,(N) \end{bmatrix} \quad (3)$$

Window size (L) depends on sampling frequency and from (3) J denoted as $\mathrm{J} = \mathrm{N} - \mathrm{L} + 1$, all anti diagonal elements of above matrix are identical. In second step obtained matrix decomposes to 'L' matrices, covariance matrix is also calculated as $\mathbf{C} = \mathbf{YY}^T$. For this covariance matrix, eigen vectors (v) and eigen values (λ) are determined and they are arranged in descending order. At i^{th} value trajectory matrix expressed as

$$Y_i = \sqrt{\lambda_i} v_i u_i^T, \qquad i \in \{1,2,\dots,L\} \quad (4)$$

u_i value is substituted as $u_i = Y^T v_i / \sqrt{\lambda_i}$ in equation (4) then in terms of eigen vectors, matrix Y represented as

$$Y_i = v_i v_i^T Y \quad (5)$$

In above equation, $v_i v_i^T$ term denotes subspace component at i^{th} value. Matrix Y projects into subspace then it generates trajectory matrix at i^{th} value. Hence trajectory matrix is reconstructed as

$$Y = \sum_{i=1}^{L} Y_i \quad (6)$$

Trajectory matrix is divided into 'd' categories depending on conditions of eigen values in grouping step. For 'k' indices, eigen values are represented, trajectory matrix at K^{th} value as $\hat{Y}_K = \sum_{l=k_1}^{k_q} Y_l$. By grouping 'L' eigen values, disjoint subsets 'd' are formed then matrix are formed then matrix Y represented as

$$Y = \sum_{m=1}^{d} \hat{Y}_{K_m} \quad (7)$$

Finally in reconstruction step, matrix Y again maps to single channel matrix $\hat{Y}_I$, I denote eigen value indices.

In SSA, identification of signal subspace [27] is significant step. New grouping criterion is considered it is based on local variations of eigen vectors. For eigen vector with 'L' samples, local variants are represented as

$$m_v = \frac{\sqrt{\frac{\sum_{j=1}^{L-1} z^2(j)}{L-1}}}{\sqrt{\frac{\sum_{j=1}^{L} v^2(j)}{L}}} \quad (8)$$

Successive samples of v are represented as $z(j) = v(j) - v(j-1)$. To determine noise subspace for each eigen vector local mobility is calculated, based on prior knowledge selected threshold value, then arguments are calculated for respective eigen vectors and by using equation (5) trajectory matrix is calculated.

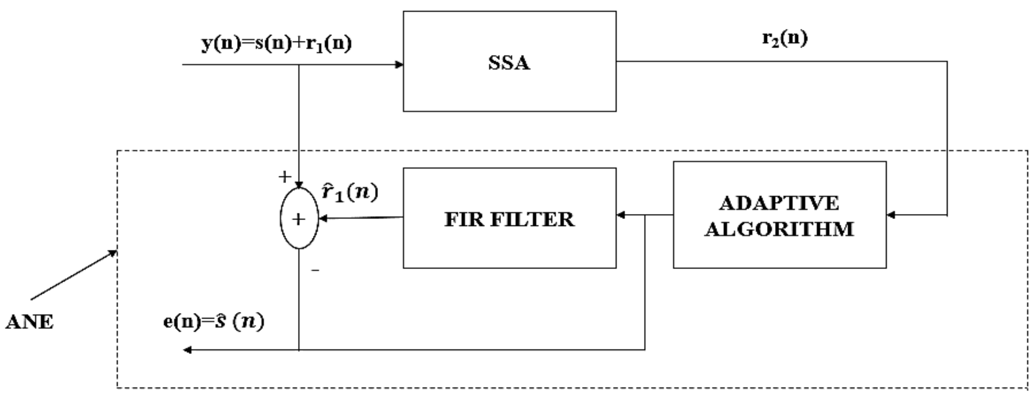

Fig.1 Block diagram of SSA using adaptive algorithm

B.Singular Spectrum Analysis based Adaptive Noise Cancellation

Contaminated speech signal given as primary input to ANC, generated reference signal using SSA given as reference input to ANC. In adaptive filters, it updates filter weights with consideration of $\mathbf{r}_2$ samples then estimated signal $\hat{r}_1(n)$. For every time instant 'n' speech signal is subtracted from contaminated speech signal and finally we get desired speech signal as $\hat{s}(n)$, it is performed on individual data blocks. In practical applications, proposed method has more advantage because time taken to get desired speech signal takes less time when compared to sampling interval of speech signal. In Fig. 1, block diagram of SSA using adaptive filtering technique is shown. In ANE, it consists of FIR filter and weight update mechanism. Several strategies are considered to update weight equation of filter. Length of LMS filter is taken as M. Input of SSA and adaptive filter has contaminated signal y(n), in which it contains desired signal s(n) and noise signal $r_1(n)$. We get reference signal $r_2(n)$ from output of SSA and it is correlated with contaminated speech signal with noise components. Now let us consider, error signal is e(n), FIR filter impulse response as p(n), q(n) is output, then for conventional LMS adaptive learning update equation is represented as,

