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Hum Noise Reduction using Novel Complementary Pair VSSLMS Algorithm

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Abstract: This paper presents a novel Complementary Pair Variable Step-size (CPVSS) Least Mean Square Algorithm which is implemented for active noise cancellation application. The result presents the effect of filtration to remove the 50 Hz ac hum noise from the 500 Hz audio tone. Discrete Fourier Transform, Short Time Fourier Transform, and Welch Periodogram of the noisy signal and filtered signal have been presented which shows effective improvement in SNR. The simulation study has shown the superiority of this algorithm over other algorithms under consideration.

Keywords: active noise cancellation, complementary pair variable stepsize LMS, hum noise, short time Fourier transform

I. INTRODUCTION

An adaptive filter is a filter that self adjusts its transfer function according to an optimizing algorithm. Adaptive algorithm allows the filter to learn the initial statistics of the input signal and track them afterwards for any further changes. The adaptive filter is essentially a closed loop system and employs feedback mechanism using error signal. This process tunes filter coefficients in order to minimize cost function which is a criterion for optimum performance of the filter. Adaptive filter can be implemented either as FIR or IIR; however FIR filter is characterized by various advantages like linear phase, guaranteed stability, no feedback requirement and disadvantages like higher order and resulting higher computational time. So when high quality filtering is the requirement, FIR filter is correct choice and when cost is major concern, IIR filter is more suitable. Therefore, the adaptive filters are mostly implemented as FIR filter. There are different realizations of adaptive FIR filter, but the most common is Direct Form transversal structure, also called as tapped delay line. The adaptive filters can also be classified as linear and non linear filter; however an adaptive filter is mostly a linear system.

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The linear filters are based on Stochastic Gradient Approach (SGA). The idea of a nonlinear adaptive filter was first put forth by Gabor in 1954 using a Volterra series but that could not become much popular [1]. Currently, the non linear algorithms are based on neural network or Neuro-Fuzzy design. Adaptive filters are useful when the characteristics of the incoming signal are unknown or likely to vary. An adaptive filter uses a recursive algorithm to adjust its parameters based on predetermined initial conditions. The filter output converges to target values after several iterations.

A. Selection of Fixed or Adaptive Filter

Fixed filters are useful when the characteristics of the signal, noise, and transmission channel are known and there is no spectral overlap between signal and noise. But when the characteristics of the input signal, noise, and dynamics of channel change with time and there is spectral overlap between signal and the noise, not fixed filters but adaptive filters are useful. They adapt to these changes to achieve the desired result. One typical example of adaptive filter application is recording fetal ECG. It contains mother's ECG as noise. Both fetal ECG (intended signal) and mother's ECG (noise) belong to the same frequency spectrum and noise is stronger than the signal. Such filtering cannot be done using fixed filter.

B. Applications of Adaptive Filtering

They have been employed in many different applications that include telecommunication, geophysical signal processing, radar navigation systems, biomedical signals processing etc. As the power of digital signal processors has increased accompanied with decrease in its price adaptive filters have now become reality, and are now routinely used in devices such as mobile phones, MODEM, camcorders, and medical monitoring equipments. The adaptive noise cancellation can be employed for variety of practical applications like de-noising electrocardiograph, speech signals enhancement, and cancelling of side-lobe interference in an antenna array. Adaptive filtering can be extremely useful in cases where a speech signal is submerged in a very noisy environment with many periodic components lying in the same bandwidth as that of speech. An adaptive filtering algorithm is used in various fields of digital signal processing. Few out of innumerable applications include MRI Imaging, CT scan, Audio enhancement and special effects, Speech Recognition, Video Processing, and Animation etc.

The essential difference between the various applications of the adaptive filtering arises from the manner in which the desired response is extracted. Adaptive Line Enhancement (ALE) aims to detect highly correlated signals, mainly sinusoids buried in a wideband noise. The adaptive signal processing uses certain time varying algorithms like LMS, RLS and its variants.

C. Terminology and Notations

The general notations and terminologies in adaptive filtering are; **x**[n] is reference or input signal vector, d(n) is the instantaneous value of the desired signal, e(n) is instantaneous error signal, μ is stepsize parameter, **w**[n] is the instantaneous adaptive filter weight vector, **w**(n+1) is the updated filter coefficient vector at next iteration, y(n) is instantaneous output of the filter, $e^2(n)$ is the squared adaptation error, **J**(n) is MSE cost function, and $\mathbf{w}_o$ is optimal filter weight vector. The role of the adaptive filtering algorithm is to iteratively adjust filter coefficients to minimize the cost function.

