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Enhanced Active Function model based Algorithm for Environmental Noise Cancellation

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ABSTRACT:

Active noise control is an essential part of modern technologies that help create a quiet environment in the intended location. Due to the prevalence of contemporary technology and the widespread usage of audio equipment, it has become ever more difficult to perceive sounds accurately in loud environments. C (ENC) is the solution to this problem. ENC, It is a sound processing method used in audio systems to diminish or eradicate undesired noises from the surrounding environment. In a current field of research, adaptive filter algorithms are used in conjunction with active noise cancellation technology to remove unwanted low frequencies auditory disturbances. This article explored and analyzed the active noise control (ANC) problem using the Least Means Square (LMS) and Leaky LMS methods. An adjusted variant of the LMS algorithms is offered with the aim of improving the rate of convergence. The findings are compared with those of the traditional variant LMS algorithms, and the new version additionally addresses issues with sensitivity, drifting, and excess mean square error. The suggested idea is used to identify systems and applications for noise cancellation in different noisy environments.

KEYWORDS: Environmental Noise Cancellation, Least Mean Square , Noise Reduction, Mean Squared Error

INTRODUCTION:

The World Health Organization (WHO) claims in a technical report that noise One significant environmental issue that harms people's health is pollution. The term "passive noise absorbers" refers to the conventional methods of reducing noise, which involve using substances that "absorb" the unwanted sounds. [1] In essence, the undesired sound waves are muffled by transforming them into another type of energy, like heat. [2] Passive noise absorption is an efficient method for mitigating high-frequency noise, but it is expensive and large for reducing low-frequency noise sources. [3] The Acoustic dampers are used in contemporary burning apparatuses because thermo acoustic instability can arise from the combination of irregular heat emission with acoustic waves. By lowering engine noise, the acoustic dampers help to stabilize the combustion system. The term "active" refers to the fact that active methods of reducing acoustic noise differ from passive ones in that they depend on producing a suitable "anti-noise" signal.[4] The developments in hardware implementation and digital signal processing (DSP) methods, There have been successful noise cancelling devices developed over the last few decades for a variety of applications, including cars, airplanes, headphones, air conditioning ducting, and so on. [5] The primary tool for removing unnecessary information from a signal, reducing background noise, and isolating pertinent data for further analysis is a filter.

Among the most often used adaptive filters methods is the least - mean – square (LMS) approach, which is straight forward and simple to analyze. Most academics have therefore focused on improving the LMS algorithm and fixing some of its flaws. The normalized least – mean – square (NLMS) and variable step – size least – mean – square (VSSLMS) are two of these improved techniques. These improved methods frequently improve the LMS method's mean – square – error (MSE) value and convergence rate. [6]

LITERATURE REVIEW:

For reducing, the active noise using the active function like tanh, sigmoid. The Variable Leaky LMS Adaptive the algorithm is an altered iteration of the LMS standard algorithm that is intended to combat the sluggish convergence of the standard LMS algorithm when there is a lot of input Eigen value disperse. We experimented with various step size values. We have looked at the output for both the colored noise signal and the recorded audio noise signal with various step size values.

METHODS OF NOISE CANCELLATION:

PASSIVE NOISE CANCELLATION:

Passive noise cancellation is a technique used to reduce or block out external sounds by physical means, such as the design and materials of headphones or earbuds. Foam pads or earmuffs are the most popular materials used in passive noise cancellation because they form a barrier around the speaker and prevent outside noise from entering. Because passive noise cancellation headphones don't require any power and instead rely on absorbing outside noise via foam barriers, earmuffs, or the headphones own ear cups, they can be quite helpful. However, passive noise cancellation may not be as successful in cancelling out background noise as active noise cancellation because it merely blocks sound.

ACTIVE NOISE CANCELLATION:

Active noise cancellation (NC), occasionally known as active noise reduction (ANR) or active noise control (ANC), is a technique for decreasing undesired by including a second sound, which is especially intended to revoke the initial. The idea was first conceived in the late 1930s, and later research and development starting in the 1950s led to the creation of commercial aircraft headsets, with the technology being made accessible in the late 1980s. Additionally, earbuds, headphones, mobile phones, and automobiles all use this technology.

