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A NOVEL NOISE REDUCTION FRAMEWORK FOR SPEECH SIGNALS IN ADAPTIVE CHANNELS USING VARIABLE STEP SIZE NORMALIZED DIFFERENTIAL LMS (VSSNDLMS) ALGORITHM

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Abstract – Human communication is mostly based on speech. This technology is used in variety of ways, including human-machine communication, technical equipment, and even virtual support or search engines. This kind of communication is often carried out using a device that is sensitive to background noise. Voice or audio signals may be negatively affected by noise that is accidentally inserted into the communication route or medium. The quality of the voice signal may be drastically diminished as it travels from transmission to reception undergoes signal conversations at both ends. The Variable Step Size Normalized Differential Least Mean Square (VSSNDLMS) Algorithm is used in this study to present a novel framework for noise reduction in adaptive channels. The value of alpha parameter is changed to reduce background noise in speech communications.

Keywords—Adaptive channels, noise reduction, LMS, Variable Step Size LMS, Variable Step Size Normalized Differential LMS, SNR, MSE.

I. INTRODUCTION

Noise and distortion in hearing aids and other audio devices degrade speech quality. Speech based systems such as speech recognition, speaker identification and pathological voice analysis may suffer performance degradation during operation due to acoustic incompatibilities between training and operational situations. In speech-based systems, nonlinear distortion and background noise are the most common types of degradation. For a deteriorated speech signal, the following terms may be used to characterise additive noise reverberation and nonlinear distortion.

$$y_n(t) = S_n\,(k) + r(t) \tag{1}$$

$$y_r(t) = S_n\,(k) * h(t) \tag{2}$$

$$y_o(t) = \Psi(S_n\,(k) \tag{3}$$

where t represents the indicator index (t) , the microphone’s output signal $S_n(k)$ is used to make clear voice recordings, while the other sounds in the signal chain include an extra sound r(t),Ψ illustrates an additional function (nonlinear), the room’s impulse response h(t), and the signal processing operation y.

Convolution is represented by a nonlinear function known as room impulse response (RIR) is represented by a symbol and the convolution processes is shown by the symbol. In reality, the deterioration processes are far more involved. An example of this would be a time limit. Noise reduction, dereverberation and the restoration of specific nonlinear distortions have all been used to improve deteriorated speech signals. If there are a lot of people at a conference, it becomes almost difficult to communicate without noise reduction. Several factors must be taken into account if noise reduction is to e effective. Therefore building a flexible algorithm that works in a number of scenarios is very challenging and it is possible that reducing background might increase the quality and understandability of spoken conversations using a noise reduction technique known as speech enhancement. There is however, optimism in the current study on whole speech enhancement, which addresses both additive noise and reverberation.

II.LITERATURE SURVEY

S. Brarun, H. Gamper, C.K. Reddy, and I. Tashev [1] used a huge dataset that includes reverberation as well as speech sounds to study recurrent and convolutional-convolutional network architectures for voice improvement. They show surprising tradeoffs between computational complexity and voice quality on real recordings using a highly accurate MOS estimator. One of the primary components of the system proposed in [2] is a spectral Feature Extraction Module (FEM), Glance and gaze Module (GGM). After each convolution layer, the UNet-block in FEM may be used to calibrate a feature at various scales. Each GGM divides multi-target optimization into two sub-tasks to better handle the complexities of the complicated spectrum. Glance focuses on reducing noise while Gaze compensates for the loss of spectrum information in the magnitude domain. Combining the two approaches yields a spectral estimation with two opposing perspectives. By periodically unfolding the GGMs, we may iteratively enhance the intermediate result, which can then be used as a starting point for the ultimate spectrum estimate. For patients with Mandarin-speaking cochlear implants [3] tests the clinical efficacy of a new deep learning-based NR technique in noisy environments at low signal to noise ratios (SNR). Recurrent and convolutional neural networks may be used to improve speech quality, according to [4].

Their model doesn't make any assumptions about the nature of the noise based on the data we ensure but Neural network topologies based on convolution and recurrence are taking over from MLPs. As a result, we may take advantage of local structures in frequency and time employing their technique. Here we have an all-encompassing model capable of handling both visible and invisible noise. Recurrent Neural Networks (RNNs) may improve both objective and subjective quality of voice augmentation in real time, according to [5]. A single-frame RNN that boosts short-term speech spectra, rather than any other technique, is the subject of this study. Individual control of voice distortion and noise reduction may be achieved using two innovative mean-squared-error-based learning goals. In order to assess the quality and intelligibility of the suggested loss functions, objective quality and intelligibility measurements are used. In order to improve ASR noise resistance, Generative Adversarial Networks (GANs) are studied in detail in [6].

Even while GANs had previously been shown to be successful in reducing noise in raw waveform speech signals, this method was not appropriate for ASR. Using GANs to enhance speech that has been affected by both additive and reverberant noise is the focus of their research. Using log-Mel filter bank spectra instead of waveforms to run GANs, which takes less computing resources and is more resistant to reverberant noise, they came up with the idea. When it comes to increasing ASR systems noise tolerance, [7] looks at using GANs for voice augmentation. This technique was not suitable for ASR due of its complexity, even though GANs may efficiently reduce noise in raw waveform speech inputs. Additive and reverberant sounds degrade speech, and GANs are being used to see how well they can enhance it. A less computationally expensive and more resilient method of training GANs is to use log-Mel filter bank spectra rather of waveforms. Under harsh circumstances, unscented Kalman filtering may be used to denoise and de-veberate recorded voice. Denoised signals are created and updated using state space features such as mean and covariance. Cross correlation and other denoising and dereverberation methods are used to compare this algorithm's performance in terms of speech quality and intelligibility. Cochlear implant users listening effort was evaluated using pupillometry to see how speech recognition Working Memory Capacity (WMC), and Noise Reduction Algorithm (NRA) influenced it. The quantization and noise shaping methods used in sigma-delta AD and DA converters may decrease these delays practically to zero without significantly increasing processing effort [11].

The typical filter has been replaced with sigma-delta AD/DA converters. Creating the controller filter impulse response with just a few bits allows the filter to be able to operate at a high frequency while requiring little computing resources and it doesn't need to use an AD down-sampling filter or DA reconstruction since noise shaping forces acoustic transducers to automatically filter out high-frequency quantization errors. The control filter is determined using a low sample frequency in adaptive filtering techniques. With frequent updates of the filter weight coefficients, convergence speed and resilience are greatly enhanced [12].