D. Theory of Weiner Filter

The work of *Wiener* and *Kolmogorov* gave rise to optimal filter which is also known as *Wiener filter*. This filter is the basis of adaptive filter theory. Normally filters are designed using frequency domain concepts, but Wiener filters are developed using time-domain concepts. The quality of estimation is a function of the error signal, which is the difference between the output obtained from true system and the estimated system. The best choice for cost function is the mean-square error (MSE) since it is always positive and non-decreasing. Therefore, LMS family of algorithms uses MSE cost function which is expected value of squared error E[e^2(n)] as shown in (1). The determination of optimal Wiener solution is nothing but finding filter weight vector **w**(n) so as to minimize the cost function.

$$\boldsymbol{J}(n) = E[e^2(n)] \tag{1}$$

The input signal vector and filter coefficient weight vectors are represented in (2) and (3) resp. The output of the underlying filter of adaptive filtering system forms an estimate of the desired signal.

$$\mathbf{x}(\mathrm{n}) = [\mathrm{x(n)\,x(n-1)\ \dots x(n-N+1)}]^{\mathbf{T}} \tag{2}$$

$$\mathbf{w}(\mathrm{n}) = [\mathrm{w(n)\,w(n-1)\ \dots w(n-N+1)}]^{\mathbf{T}} \tag{3}$$

The optimal Wiener solution is as given in (4).

$$w_0 = R^{-\mathbf{1}}p \tag{4}$$

Although the Weiner solution is the optimal solution; it cannot be practically implemented due to various reasons. The Wiener solution requires the values of autocorrelation matrix **R** and cross correlation vector **p** but these are not directly available. At the same time, it also requires computationally intensive matrix inversion of **R**. But in practice this information is not available for non stationary signals. Thus Wiener filter cannot be used for practical signals which are non stationary. Therefore, instead of directly calculating Weiner solution, an iterative approach is adopted to approximate it. There are a number of algorithms available for this purpose; and the choice of the recursive algorithm for adaptive filter depends upon prioritization of the adaptive filter characteristics such as rate of convergence, misadjustment, tracking, computational requirements, structure, and numerical robustness etc. The MSE is a quadratic function which means there is existence of a unique minimum corresponding to optimal weight $\mathbf{w}_0$ that minimizes the MSE. The LMS algorithm approaches towards the optimal weight by ascending/descending down the MSE versus filter weight curve.

II. LMS ALGORITHM

The most popular and simplest algorithm for adaptive filtering is Least Mean Square (LMS) algorithm. The robustness, tracking capability, and stability of LMS algorithm outweigh other algorithms. The legendry LMS Algorithm was invented in 1959 by Bernard Widrow, Professor at Stanford University and his first doctoral research scholar, Ted Hoff through their studies of pattern recognition. This algorithm gives robust design with ease in implementation. LMS algorithm stands as the benchmark against which all other adaptive filtering algorithms are judged. The implementation of the LMS algorithms utilizes fewer computational resources and memory. It has been extensively appeared in literatures. There are a large number of variants of the LMS algorithm, and the original algorithm is called as standard LMS algorithm.Actually RLS performs superior to LMS and it is best suited for application where faster convergence is required, but its computational complexity makes it a less popular choice. Thus there is a tradeoff between convergence speed and computational complexity. A number of variants of LMS algorithm exist such as Standard LMS, Leaky LMS, Normalized LMS, Sign LMS, and Block LMS etc. Each of these types has their own merits and demerits. The major drawback of LMS algorithm is that LMS algorithm can search only local minima but not the global minima. However, by simultaneously starting the search at multiple points, this drawback of LMS algorithm can be overcome. Computational complexity of LMS algorithm is O(N), i.e. a filter of N taps requires N+1 multiplication and N additions to implement (5) for weight update. The filtering process to produce y(n) requires N multiplications and N-1 additions. The equation for e(n) requires one addition. Therefore total number of operations per iteration is 2N+1 multiplication and 2N addition.

$$\mathbf{w}(\mathrm{n}+1) = \mathbf{w}(\mathrm{n}) + \mu\mathbf{x}(\mathrm{n})\mathrm{e}(\mathrm{n}) \tag{5}$$

A. Stability Condition for LMS Algorithm

The LMS algorithm is convergent in mean square only if the stepsize parameter is bounded by (6) where, $\lambda_{\max}$ is largest eigenvalue of the correlation matrix of the input signal.

$$0 < \mu < \frac{2}{\lambda_{max}} \tag{6}$$

But in practical situation, the eigenvalues of the correlation matrix are not known which makes this equation not much useful. A more useful and strict equation for maximum stepsize is given in (7), where the term $||x[n]||$ is called as Euclidean norm of the input signal. This represents the power of the signal and is usually known or can be estimated a priori.