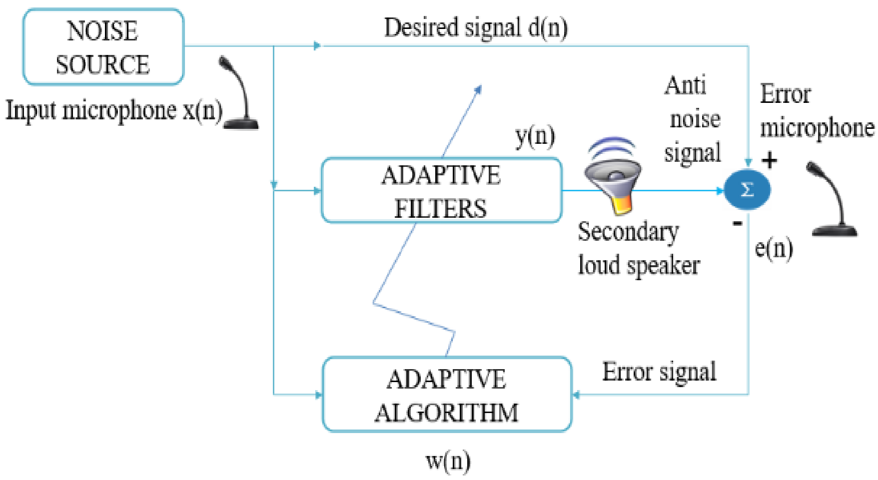


Fig. 1: Block diagram of Active Noise Control

The ANC diagram as shown in Fig. 1. In that, a source signal, is obtained from either noise sources or sensor with unknown frequency, which is passes through a primary path and produces a desired signal. In the fig the primary path and the adaptive filter are coupled in a parallel manner so, he same noise signal excites it, producing a secondary signal that is deducted from the intended signal to get a residual signal. By utilizing several adaptive algorithms to modify the filter weights, the residual signal that is obtained is gradually reduced.

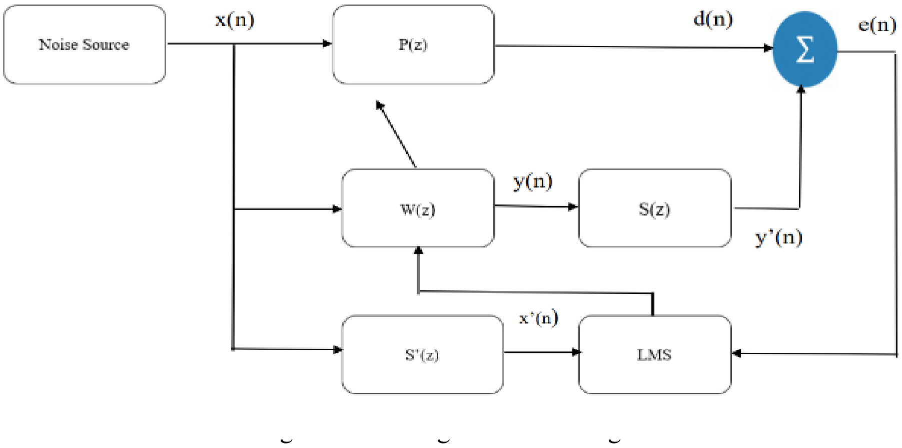
VARIOUS TYPES OF NOISE CANCELLATION ALGORITHMS:

NOISE CANCELLATION USING LMS ALGORITHM:

A kind of filter used in signal processing that cleverly makes use of stochastic gradient descent is the Least Mean Squares (LMS) method. It is an adaptive filter that offers several approaches to handling signal processing. By determining the filter coefficients associated with generating the LMS algorithm may be used to mimic a desired filter by calculating the least squared mean values of the erroneous signal, or the distinction in between the planned and actual signal. Due to the filter is only modified in response to the error at that particular moment; it is a stochastic gradient descent technique.