The FxMCC-CG approach performs better in the presence of spurious noise thanks to on the-fly modification of the kernel size of the maximum correntropy criterion to the variance of the reference signal. There are two ways to estimate a clean voice signal using the MKF method, inter-frame modulation-domain temporal evolution of speech, and inter-channel spatial correlation [13]. Voice improvement requires a delicate balancing act between reducing speech distortion and preserving its natural sound. An MKF with a parameter for fine-grained control over speech enhancement behaviour at different time frequencies is discussed in this study. Because of this, PMKF now has a new cost function that takes the controlling parameter into account when calculating the relative relevance of the noise reduction and voice distortion components. The ideal PMKF gain is determined using MMSE criteria. Evaluations and explanations of both MKF and the Speech Distortion-Weighted Multichannel Wiener Filter are provided (SDW-MWF). PACDNNs (Phase-Aware Composite Deep Neural Networks) have been developed in [14] to overcome these issues.

In order to improve magnitude and phase spectra concurrently, it is recommended that the new network use spectrum masks for magnitude processing and phase derivatives for phase reconstruction. So, PACDNN (Phase-Aware Composite Deep Neural Network) is a good solution for this problem. Combining magnitude processing with a spectral mask and phase reconstruction using the phase derivative is advised for the innovative network in order to improve the magnitude and phase spectrum at once. The DNN takes advantage of crucial speech related temporal and spectral correlations to speed up processing even more. The MEL filter may be used to reduce noise, according to [15]. Variable step size adaptive filters, as those developed by [16] and others, may be seen as an example of several different adaptive filtering approaches. The general adaptive filter includes adaptive algorithms like VSS Least Squares, Normalised LMS (VSSNLS), and affine projection methods (VSSAPA). VSS Pradhan-Reddy subband adaptive filter (VSSPRSAF) technique is discussed in their article.

A novel HPSO-NLMS technique for voice enhancement is proposed in [17]. This novel dual algorithm and forward BSS structure has been presented to improve the quality of the speech signal. VSSNDLMS (Variable Step Size Normalized Differential LMS) was used to filter speech sounds. This approach was first proposed in [18]. Adaptive Least Mean Square (LMS) ANR (modified) is used in [19] to improve the sound quality of the Tamil voice stream. Multi stage adaptive filtering is suggested in [20], where a noisy signal is processed successively. The suggested signal de-noising technique involves an automated selection of cascading stages in order to achieve the lowest steady-state MSE. The LMS adaptive filter's step size is automatically adjusted at each stage for quicker convergence. By determining the number of stages to be cascaded and using a different step size for each stage, it is feasible to lower steady state MSE while still obtaining rapid convergence. The filter's performance is evaluated using the MSE, SNR, ANR, and convergence time for signal de-noising applications.

In [21], the author invented real-time speech signaling. When the LMS approach is used in conjunction with the diffusion least mean-square algorithm, adaptive filtering capabilities are improved. Both FLMS and Fractional Normalised Least Mean Square (FNLMS) are suggested in [22] for cancelling echo in the signal. Results from ordinary non-linear least squares and block discrete Fourier transform are also used to compare FLMS with FNLMS. There is a new way of approaching the Least Mean Square (LMS) method in [23]. Using variable step sizes, LMS filters may be built to have a quicker convergence rate. The cavities in [24] may be reduced by using a VSSLMS technique with an adjustable step size least mean square. LMS and Filtered-x LMS filters may be used to estimate system coefficients based on analysing the detuning signal (FxLMS). Because of its lower computational cost and better tracking ability, this method is recommended over the others in simulations.

3. PROBLEM STATEMENT

However, nonlinear approaches may be beneficial for modelling or analysing the nonlinearities of signal and/or noise generation systems, as well as those of the signal acquisition system and the transmission channel. Nonlinear methods, on the other hand, are more effective at solving issues that linear methods fail to address. For example, nonlinear processing approaches (neural networks, homomorphic, polynomial, morphological and ordered statistics filters, and so on) lack a unified framework. With nonlinear approaches, the computational overhead is frequently higher. Also, adjusting the step size might be a challenge. Improved nonlinear filter analysis has been attempted to solve step size difficulties as well. However, each approach has its own drawbacks. As a result, an effective method is required to overcome all current disadvantages.

IV. PROPOSED WORK

Adaptive filtering is a signal processing technique in which the variables used to transmit signals are changed in response to a set of criteria as shown in Figure.1.

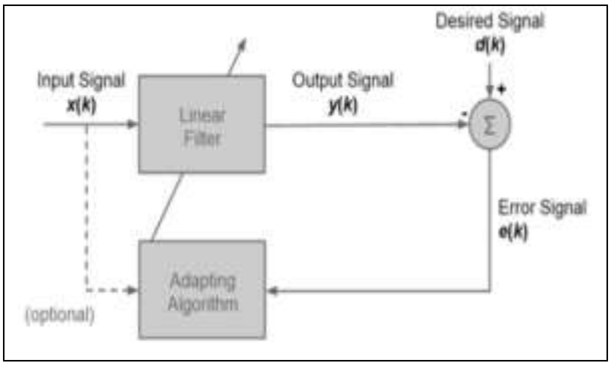

Figure.1 Adaptive Filter

Adaptive filtering may be used to process signals when the filtering parameters change based on a set of criteria. The correlation coefficient or estimated mean squared error is often used as criteria. A performance requirement dictates that the adaptive filters settings must be constantly updated. As a result, it can be shown that an adaptive filter can perform the approximation step in real time. The approximation step in fixed filter design often conceals a reference signal, which is necessary for determining the performance requirements. As of from Figure 2 and Figure 3, the adaptive filtering environment is designed as a whole with reference signal and without reference signal. Based on the error, the adaptation algorithm creates a "performance function or "objective function." which it then uses to alter the filter coefficients. If the objective function is minimised, there will be no change in the output signal. An adaptive filter is one that adjusts its transfer function in response to an erroneous signal. The bulk of adaptive filters are digital filters due to the complexity of optimization methods.