$$0 < \mu < \frac{2}{||x[n]||^2} \tag{7}$$

B. Performance Factors of Adaptive Filtering Algorithm

Standard LMS Algorithm
Initialization:
$\mathbf{w}(0)=\mathbf{0}$
Algorithm:
For n=0, 1, 2, …
$y(n)= \mathbf{w}^T(n)\mathbf{x}(n)$
$e(n)= d(n)-y(n)$
$\mathbf{w}(n+1)=\mathbf{w}(n)+ \mu\, \mathbf{x}(n)\, e(n)$

The Misadjustment mentioned in (8) and (9) is a measure of steadystate MSE of the algorithm w.r.t the Wiener solution. Here Jex is the excess MSE and Jss is steady state MSE of cost function. A smaller misadjustment indicates better accuracy of the filter.

$$M = \frac{Jex}{J\min} \quad (8)$$

$$M = \frac{J_{ss} - J_{min}}{J_{mim}} \quad (9)$$

MMSE represents the portion of the primary signal which cannot be cancelled by the optimal filtering. It is defined in (10) as the average output signal powers over samples after which the algorithm reaches the steady state, where K is total no of iterations and P is the no of iterations at which algorithm reaches steady state. Signal to noise ratio is defined as the ratio of signal power to noise power. The input SNR, Output SNR and SNR improvement w.r.t. ANC perspective are represented in (11-13).

$$MMSE = \frac{1}{K-P}\sum_{K-P}^{K} |e(k)|^2 \quad (10)$$

$$\text{Input SNR} = 10 * log_{10}\frac{d^2(n)}{v^2(n)} \quad (11)$$

$$\text{Output SNR} = 10 * log_{10}\frac{e^2(n)}{v^2(n)} \quad (12)$$

$$\text{SNR Increase} = \text{Output SNR-Input SNR} \quad (13)$$

III. LITERATURE REVIEW

Since 1950s, the research about adaptive filtering has generated an increasing interest amongst signal processing community. The major breakthrough in the research of adaptive filtering took place in 1975 when Widrow proposed Adaptive Noise cancelling: Principles and Applications [2]. This literature described the concept of active noise cancellation applied for enhancement of signal corrupted by additive noise. For a fixed rate of adaptation it is shown that the LMS algorithm has a misadjustment proportional to the number of adaptive parameters, while some other algorithms described in the literature have misadjustment proportional to the square of the number of adaptive parameters. Widrow et al (1977) proposed stationary and non stationary learning characteristics of the LMS adaptive filter which evaluates the performance parameters of LMS adaptive filter for stationary and nonstationary signals [3].

There are a large number of variants of standard LMS algorithm. Large memory applications like echo cancellation need an adaptive algorithm with speedy convergence and lesser computational complexity. On the other hand, some non real time biomedical applications like ECG denoising need adaptive filter with minimum misadjustment. Many woks have been done in past to improve the standard LMS algorithm. This has led to development of different variants of LMS algorithm. The first modification of the LMS algorithm was done independently by Nagumo and Noda [4], and by A. E. Albert [5]. This was in fact normalized LMS algorithm; however, this name was not proposed by the authors but appeared in the literature much later. Actually, the Normalized LMS (NLMS) algorithm may be considered as the first variable step-size modification of the LMS. The NLMS algorithm is still one of the most favored algorithms particularly for nonstationary data processing because of its simplicity, numerical stability and superior performance.

S. C. Chan et al (2008) have proposed a new noise-constrained normalized least mean squares adaptive filtering algorithm [6]. The authors have studied mean and mean square convergence behavior of the NLMS algorithm with Gaussian input and additive white Gaussian noise. Rath and Chakraborty (2010) proposed a Low Complexity Realization of the Sign-LMS Algorithm [7]. This paper presents an efficient realization of the sign-LMS based adaptive filters which enjoy a special.
hardware advantage in the form of multiplier free weight update loop that requires only adders and subtractor. To reduce the complexity of multiplication that arises in the filtering part of the sign-LMS algorithm, a special radix-4 format is presented in this paper to represent each filter coefficient which guarantees sparsity of at least fifty percent. Gear shifting is a popular approach by Widrow, which is based on using large step-size values when the filter weights are far from the optimal solution and small step size values when near the optimum solution. The resulting algorithm is called as VS-LMS algorithm. The majority of the VSSLMS algorithms use scalar stepsize, and the coefficient update takes place as per (14) where μ(n) is the instantaneous step size calculated with an appropriate formula depending upon VSS algorithm. Few VSSLMS algorithms use individual step sizes for each of the filter taps; such VS-LMS algorithms update the filter coefficient as per (15) where **M**(n) is the instantaneous step size vector. The orthogonality principle states that (under some assumptions) the necessary and sufficient condition for the MSE to attain its minimum value is that the e(n) and x(n) are orthogonal. Most of the VSSLMS algorithms are based on this principle and use the input signal and the error signal that are orthogonal to each other.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}(n)e(n) \quad (14)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{M}(n)\mathbf{x}(n)e(n) \quad (15)$$