Mean Square Error (MSE) is minimized by the LMS algorithm by adjusting the coefficients varying across samples. Every sample has an updated weight vector within the LMS using the sharpest drop technique, which is the basis for the system.

In figure 2 the block diagram of LMS algorithm consists the Noise Source, error signal e(n), desired signal d(n), primary path signal p(n), weights of the filter w(z), output signal y(n).



Based on the discrepancy between the intended signal and the filtrate output, the LMS algorithm continually modifies the adaptive filter's weights. This iterative process minimizes the mean squared error, allowing the filter to adapt to changes in the input signal and approximate the desired signal.

In this algorithm the filter weights are updated based on gradient descent stochastic method . From the diagram of ANC Fig 2, the impulse response of linear system with input signal x(n) can be represented by

$$d(n) = h^T x(n) \tag{1}$$

Where T is the transposition factor, x(n) is the tap -input signal, and h is the system's impulse response.

$$y(n) = \omega^T x(n) \tag{2}$$

The desired signal d(n) and y(n) is given by

$$e(n) = d(n) - y(n)$$

$$e(n) = d(n) - w^T x(n) \tag{3}$$

The gradient estimate into the steepest descent algorithm is given by

$$\mathrm{w(n + 1) = w(n)} - \frac{1}{\mu}\nabla\xi^2 \tag{4}$$

The cost function for faulty signals is given by

$$\xi(n) = e^2(n) \tag{5}$$

To simply the cost function into instantaneous gradient of a one squared sample of error is given by

$$\nabla\xi(n) = 2[\nabla e(n)]e(n) \tag{6}$$

$$\nabla e(n) = -x(n),$$

The gradient estimate becomes

$$\nabla\xi(n) = -2x(n)e(n) \tag{7}$$

Substitute Eq. (7) into in Eq. (4)

$$w(n+1) = w(n) + \mu x(n)e(n) \tag{8}$$

Where μ is the step-size factor defined by

$$0 < \mu < \frac{2}{LPx} \tag{9}$$

Where L is the order of the filter and is the autocorrelation input signal power.

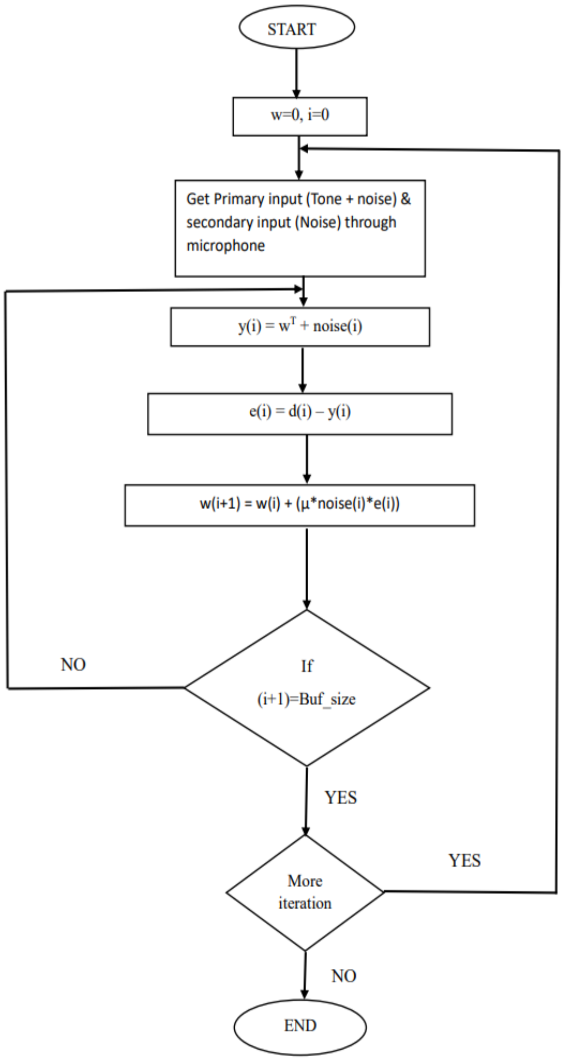


Fig. 3 Flowchart of LMS algorithm

In figure 3 The initial values of the weight variable (w) and the loop parameter (i) are both 0. The input signals coming from the microphone were then collected. In the phase that follows, the result of the calculation of the filter is utilized to create an approximate of the indication of error. Next, the filter parameters are modified by setting the step length value (μ) to a steady. The above process is continued prior before the loop variable equals the size of the buffer. We demonstrate this implementation.