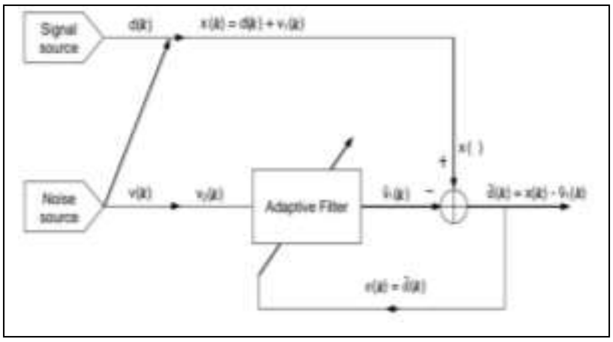

Figure.2 Cancellation of noise by Adaptive Filter with reference signal

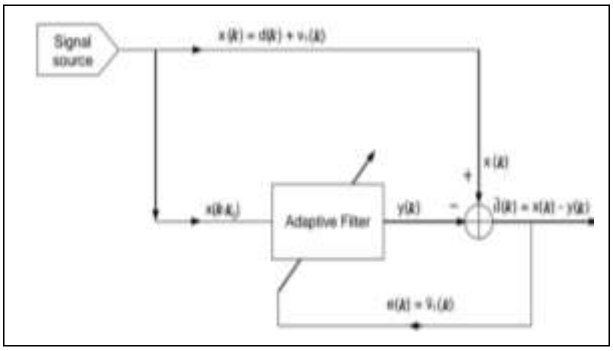

Figure.3 Cancellation of noise by Adaptive Filter without reference signal

However, the transfer function of a non-adaptive filter remains constant. If the proposed processing procedure (such as the arrangement of reflected surfaces in a reverberant zone) has unknown characteristics, adaptive filters must be used. In order to adapt to shifting parameters, the adaptive filter receives input in the form of an error signal. It is an adaptive process that determines how to adjust filter transfer functions to minimise the next iteration's cost based on a cost function, a requirement for optimal filter performance. Adaptive filters have become increasingly common in gadgets like mobile phones, cameras, and medical monitoring equipment as the capabilities of digital signal processors have improved. In addition to echo cancellation, other adaptive filter applications include noise cancellation, adaptive feedback cancellation, and adaptive feedback. Adaptive filtering techniques come in number of flavors. Adaptive filters may be developed using these methods. In order to improve the recorded audio, these filters are applied to the noise-masked speech. There were several criteria for evaluation that were based on the estimated mean squared error, sometimes known as "the association."

The least mean square is an adaptive filtering technique that utilizes the noise and noisy signal given as input to tuning the filter coefficients. Based on the analysis, it observed that most of the researchers removed noise by tuning the filter parameters or the step size. Hence, in this, a VSSNDLMS algorithm was used to find the alpha value for better denoising process in variable step size least mean square filter proposed. As part of their research of a pattern-recognition computer called as the adaptable linear element, or Adeline, Widrow and Hoff created the LMS algorithm. Each transversal filter tap weight is weighted in accordance with the instantaneous gradient from squared error signal to tap-weighting question, which is a stochastic gradient method. Even after 40 years in use, the LMS filter is still an essential element of the adaptive signal processing set of tools. This is due to the LMS filter's simplicity and desired features, as well as its practical uses. The LMS filter has stood the test of time, in a nutshell. Assuming a small step-size parameter, the LMS filter exhibits Brownian motion in a stationary environment, which illustrates the filter's stochastic character. The discrete-time Langevin equation nearly perfectly describes the LMS filter's short step-size theory.

$$\Delta S_n(k) = S_n(k+1) - S_n(k) = -\mu\lambda_n S_n(k) + \varphi_n(r_n) \qquad (4)$$

where, k = 1, 2,.... M, in the above equation.

In the case of local error per step, $S_n(k+1)$ may be used, where r_n is the local error (normalised by dividing by the step size if error per unit step is necessary; in this instance, k = 1,2,.... M). λ is the desired tolerance, and φ is the safety factor between 0 and 1. (often set to 0.8 or 0.9).

Because of its stochastic and nonlinear character, the LMS filter's mathematical analysis is very difficult to perform. Work requirements dictate that the adaptive, LMS filtering settings are continually being adjusted. Adaptive filters may be thought of as filters that execute an approximation in real time when seen from this angle. It has often been necessary to have a reference signal in order to determine how much effort is needed during the approximation phase of fixed-filter design. As part of the suggested work, we must determine whether or not the noise is there. When there is noise, the VSSNDLMS filter is used to remove it, and therefore the output enhancement signal appears.

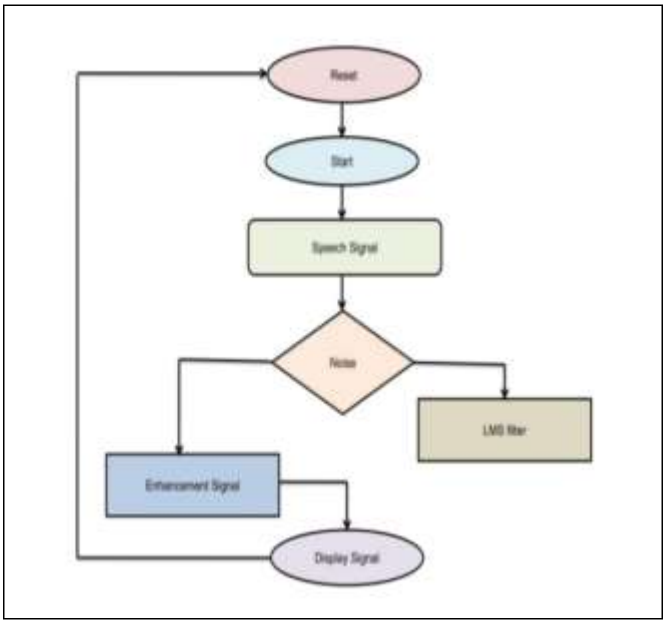

Figure.4 Schematic representation of the suggested Methodology

An example of an adaptive filter framework is shown in Figures 1, 2 and 3, here k represents the iteration number and the input signal is represented by $\nabla X(k)$. The adaptive filter output is represented by $\nabla e(k)$, $S(k)$ and $d(k)$, $v(k)$ is the essential signal.