Kwong and Johnston (1992) proposed VSSLMS algorithm in which the step size changes from iteration to iteration in order to minimize MSE [8]. This technique uses larger stepsize when the error is large and smaller stepsize when the error is small. The motivation is that when there is large prediction error, the stepsize should be increased to provide faster tracking; and when there is small prediction error the stepsize should be decreased to achieve smaller misadjustment. This algorithm uses two tuning parameters α and γ which are in the range $0 < \alpha < 1$ and $\gamma > 0$. The parameter γ influences both the speed of convergence and the EMSE, and it should be small. This algorithm shows faster convergence speed compared to other VSSLMS algorithms.

IV. PROPOSED ALGORITHM

The proposed Novel Complementary Pair Variable Stepsize Least Mean Square (CPVSSLMS) algorithm is obtained by modifying existing CPVSS LMS algorithm. This modification primarily targets to improve SNR and reduce MSE.

A. Complementary Pair Algorithm

With standard LMS we cannot achieve faster convergence with smaller misadjustment. But in CPLMS algorithm which is originally proposed by MinSoo Park and Woo-Jin Song (1998), an attempt has been made to achieve both the desirable parameters simultaneously [9]. The CPLMS category of algorithm consists of parallel structure of two filters, *speed mode* filter and *accuracy mode* filter as shown in fig.1. The speed mode filters is characterized by faster convergence and higher value of μ and the accuracy mode filter is characterized by smaller misadjustment lower value of μ. The speed mode filter belongs to Fixed Step Size (FSS) category while the accuracy mode filter belongs to VSS category. The accuracy mode filter is the default filter of the adaptive filtering system while the use of the speed mode filter is for decision criteria evaluation.

For original CPVSS-LMS algorithm, the update equation of the speed mode filter is given in (16) where $\mathbf{w_1}$ *(n)* and $\mathbf{x}(n)$ are the filter coefficients vector and input signal vector respectively [10]. The error signal $e_1(n)$ and $e_2(n)$ of the speed mode filter and accuracy mode filter are represented by (17). The minimum step size μ_3 is chosen in such a way to achieve convergence within the given training length.

$$w_1(n+1) = w_1(n) + \mu_1 e_1(n) x(n) \tag{16}$$

$$\begin{aligned} e_1(n) &= d(n) - y_1(n) \\ e_2(n) &= d(n) - y_2(n) \end{aligned} \tag{17}$$

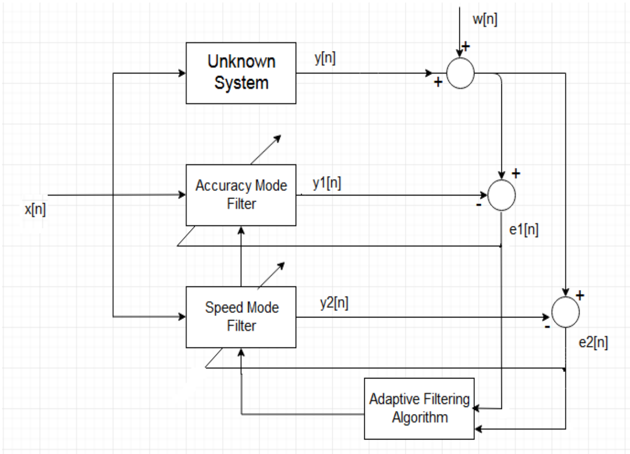

Fig. 1.Structure of Adaptive Filter Using CPVSS-LMS Algorithm.

For accuracy mode filter of original CPVSSLMS algorithm, the coefficient update equation, stepsize update equation and decision criteria are represented in (18), (19), and (20) resp. [10]. These equations indicate that after every fixed number of iterations (say T iterations) the MSE of both the filters are compared, and if the local average of the squared error of speed mode filter is smaller than that of accuracy mode filter, then accuracy mode filter is updated with the coefficients of the speed mode filter; otherwise the coefficient of accuracy mode filter are updated as per standard LMS algorithm. The value of *T* should not be too large or too small; the general rule of thumb is T should be approximately 1% of the total number of iterations. This strategy improves rate of convergence as well as maintains smaller misadjustment. The number of computations required per test interval for this algorithm is: $2T + 2N + 7$ multiplications and $2T + 4N + 1$ addition [10]. The algorithm belongs to VSS category because (18) indicates that the stepsize of accuracy mode filter is time varying.