NOISE CANCELLATION USING LEAKY LMS ALGORITHM:

An improved version of the LMS method known as the Leaky Least Means Square (LLMS) approach uses a leakage factor to control the weight of the LMS algorithm update. This leakage factor fixes the meandering problem in the LMS technique and bounds the parameter estimation. Another variant of the LMS algorithm is the Variable Leaky LMS method is intended to address the gradual convergence of the conventional LMS when an input Eigen values spread is large. To vary the leak, the method combines a quantization leak adjustment function with a greedy punish/reward heuristic. The proposed technique can perform much better than regular LMS when the supplied Eigen value dispersion is high, as confirmed by the simulation results.

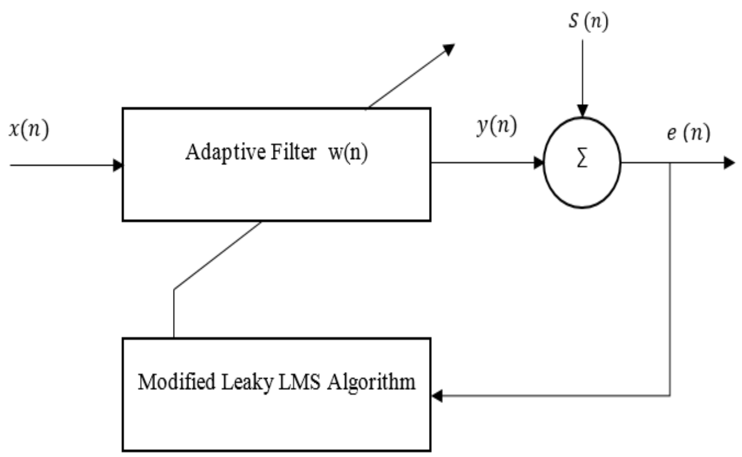


Fig. 4 Block diagram of Leaky LMS

In figure 4 the block diagram of Leaky LMS consists the Adaptive Filter w(n), Modified Leaky LMS algorithm, output signal y(n), error signal e(n), input signal x(n).

The Leaky LMS algorithm balances the need for adaptation to changes in the input signal with a regularization mechanism provided by the leaky factor. This can be useful in scenarios where preventing the weights from diverging is important for the steadiness and long-term the adaptive filter's performance

In system identification, given an input of x (k), the output of a linear system is given by

$$d(k) = h^T x(k) + v(k) \tag{10}$$

where T is the transposition operator, v(k) is an additive noise, h is the system's impulse response, and x(k) is the tap-in signal. The leaky LMS's cost function is provided by

$$J(k) = e^2(k) + \gamma w^T w(k) \tag{11}$$

Where, w(k) is the weight of the filter-tap, γ is the leakage factor ($0 < \gamma < 1$) and e(k) is the mistake as described by

$$e(k) = d(k) - w^T(k)x(k) \tag{12}$$

It is possible to update the filter-tap recursively by

$$w(k+1) = (1-\mu\gamma)w(k) + \mu x(k)e(k) \tag{13}$$

where, μ is the step-size that is defined by

$$0 < \mu < \frac{2}{\gamma + \lambda\, max(R)} \tag{14}$$

where, λ_{max} is the maximum auto corelation matrix representing the tap vector input