$$x(k) = d(k) + v(k) \tag{5}$$

$$\nabla X(k) = \nabla e(k) + S(k) \tag{6}$$

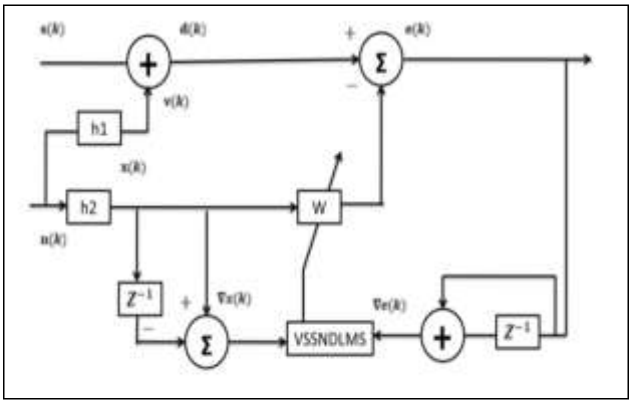

Figure.5 Proposed Filter Processing

The VSSNDLMS method is used, as shown in the Figure 5. It is determined by comparing the average power of the original signal to that of its noise, and this is done by calculating the signal to noise ratio (SNR). For quicker tracking, a lower SNR will lead the step size to rise, conversely, a big SNR will force it to drop, resulting in a smaller tracking misalignment. Figure.4 depicts the noise canceller (NC) using the Variable Step Size NLMS method, whereas equation (1) depicts the noise canceller (NC) (7).

$$SNR = 10 \log U_s(k) / U(k) \ dB \tag{7}$$

where $U_S(k)$ and $U_n(k)$ are the average power of the speech and noise signal. The normalized filter coefficients must be updated by,

$$S(k+1) = S_k(k) + (\mu / X_n^T X_n) e(k).X(k) \tag{8}$$

where, 'μ' is the step size coefficient. The SNR determines the step size 'k'. Step size μ is set to a high value for quick convergence when SNR is small. Other than that, the step size has been reduced.

New methods for adjusting weight are discussed in this section. The goal is to come up with an algorithm that can handle both strong and weak signals. As a result, the weights should be updated anytime the filter's inputs and outputs change.

The weak error signal $\bar{Q}_t(h)$ has been shown to be the difference between d(k) and v(k) according to the research. The adaptation algorithm uses the error as a guide to offer a task that may be utilized to calculate the suitable filter measure update. The adaptive filter output signal must be close to the appropriate signal if the objective task is lowered.

$$W_l^{MA}(\Theta) = \frac{1}{H} \Sigma_{h\varepsilon H} X(k) \left(\bar{Q}_t(h) - \bar{Q}_t^{\,ideal}(h)\right)^2 \tag{9}$$

$$Q_l^{ideal}(h) = Q_l^{IRM}(h) = \left(\frac{|\nabla e(k)|^2}{|\nabla e(k)|^2 + |s(k)|^2}\right)^{1/\beta} \quad (10)$$

Where $W_l^{MA}(\Theta)$ represents the adaptive filter output, $\bar{Q}_t(h)$ represents weak signals, $Q_l^{ideal}(h)$ represents the acceptable error, β illustrates the height of the noise distribution.

The improper signal driving the suggested filter would cause it to self-adjust its transfer function throughout the optimization phase. Due to the complexity of the optimization methods. the majority of adaptive filters seem to be digital filters. Feedback in the form of an error signal is used by the filter in response to changing factors. As criteria for determining how to alter the filter transfer function in order to minimize the subsequent iteration's cost, an algorithm is provided a cost function during the adaptive channel phase. As digital signal processors have been more widely used in devices such as mobile phones, various communication systems. recorders, and webcams, filters have become more commonplace. Filtering methods are based on a set of criteria, which indicates the variables utilized to examine signals could alter. The calculated mean squared error or correlation is a common criterion. Filter settings are dynamic because they are constantly tweaked in order to meet performance targets. The procedures appear to be a Variable Step Size Normalizes Least Mean Squares and a Normalized Least Mean Squares. The proposed filter or system identification issue might be solved by updating a set of filter weights such that the output follows a given signal. Let the input vector to the system be denoted by $\hat{X}$, and the desired scalar output is d(k). The equation assumes that the weighing factor can be updated.

$$\hat{X}(m+1) = \hat{w}(m) + \mu\, z(m)[q(m) - \hat{X}^{l}(m)z(m)]^*$$

$$= P_h(m+1) - P_h(m)$$

$$\Delta P_h(m) = -\mu\lambda_h P_h(m) + \varphi_h(m),\ h=1,2,3\ldots \quad (11)$$

Where P(m) is a zero mean Gaussian independent sequence, independent of the input process φ_h. Wt has been fluctuating in weight at random intervals, where z is less, but near to 1, and L is an independent zero mean sequence. There are two possible outcomes. The first scenario depicts a static building or environment, while the second depict a non-stationary structure or setting .These are suitable for the proposed designs.

- Pi is a constant in the proposed algorithm. A surface gradient estimate is used to determine the level of the time-varying variable Pk, based on the degree of sign change.
- To maintain a healthy step size Pk, do the following:
- Despite the fact that the choice has no effect on the process, it is common practice to begin with a step size of Pmax.
- If the prediction error is more than the step size PI, the PI will always be positive.

Step size may be increased when there is a high prediction error in general .As the prediction error decreases the step size would be lowered in order to minimize the mal adjustment. Mean square error (MSE) is kept within acceptable limits by using P_{max} as the constant. P_{min} was utilized to provide a basic degree of monitoring for pma in order to ensure confined MSE. In most circumstances, the p value given for the constant step size(CSS) technique will be close to the P_{min} value .In order to enable exponential forgetting, the value of a must be between 0 and 1.The step size was calculated by multiplying the number of feet in our estimated distance by the number of steps between the first and second marks .The step size is defined as the voltage difference between one digital level(for example,001) and the next(i.e.0010 or 0000).Here, depending on the signals, the step size may be changed .The greatest voltage an ADC can convert, divided by the number of quantization levels, is the quantization step size, q, which is 2^N-1;hence,q=Vmax/2^N-1.

Distance in feet/number of steps=step length, For the purpose of determining the value of N, we may consider the following scenarios:

- $N_0=1, N_1=\phi$_with each directional shift, the algorithm's step sizes shrink,
- $N_0>1, N_1=\infty$_if m0 consecutive sign changes occur, the algorithm reduces the step sizes,
- $N_1>N_0>0$_For stationary input signal processing, the authors claim that their technique results in smaller step sizes,
- $N_0=N_1>1$_for non stationary signal processing, the authors recommend using the symmetric increase or decrease approach.