$$\boldsymbol{w}_2(n+1) = \begin{cases} w_1(n+1) & if\ n \bmod T = 0\ and\ C(m) = 1 \\ w_2(n) + \mu_2(n) e_2(n) \boldsymbol{x}(n) & if\ n \bmod T = 0\ and\ C(m) = 0 \end{cases} \tag{18}$$

$$\mu_2(n+1) = \begin{cases} \dfrac{\mu_1 + \mu_2(n)}{2} & if\ n \bmod T = 0\ \&\ C(m) = 1 \\ \max\{\alpha\mu_2(n) + \mu_3 & otherwise \end{cases} \tag{19}$$

$$C(m) = \begin{cases} 1 & if\ \sum_{i=m}^{m+T} e_1^2(i) < \sum_{i=m}^{m+T} e_2^2(i) \\ 0 & otherwise \end{cases} \tag{20}$$

B. Novel Complementary Pair Algorithm

The equations (18-20) of original CPVSS LMS algorithm are applicable to Novel CPVSSLMS algorithm. But the Novel CPVSS algorithm has been modified by incorporating Kwong's VSSLMS algorithm for accuracy mode filter which is found to improve SNR along with other parameters of the adaptive filter. After every T iterations, the stepsize is increased or decreased depending upon the decision criteria C(n).

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This value equal to one indicates that the speed mode filter is closer to optimal filter. Therefore, the stepsize of the accuracy mode filter is increased and the coefficients of speed mode filter are copied into accuracy mode filter. On the other hand, the value of the decision criteria equal to zero means that the accuracy mode filter is closer to the optimal filter, and therefore the stepsize of the accuracy mode filter is decreased and coefficients of accuracy mode filter are updated as per standard LMS algorithm update equation. In the Novel CPVSSLMS algorithm at all but T^{th} iterations, the step size of the accuracy mode filter is updated by (21) where the values for beta and gamma are equal to 0.9 and 0.01 resp.

$$\mu_2(n+1) = \beta\mu_2(n) + \gamma e_2^2(n) \tag{21}$$

V. ACTIVE NOISE CANCELLATION

Active Noise Cancellation (ANC) is a technique to reduce the unwanted acoustic noise by generating anti-noise sound through a noise-cancelling speaker.
Anti-noise is a sound wave with the same amplitude, but with opposite phase compared to the original noise. As shown in fig.2, the unwanted noise and anti-noise superimpose acoustically that result in noise cancellation.

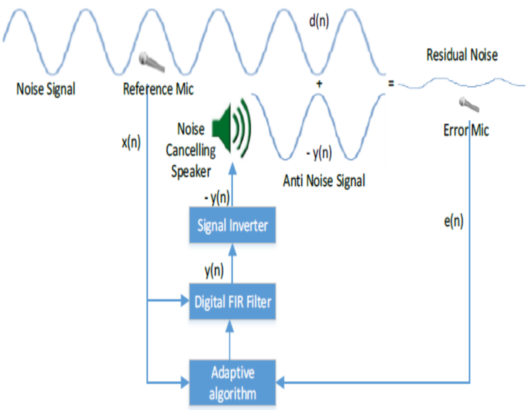

Fig. 2.Active Noise Cancellation.

Although the concept ANC has been around for more than seventy five years, it is still an active and important research topic because of its wide range of applications that include:

a) Providing quiet environment in automobile and aero plane cabins
b) Reducing noise from motors, heavy machinery and engines
c) High-end headphone systems
d) Reducing mechanical wear out and fuel consumption through vibration control
e) Reducing background noise in communication systems e.g. radio

The adaptive noise canceller for speech signals needs two inputs. As shown in fig.3, the primary input d[n] contain the voice corrupted by noise, means (*speech* + *noise)* forms the desired signal. The input **x**(n) contains noise correlated in some way to the noise of primary input. Thus, noise' is the input signal to the filter which is correlated with *noise* in the desired signal. The system filters the x[n] to generate noise estimate y[n] which is subtracted from the d[n] to obtain error signal. Ideally ANC system should remove noise and keep intact the speech signal but the practical systems do not remove the noise completely but reduce its level substantially. Transversal FIR filter structure is used as the filtering element in adaptive filter. The practical difficulty with ANC system is that most of the times the input signal to the filter contain some part of uncorrelated noise and some part of correlated signal w.r.t the desired signal.