$$p(n+1) = p(n) + sy(n)e(n) \quad (9)$$

P(n) represents weight vectors with size 'M', y(n) is input sequence with elements $y(n) = [y(n)\, y(n-1) \ldots y(n-M+1)]^t$, $e(n) = y(n) - p^t(n)r_2(n)$ and step size with 's', it has major role in any practical application of adaptive algorithm. Convergence rate is fast & MSE raises for larger step size values and convergence rate is slow & MSE is low for small step size values. Therefore, step size is key parameter for performance of adaptive filter. To improve adaptive algorithm performance, value of step size considered as

variable than fixed step size. In any adaptive algorithm, at initial values step size value should be larger after reaches steady state it should be small then it's called as variable step size algorithm. This variable step algorithm is developed by including variable step size in weight update equation of LMS algorithm. To improve convergence rate and to reduce noise components step size value updated continuously in effective way. In speech related applications, amount of noise components contaminated in speech signal changes rapidly, so variable step methods are better when compared to fixed step size value. Depending on this phenomenon, new adaptive algorithms with reference to error variable, data variable, step variable and time variable methods are considered for eliminating noise components. By using these four types, LMS based algorithm are proposed. In data variable LMS, variable step size is inversely related to total energy weights of input vector. Data variable LMS converged faster when compared to LMS due to usage of variable convergence output error is minimized. In this method, step size is varied according to input data squared norm, then weight update equation of data variable LMS algorithm is represented as

$$p(n+1) = p(n) + s(n)y(n)e(n) \quad (10)$$

Here *s(n)* is expressed as,

$$s(n) = \frac{s}{u + y^t(n)y(n)}$$

In above equation parameter 'u' is selected so that to avoid small denominator value it leads to larger step size.

In error variable LMS according to error vector value of step size is normalized. Number of iterations are considered as error vectors size. In this method, step size is varied according to squared norms of e(n) error vector, then signal distortions are reduced with this proposed algorithm. In this algorithm, individually step size is chosen and it doesn't depend on signal power and weights of filter. Weight update equation of error vector LMS algorithm is represented as

$$p(n+1) = p(n) + s_e(n)y(n)e(n) \quad (11)$$

Here $s_e(n)$ is error normalized step variable parameter denoted as,

$$s_e(n) = \frac{s}{u + e^t(n)e(n)}$$

It is very difficult to set step variable value for unspecified speech signals, for this type of signals time variable based LMS algorithm is considered with decay function and its weight update equation is expressed as

$$p(n+1) = p(n)+s \times y(n) \times e(n) \qquad (12)$$

For every iteration step size varies and it is updated using below equation

$$s(n) = \alpha(n) \times s(0)$$

Decaying factor is given as

$$\alpha(n) = C(1/(1 + b^n \times d))$$

Where b, d and C are positive parameters considered for determining $\alpha(n)$ value. For fixed step size value, time variable adaptive algorithm performs when compared to LMS algorithm and noise is eliminated efficiently.

When a desired speech signal contaminated with gradient noise, adaptive filter weights are changes in random in nature without terminating on Weiner solution. These difficulties are solved by step variable based adaptive algorithm with addition of fourth step to LMS algorithm and its weight update equation and step size parameters are represented as

$$p(n+1) = p(n) + s_s(n)z(n)r(n) \qquad (13)$$

$$s_s(n+1) = s_s(n) + \rho \times s(n) \times e(n) \times \gamma(n)$$

Where $\gamma(n)$ is partial derivative of $p(n)$ with respect to s(n) and ρ is positive constant with small value.

$$\gamma(n) = \frac{\delta p(n)}{\delta s(n)}$$

It converges faster when compared to existed algorithm because its step size of present iteration depends on error vector and input vector of previous iterations.

III. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, variable step size-based algorithm simulation results are discussed. In Fig. 2, convergence characteristics various step-based algorithms are shown. It is defined as rate, in which system converged to resultant state. For any adaptive system, fast convergence is main requirement, where other parameters do not influence convergence characteristics. There is a trade off with other parameters: increase in performance characteristics with decrease of performance convergence and vice versa. If we considered higher convergence rate, system stability is decreased so that system becomes diverges to get proper solution and also in another side more stability is obtained with decrease of convergence rate. When compared to other adaptive algorithms, faster convergence is obtained with step variable adaptive algorithm

Various speech enhancement techniques are developed with proposed step variable based adaptive algorithms. Window size is considered as five for all these adaptive filter algorithms. In simulation results, noise components are eliminated initially by using additive white Gaussian noise, then real noise is used in different speech signals. For experiments five sample speech signals are considered from database, the performance is evaluated for both real noise and synthetic noises with proposed algorithm, then considered tracking performance of non-stationary adaptive algorithms. Types of noises considered for our experiments are cockpit noise, crane noise, high voltage murmuring noise. A diversified noise component is used in our experiments to prove the ability of the proposed adaptive learning algorithms. Performance of various proposed algorithms in terms of SNRI are shown in Table 1. Speech signals wave-1 to wave-5 are considered. 53570 samples are observed with wave-1, it is recorded signal with anc.wav. Male speech signals considered from database with samples of 95232 and 100864 are taken in wave -2 & wave-3 respectively whereas wave-4 and wave-5 are female speech signals with samples of 103936 and 114176. Performance of proposed algorithm is evaluated and its output is shown in Fig. 3. Step variable based adaptive algorithm performs well when compared to other adaptive algorithms in terms of noise reduction. In this paper, wave 1 speech signal is considered, it is a helicopter noise. By means of signal to noise ratio improvement, improvement of speech signal is shown.

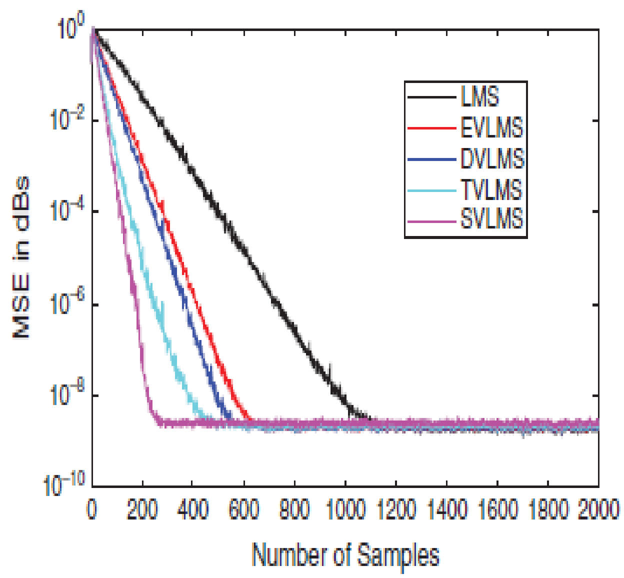

Fig. 2 Convergence mechanism of various ANCs based on adaptive learning algorithms.

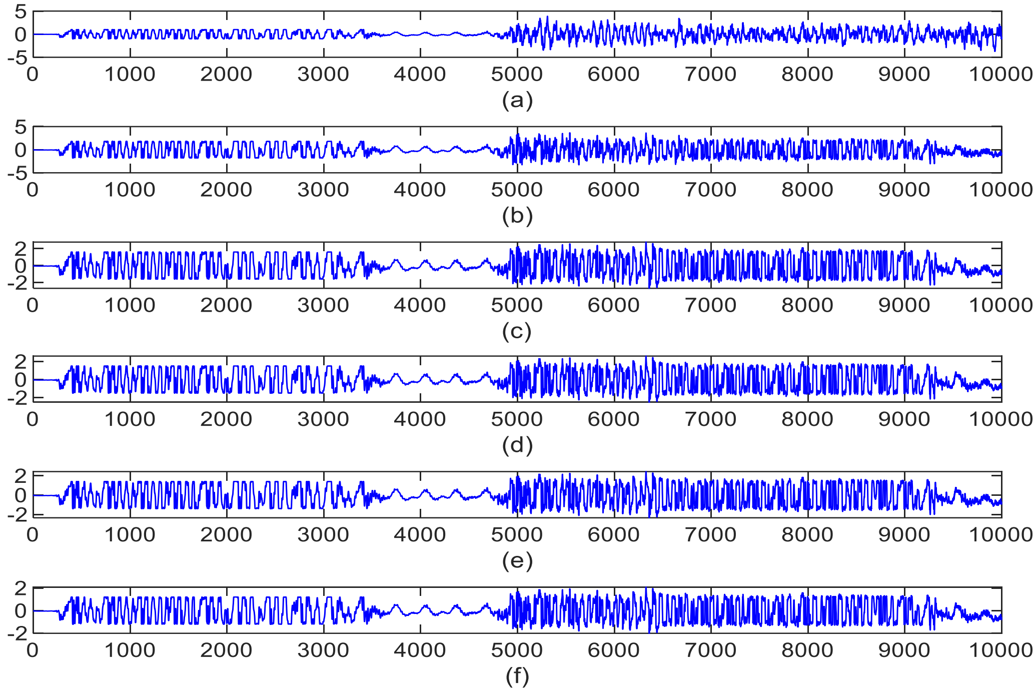

Fig.3 Crane Noise Removal Filtering Results for Sample – I (a) Noisey Speech Signal, (b) LMS based enhanced signal, (c) DVLMS based enhanced signal (d) EVLMS based enhanced signal (e) TVLMS based enhanced signal (f) SVLMS based enhanced signal.