A value of a=0.97, for example, has been found to work effectively in testing. The small component y may be utilized in conjunction with the large factor a to meet the maladjustment criteria, as demonstrated in the following computations .It would only add a silver to the FSS method's cost to have to make an additional weight adjustment at each stage instead.

As an AF,ANC employs the variable step size Normalized Differential LMS Algorithm to reduce background noise from the speech stream .For the STT transformation model, quiet dialogue is required .It is suggested to enhance discourse handling by combining the NDLMS and VSSLMS into a single, more productive algorithm known as the variable step size Normalized Differential LMS(VSSNDLMS).It is the goal of his algorithm's design to device a workable adaptive channel for reducing background noise and enhancing conversation signals .The Normalized Differential LMS algorithm is particularly well-suited for gradually shifting indications and is less sensitive to the variation of desiring signal force .NDLMs Algorithm is used to reduce the trade-off between LMS Algorithm's maladjustment and following capability .The VSSLMs also reduces the maladjustment's affectability to non-fixed levels .Algorithms for VSSLMS and NDLMS are summarized, and the VSSNDLMS Algorithm is presented.

When using the LMs algorithm in a non-steady climate, errors occur that cause channel loads to deviate from the ideal load .Changes in the step size of the proposed algorithm meet this requirement .In comparison to the NDLMs method, VSSLMS algorithm has a minimal MSE .Recovered signal and differential over input signal will be used to measure the loss of information .The MSE has a greater impact than a specified filter .The VSSNDLMS algorithm swiftly combines MMSE with VSS and NDLMS .The following is a representation of the VSSNDLMS Algorithm:

Step1: Input discourse signal in (*.wav) design
Step2: Select the VSSNDLMs Algorithm
Step3: Select N step size
Step4: Update weight vector
Step5: Compute info and yield
Step6: Compute MSE
Step7: Check blunder e(k)=0,if off limits to step3
Step8: Stop

The noise signal is addressed by d (k).

$$d\ (k)=\frac{b}{s+||i(m)||^2}\, a(m)i(m) \qquad (12)$$

Hence the error ration can be calculated as follows,

$$MSE\ (m) = 10log_{10}\, U_g(m) / U_m(m)qt \qquad (13)$$

The signal reduction can be done using the filter,

$$S\ (W_l^{MA}(\Theta)+1) = X(k) + \frac{\mu}{I^{H}(k)\, X(K)}\, n(K)S(K) \qquad (14)$$

Where,

$X\ (k) = \frac{\mu}{[c(||a(k)||^2+\mu||i(k)||^2)]}$

Finally the error free signal was obtained.

In the end, it is possible to compute the factor of convergence, system output converges on a collection of signals in the area of convergence. Finally, it is feasible to proven that, in order to ensure that the mean coefficients are converging, the algorithms convergence factor must be selected in the range of max 1

$$0 < S(W_l^{MA}(\Theta)+1) > \frac{1}{\mu_{max}} \qquad (15)$$

In this case, the input signal vector's biggest Eigen value is μ_{max}. The proposed algorithm's convergence time is dependent on the step size. Convergence may be delayed if the value of μ is small. In this case, by using the proposed filter may be counterproductive. Due to this phenomenon, it results that the algorithm will never be finished. The impact of the environment on the value should be considered while computing scientifically.

V. RESULT AND DISCUSSION

Least squares least mean square filter with configurable step size suggested and implemented in MATLAB under windows 10 it is done in adaptive channels, using the VSSNDLMS Algorithm, to eliminate noise from the speech stream. Mathematical modeling software, MATLAB, is used to reproduce findings from a speech signal created by the speaker. Eight primary dialect divisions of American English are represented by 630 male and female speakers, each of whom recites ten phonetically rich sentences, according to this dataset, which contains 6300 individual words and phrases.

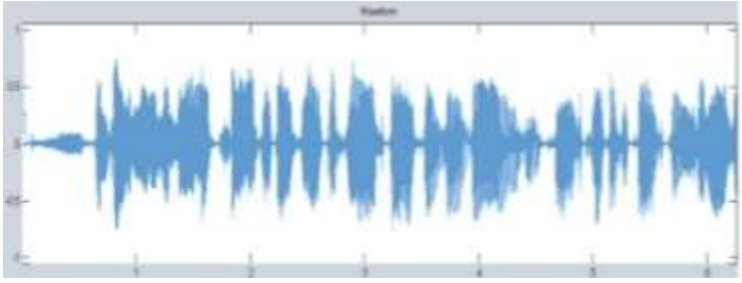

Figure.6 (a) Applied Input Signal

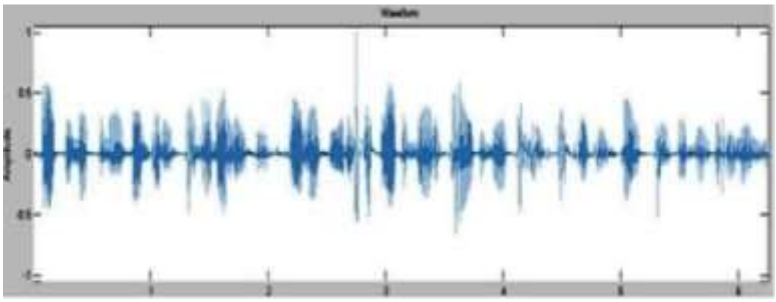

Figure.6 (b) Output recovered signal

The results and simulations of Sinusoidal wave with noise as Input signal and Output of NDLMS and MSE of the recovered signal is shown in Figure.7, Figure.8 shows results and simulations of Sinusoidal wave with noise as Input signal and Output of VSSLMS and MSE of the recovered signal. Similarly Figure.9 shows the results and simulations of Sinusoidal wave with noise as input signal and output of VSSNDLMS and MSE of the recovered signal.