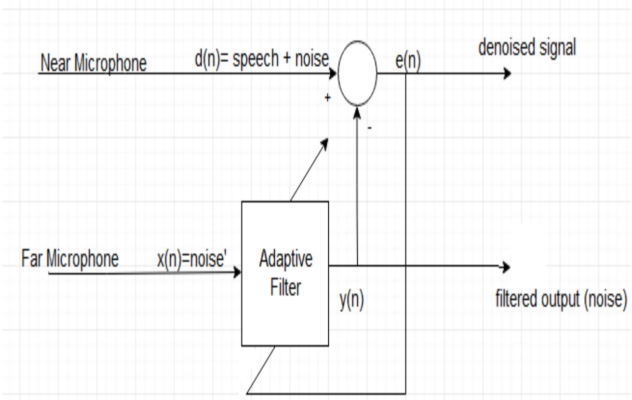

Fig. 3.Active Noise Cancellation Using Two Microphone

Simulation set up:

As represented in (22), the primary input d(n) consists of incoming signal that contains the clean signal s(n), the reference noise x(n) filtered through the unknown system transfer function and small measurement noise v(n).

$$d = \text{filter}(\text{h}, 1, x) + \text{s} + v \tag{22}$$

Sinusoidal signal of 500 Hz with zero mean and variance equal to 0.5 sampled at a frequency of 2000 Hz is used as a clean signal. Many times the 50 Hz AC Mains supply adds noise in the signal, which is called as ac hum noise. The ac hum noise with zero mean and variance equal to 0.5 used as reference signal, which is considered to travel through unknown channel and got mixed in the clean signal. Since signal frequency and noise frequencies are different, we can say that the noise is uncorrelated with signal and correlated with noise of desired signal. A small measurement noise with zero mean and variance of 0.0004 is added in d[n] as well as the x[n]. The simulation of 50 independent Monte-Carlo analyses of 10000 iterations each are carried out to evaluate the effectiveness of the proposed algorithm in removing ac hum noise and thereby increasing SNR. The unknown channel which degrades the signal is considered as of first order and its coefficients are taken as [2 3]. The stepsize μ is calculated using equation (6) and equation (7) and smaller of these two values is selected. The stepsize of the speed mode filter is equal to 0.4624 and the stepsize of the accuracy mode filter is initialized at 90% of the stepsize of the fixed mode filter.

The minimum stepsize is equal to 1% of the stepsize of the speed mode filter. The mean and variance of the reference signal and desired signal over the sampling interval is found to be (2.6401e-005, 0.5005) and (2.6717e-005, 12.9280) resp.

VI. RESULTS

The MSE obtained with proposed algorithm and optimal solution are equal to 0.532663 0.502426 resp. In ANC perspective, the de-noised signal is contained in the error signal, therefore the MSE doesn't reflect actual residual noise. The MSE due to residual noise only is equal to 0.008159. Minimum MSE and Excess MSE are equal to 0.000049 and 0.004255 resp. The theoretical and practical misadjustment is equal to 0.229376 and 0.000284 resp. Steady state is considered where MSE is below three times of MMSE. The average Mean square deviation is equal to 0.017966. The steadystate misadjustment is equal to 0.008532. The final average SNR improvement over all iterations is equal to 31.07 dB. In steady state, the adaptive filter coefficient becomes equal to [2.140022 2.872225] which is not very closer to the actual value of the unknown system coefficients. The proposed adaptive filter is also analyzed using the tools of Short time Fourier transform, discrete Fourier transform etc.

A. Discrete Fourier Transform (DFT)

Discrete Fourier transform of clean signal, noise, measured signal and enhanced signal are shown in the fig.4.

The DFT of clean signal indicates a single pulse of 500 Hz which represents audio tone of 500 Hz. The DFT of noise indicates 50 Hz AC hum tone. The DFT of desired signal indicates a strong noise of 50 Hz, and comparatively weaker signal of 500 Hz. Here, the noise level is stronger than the clean signal. The DFT of filtered signal clearly indicates substantial improvement in SNR.