TABLE I: Performance of various adaptive learning algorithms in terms of SNRI (SNRI)

Sl.no	Noise type	Speech Number	LMS	DVLMS	EVLMS	TVLMS	SVLMS
1.	Cockpit Noise	**I**	9.7763	16.1526	18.6483	24.8353	28.8443
		II	9.8754	16.3298	18.3983	24.0472	28.4645
		III	9.4367	16.3876	18.0932	24.1634	28.8933
		IV	9.8754	16.3672	18.3876	24.8565	28.5422
		V	9.5431	16.3982	18.3765	24.5823	28.8466
		Average	**9.7013**	**16.3270**	**18.3807**	**24.4969**	**28.7181**
2.	Crane Noise	**I**	8.2598	13.9835	16.6738	22.2868	26.4582
		II	8.6543	13.6532	16.3862	22.5735	26.8548
		III	8.4321	13.8753	16.3982	22.9324	26.6564
		IV	8.2309	13.5287	16.7365	22.0272	26.7376
		V	8.6520	13.8732	16.2398	22.9362	26.0754
		Average	**8.4452**	**13.7827**	**16.4869**	**22.5512**	**26.5564**
3.	High Voltage Murmuring Noise	**I**	7.7605	12.9544	14.5743	21.7358	25.1653
		II	7.4532	12.6732	14.2653	21.6411	25.5979
		III	7.6521	12.6532	14.7530	21.6353	25.9767
		IV	7.6532	12.6283	14.7698	21.8307	25.6756
		V	7.6530	12.7230	14.6387	21.7847	25.9954
		Average	**7.6344**	**12.7264**	**14.6002**	**21.7255**	**25.6821**

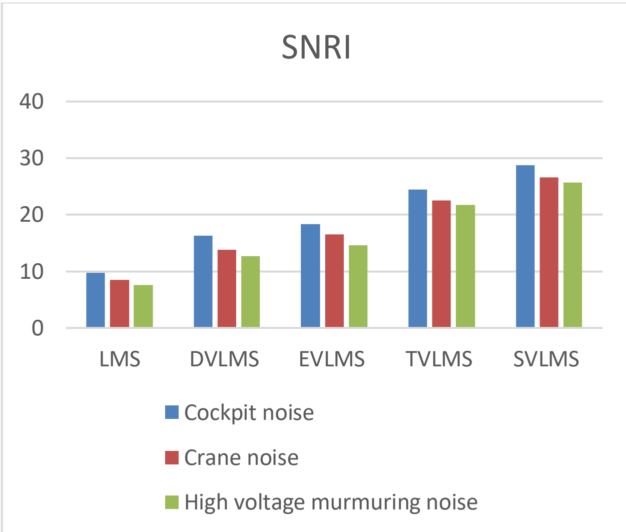

Fig.4: Comparison of SNR (dBs)for various ANCs

Enhanced speech signal is obtained with updation of every iteration. In synthetic speech signal, first half samples in a systm is kept constant but random noise is automatically changing for each iteration. Once constant impulse response is obtained then impulse response of next half samples are considered. Then observed impulse response results before and after variations, it exhibits better results for proposed algorithms when compared to data variable, step variable, time variable adaptive algorithms and it is shown in Fig.3 and their performance measure for SNR with different noises are shown in table 1. In this paper, three noises are considered and all this experiments are done for 5 samples then they are averaged. For experiments we considered five samples namely I to V with noises cockpit noise, crane noise and high voltage murmuring noise. Using threshold value and adaptive noise signals, noise signal is removed with help of FIR filters then speech signal is evaluated using MATLAB simulations. Improvement of SNR performance is shown in figure 4, better results are obtained for step variable LMS algorithm (SVLMS) when compared to other algorithms

IV. CONCLUSION

In this paper, various speech enhancement techniques are developed based on step variable for achieving better convergence and filtering capabilities. Error variable, data variable, time variable and step variable adaptive algorithms are implemented along with basic LMS algorithm, hence developed these algorithms for speech enhancement. Proposed algorithms are evaluated with eliminating noises like high voltage murmuring noise, helicopter noise, and crane noises from desired speech signal. Then performance is estimated using the performance measure SNRI. Therefore, from experimental results clear that step variable based adaptive algorithm has better convergence when compared to other algorithms. Hence step variable based adaptive speech enhancement is preferred and it is also well suited for clinical scenarios in a speech therapy application.

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