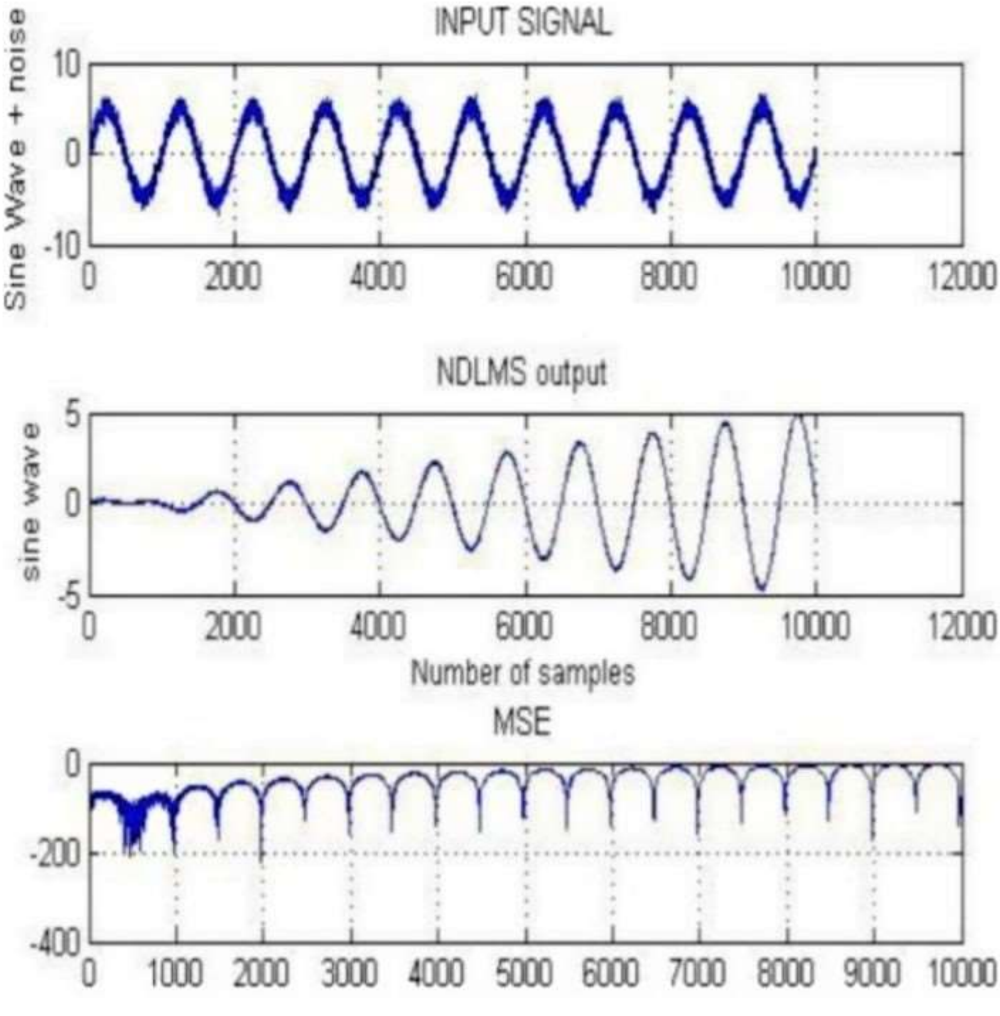

Figure.7 Sinusoidal wave with noise as Input signal and Output of NDLMS and MSE of the recovered signal

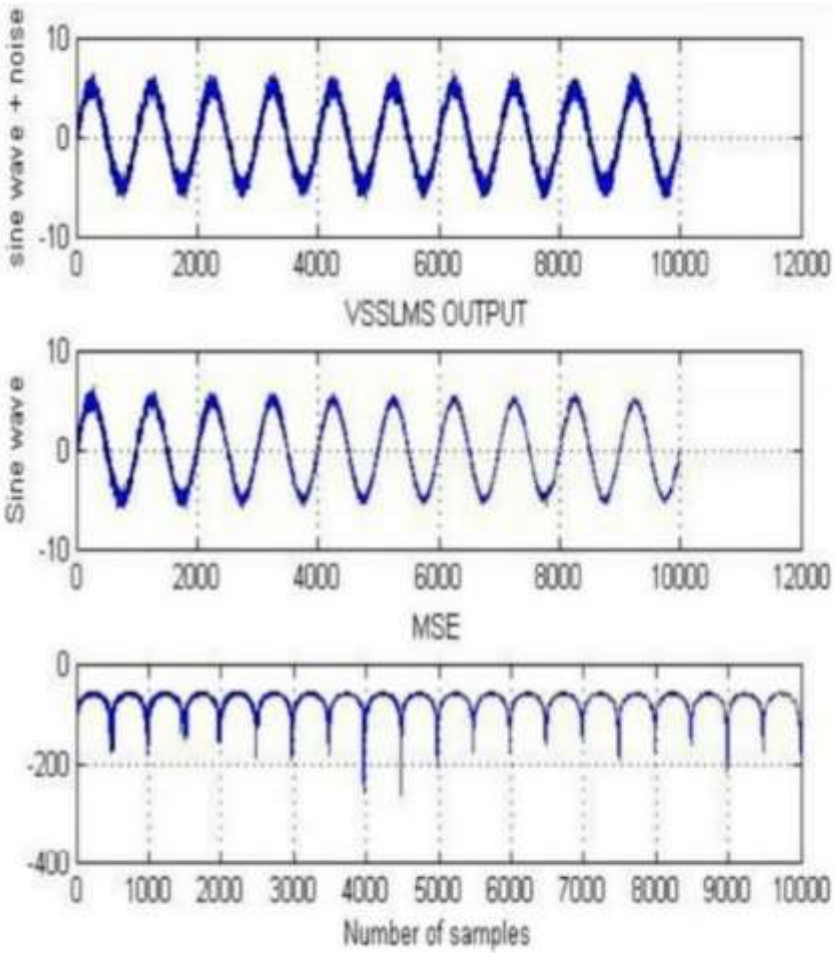

Figure.8 Sinusoidal wave with noise as Input signal and Output of VSSLMS and MSE of the recovered signal