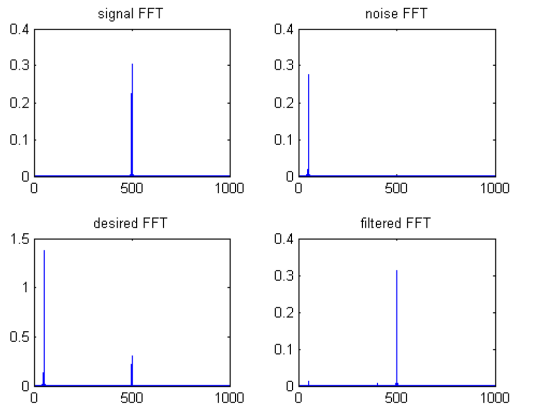

Fig. 4.DFT of Clean signal, Noise, Noisy signal and Filtered signal

B. Short Time Fourier Transform (STFT)

Many times it is required to analyze the signal in both the frequency domain and time domain. For this purpose, the signal is divided into different segments of equal timeslot and then Fourier transform of individual segment is calculated and plotted. This is called as short time Fourier transform (STFT). The technique of STFT is very useful in analyzing the signal in transient and steady state conditions. When we want to determine time varying frequency spectrum signal x[n] then every time slot is multiplied by a window of length N and then DFT is calculated. The STFT plot, also called as spectrograph, is plotted for noisy signal and enhanced signal as shown in fig.5 and Fig.6 resp. The spectrogram shows the normalized frequencies of 0.05 and 0.5 which corresponds to frequency of 50 Hz and 500 Hz resp. because the sampling frequency is 2000 Hz. The spectrogram of noisy signal indicates that it is totally embedded in white noise and has very poor SNR. The spectrogram of enhanced signal indicates the substantial improvement in SNR compared to the noisy signal.

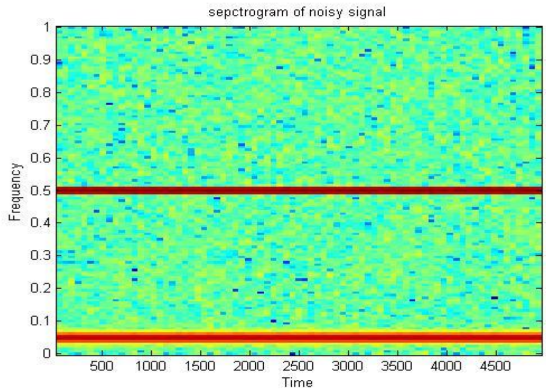

Fig. 5.Spectrogram of Noisy Signal.

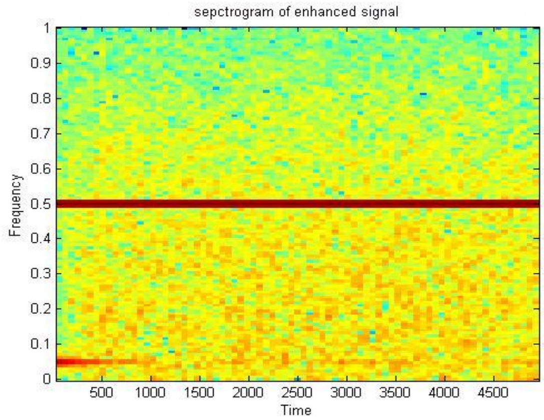

Fig. 6.Spectrogram of Enhanced Signal.

C. Welch Power Spectral Density Estimate

Welch's method is used for spectral density estimation at different frequencies which is obtained as an improvement over standard periodogram spectrum estimating method and Bartlett's method. It reduces noise in the estimated power spectra in exchange of reducing the frequency resolution. The Welch Power Spectral Density Estimate of desired signal and enhanced signal are represented in fig.7 and fig.8 resp. Considering 50 Hz noise as the main noise source which is to be eliminated, the PSD of desired signal indicates that the 50 Hz hum noise level in desired signal is about 35 dB, while this level in filtered signal is about -5 dB. Thus there is very good improvement of about 40dB in the SNR level.

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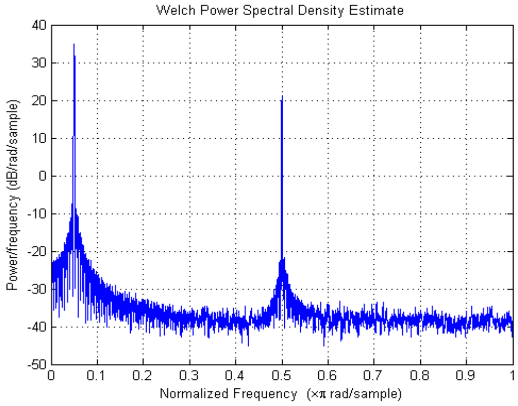