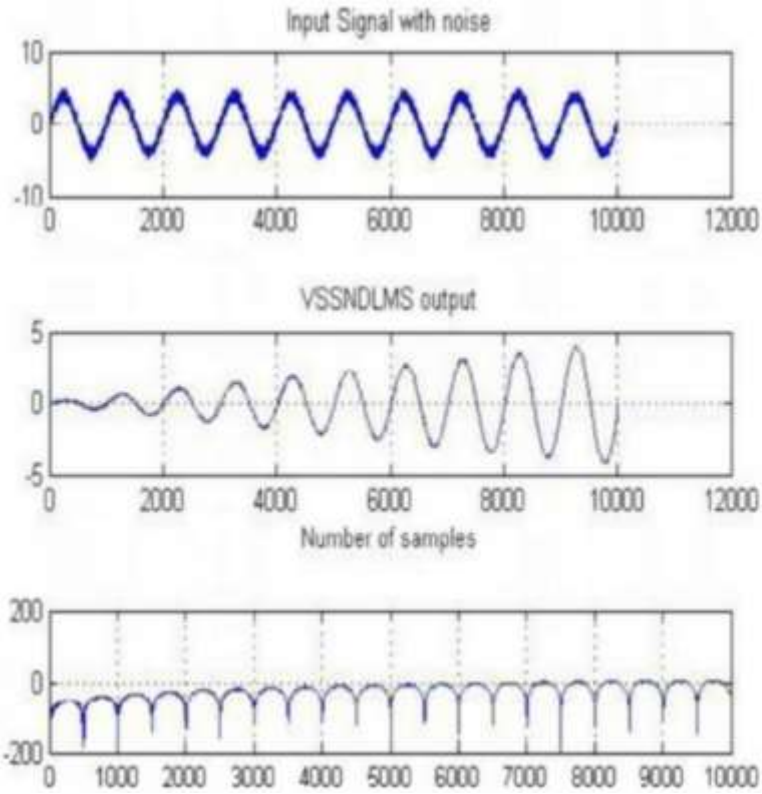

Figure.9 Sinusoidal wave with noise as Input signal and Output of VSSNDLMS and MSE of the recovered signal

The input signal is tried with VSSNDLMS Algorithm. Here, VSSNDLMS Algorithm is utilized in Adaptive channels to eliminate Noise as depicted in figure Figure.6 (a) and Figure.6 (b) .It is possible to compare the proposed approach with currently used methods in order to demonstrate its efficacy [14, 15].

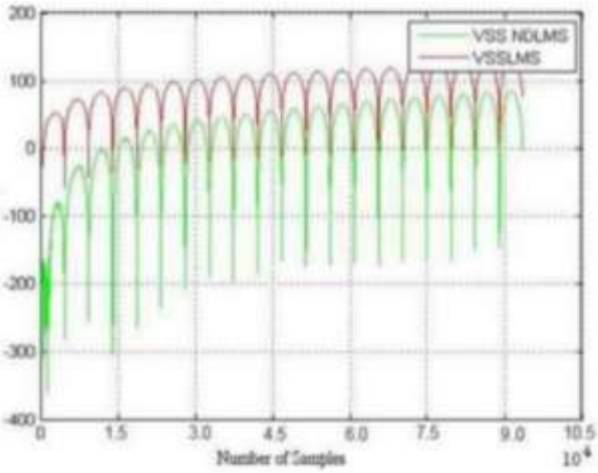

Figure.10 VSSLMS and VSSNDLMS MSE comparison for sinusoidal signal

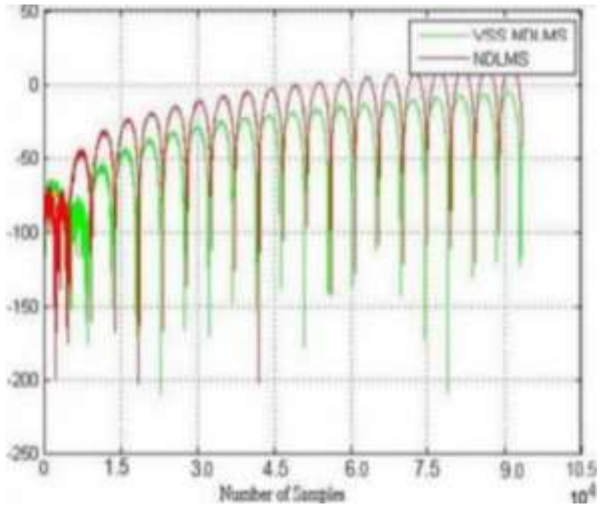

Figure.11 NDLMS and VSSNDLMS MSE comparison for sinusoidal signal

Figure.6 (a) and Figure.6 (b) shows the reproduced MATLAB input yield and MSE of the discourse signal. Similarly the Figure.10 shows VSSLMS and VSSNDLMS MSE comparison for sinusoidal signal and the Figure.11 shows NDLMS and VSSNDLMS MSE comparison for sinusoidal signal.

$$MSE = \Sigma_{M,N} \frac{[I_1(x,y) - I_2(x,Y)]}{X*Y} \tag{16}$$

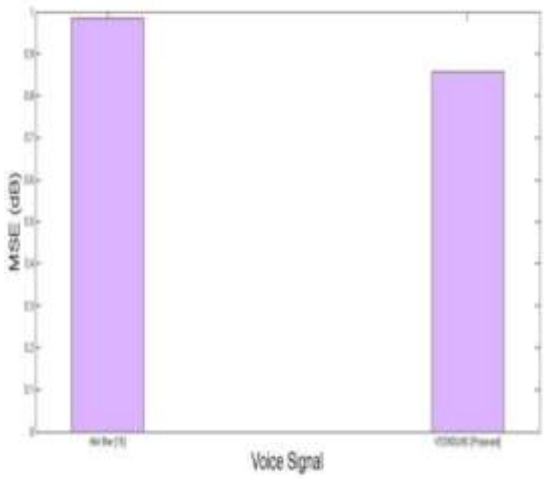

Figure.12 Input signal Vs MSE

As of from the result obtained the error rate obtained was very low in the proposed method when compared to other existing mechanisms.

Mean squared error (PSNR) is first calculated for the following equation.

$$PSNR = 10\frac{\log_{10} R^2}{MSE} \quad (17)$$

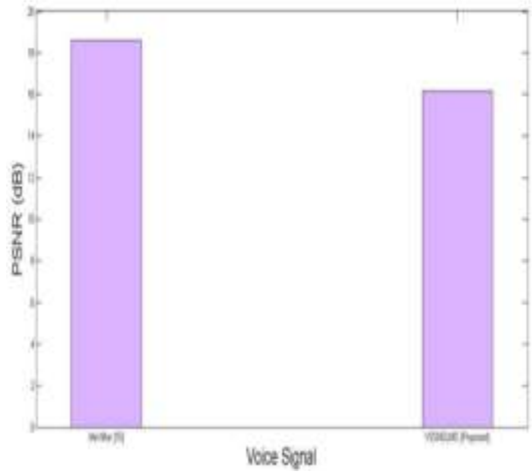

Figure.13 Voice signal Vs PSNR

The peak signal-to-noise ratio (abbreviated as PSNR) is a measure of a signal's maximum power to noise power that we utilize for fidelity evaluation (measure in dB). Figure.13 illustrates that the proposed methodology was more effective than other existing techniques in reducing the corrupting signal. When it comes to decibels, the ratio of signal to noise power is known as a "dB."

$$SNR = 10\log \frac{Signal\ power}{Noise\ power} \quad (18)$$

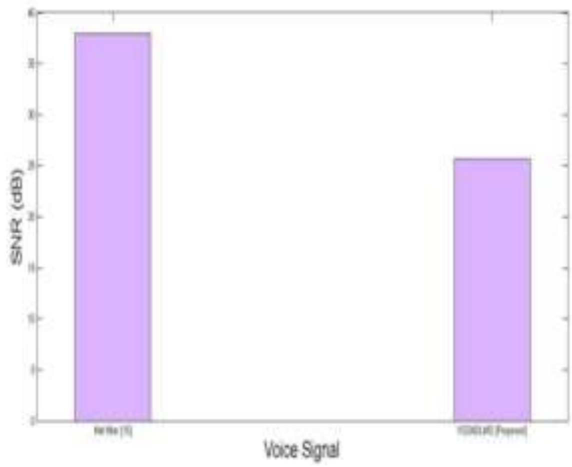

Figure.14 Voice signal Vs SNR

As the name suggests, SNR measures the difference between a desired signal and the ambient noise. Figure.14 shows that the background noise was decreased by the suggested method in a more efficient way compared to previous approaches.

We use distinct models for men and females to prove the generalizability of the desired models to different genders because of the differences in speech characteristics. Figures 15, 16, and 17 demonstrate the comparative results for TIMIT test utterances.

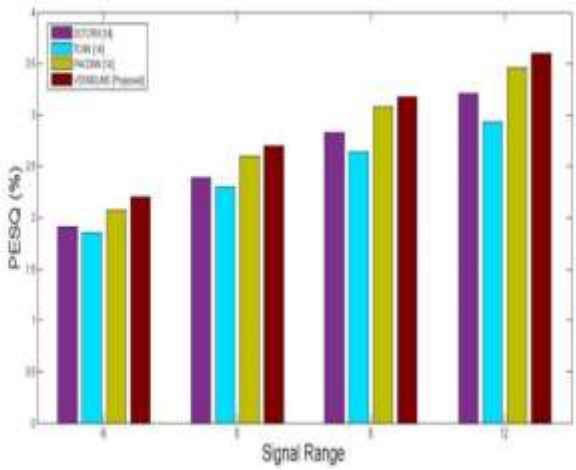

Figure.15 Signal range Vs PESQ

Evaluation of speech quality by perceptual evaluation (PESQ) is a test technique for automated evaluation of the user's perception of the quality of spoken language. Using PESQ, an objective speech quality test, is possible.

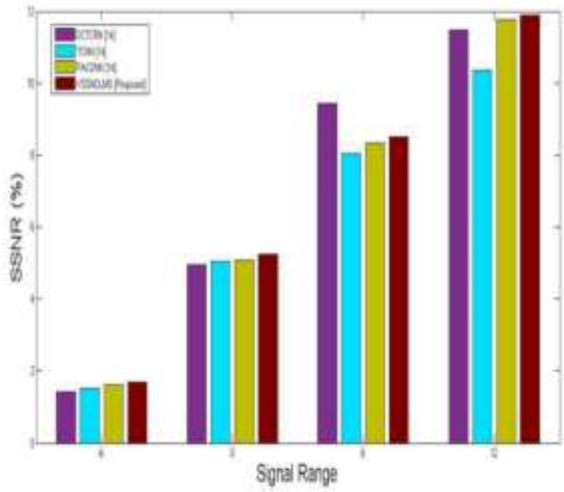

Figure.16 Signal range Vs SSNR

By calculating and average weighted SNR across segments with speech activity, segmental SSNR metrics evaluates the amount of residual noise in an improved speech.

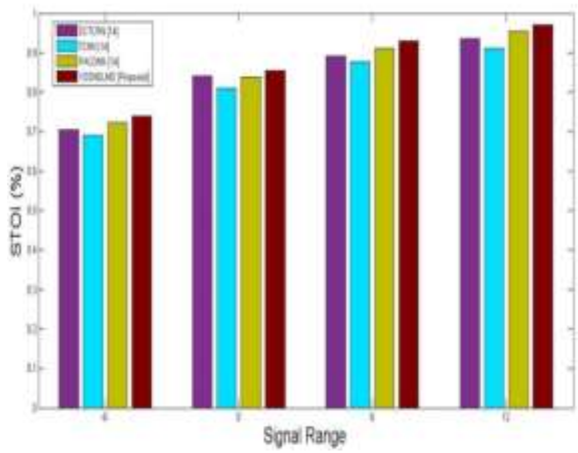

Figure.17 Signal range Vs STOI

Short-time temporal envelopes of clean and enhanced speech are correlated to assess speech intelligibility; the range is zero and one, and a higher number indicates better output. Voice quality is seen to improve in Figure.15, Figure.16, and Figure.17 after the method's implementation. According to objective quality standards, the proposed model is superior to all others.

VI.CONCULUSION

Use of VSSNDLMS algorithm for noise reduction in all hands-free communication devices was suggested in this work. The suggested technique enhances the algorithm's suitability for processing real-time voice inputs by adding adaptiveness to the channel. The suggested technique outperforms traditional filters in terms of enhancing SNR accuracy, as shown by the simulation results. SNR enhancement of more than -6 dB to +12 dB may be accomplished by utilizing the recommended strategy. This new algorithm's higher performance allows it to be used to a broad variety of real-time speech noise cancellation tasks. Aside from needing more calculations the proposed method delivers quicker convergence and lower error in comparison to an unknown system. Consequently, the proposed approach us superior to current filters.

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