Fig. 7.Welch Power Spectral Density Estimate for Noisy Signal

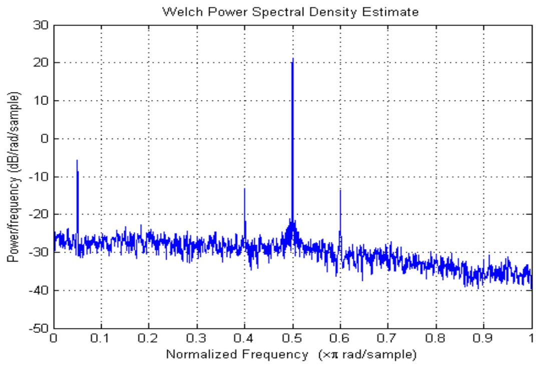

Fig. 8.Welch Power Spectral Density Estimate for Enhanced Signal

D. Simulation Result with other Algorithms

The effectiveness of the proposed algorithm is established by comparing the results with other algorithms. In this study, we compared the results with CPLMS, CPVSSLMS, Complementary Pair Normalized LMS (CPNLMS), and Noise Constrained LMS (NCLMS) algorithms. The CPLMS has no tunable parameter; the CPVSS algorithm has only one tunable parameter whose value was found to be 0.9. The NCLMS algorithm has only one tunable parameter whose value was found to be equal to 0.97. CPNLMS algorithm has two tunable parameters; alpha and beta and their values are found to be 0.4 and 4 resp. During tuning only one parameter is varied while other parameters are kept constant to optimize the result. Fig.9 indicates that the proposed algorithm provides better SNR improvement compared to other algorithms.

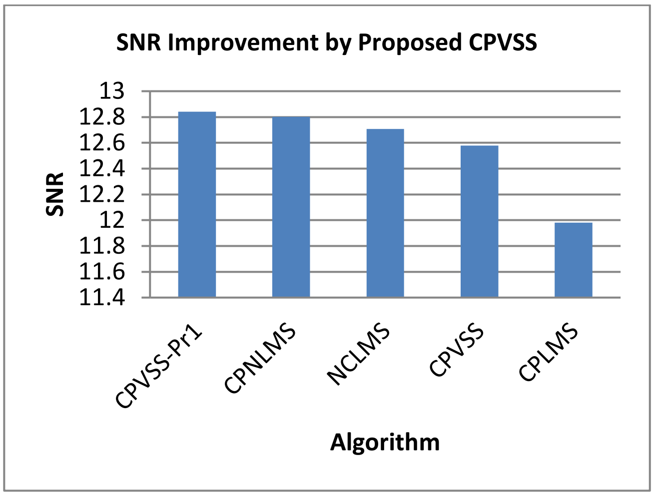

Fig. 9.SNR Improvement by Various Algorithms

VII. CONCLUSION

The proposed Novel CPVSSLMS algorithm has been derived from two algorithms; viz. CPVSSLMS algorithm by Bilcu et al. and VSSLMS algorithm by Kwong et al. The proposed algorithm has been tested to verify its effectiveness in ac hum noise reduction. There are two complexities involved in this proposed algorithm. The first is, this algorithm required three parameters to be tuned, so tuning these parameters is a time taking process and involves lot of computations to optimize the parameters. The second issue with this algorithm is that it requires more number of computations than CPVSSLMS or VSSLMS. Therefore, it can be implemented only on fast processing hardware. Inspite of these challenges, the simulation carried out indicates very good improvement in SNR of the filtered signal.

REFERENCES

1. S. S. Haykin, B. Widrow, and B. Widrow, Least-mean-square adaptive filters, vol. 31. Wiley Online Library, 2003.
2. B. Widrow et al., “Adaptive noise cancelling: Principles and applications,” Proc. IEEE, vol. 63, no. 12, pp. 1692–1716, 1975.
3. B. Widrow, J. McCool, M. G. Larimore, and C. R. Johnson, “Stationary and nonstationary learning characteristics of the LMS adaptive filter,” in Aspects of Signal Processing, Springer, 1977, pp. 355–393.
4. J. Nagumo and A. Noda, “A learning method for system identification,” IEEE Trans. Autom. Control, vol. 12, no. 3, pp. 282–287, Jun. 1967.
5. A. Albert, “Stochastic Approximation and Nonlinear Regression,” MIT Press, 1967.
6. S. C. Chan, Z. G. Zhang, Y. Zhou, and Y. Hu, “A new noise-constrained normalized least mean squares adaptive filtering algorithm,” in APCCAS 2008 - 2008 IEEE Asia Pacific Conference on Circuits and Systems, Macao, China, 2008, pp. 197–200.
7. S. S. Rath and M. Chakraborty, “A low complexity realization of the sign-LMS algorithm,” in The 2010 International Conference on Green Circuits and Systems, 2010, pp. 51–53.
8. R. H. Kwong and E. W. Johnston, “A variable step size LMS algorithm,” IEEE Trans. Signal Process., vol. 40, no. 7, pp. 1633–1642, Jul. 1992.
9. M.-S. Park and W.-J. Song, “A complementary pair LMS algorithm for adaptive filtering,” IEICE Trans. Fundam. Electron. Commun. Comput. Sci., vol. 81, no. 7, pp. 1493–1497, 1998.

10. R. C. Bilcu, P. Kuosmanen, and C. Rusu, "Improving performances of complementary pair LMS algorithm," in 2000 10th European Signal Processing Conference, 2000, pp. 1–4.

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