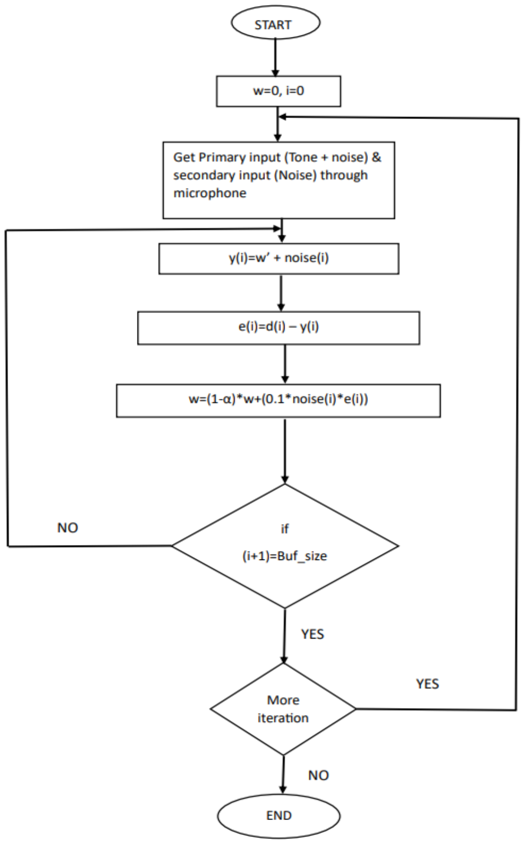


Fig.5 Flow chart of Leaky LMS algorithm

In figure 5 Both the initial values of the weight variable (w) as well as the loop variable (i) are both 0. The input signals from the recording device were then obtained. In the phase that follows, the result of the calculation of the filter is utilized to create an approximate of the error message. Next, the filter parameters are modified by setting the step length value (μ) to a steady. This method is continued before to the loop's last parameter equals the size of the buffer. This application is shown.

PROPOSED METHOD:

The exponential function is appropriately applied to the error cost function in LMS, LEAKY LMS algorithms to increase the convergence performance of the algorithms. The outcome is then utilized to update the algorithm's weights in the direction of minimizing the error function.

MODIFIED LMS ALGORITHM:

The modified error cost function of LMS algorithm defined from Eq. (5) as,

$$\xi(n) = (exp(e(n)) + \exp(-e(n))^2 \tag{15}$$

Where, e(n) is defined in Eq.(3)

The modified gradient estimated cost function defined as

$$\nabla\xi(n) = 2(-x(n)\exp(e(n)) + x(n)\ \exp(-e(n))) \tag{16}$$

The weight updating equation is provided by

$$w(n+1) = w(n) - \frac{\mu}{2}\nabla\xi(n) \tag{17}$$

Substitute Eq. (16) in Eq. (17) the new weight update Eq. becomes as

$$w(n+1) = w(n) - \mu(-x(n)\exp(e(n)) + \ x(n)\exp(-e(n)))$$

It can be written as

$$w(n+1) = w(n) + \mu x(n)\exp(e(n)) - \exp(-e(n))$$

$$= w(n) + 2\mu x(n)\sinh\ (e(n)) \tag{18}$$

The LMS algorithm is modified with the active function tanh

$$en\_lms(i) = ke * \tanh\ (\alpha * (\frac{en\_lms(i)}{ke})) \tag{19}$$

MODIFIED LEAKY LMS ALGORITHM WITH ACTIVE FUNCTION(SIGMOID):

The Leaky - LMS algorithm is modified with the active function sigmoid. The modified error cost function of Leaky - LMS algorithm defined from eq as

$$w(n+1) = (1 - \alpha * \mu)w(n) + 2\mu\frac{1}{1 + \exp\ (\gamma * e(n))} \tag{20}$$

SIMULATION RESULTS:

The proposed algorithms, leaky LMS algorithms, and typical variant LMS algorithms are studied and their convergence performance is calculated using simulation tests. Every algorithm undergoes testing and application on systems for system identification and noise cancellation in various statistical and real-time noise situations.

Mean Square Error:

Mean Square Error (MSE) is a metric commonly accustomed to measure the mean squared variation between the actual (or observed) values and the predicted values in a set of data. It is widely employed in various fields, including statistics, signal processing, machine learning, and optimization.

Output for Recorded Radio Noise:

In this experiment simulations were done using recorded Radio noise. Fig. 6 shows that the convergence performance of suggested algorithms enhanced by a factor of 35% faster than conventional algorithms.

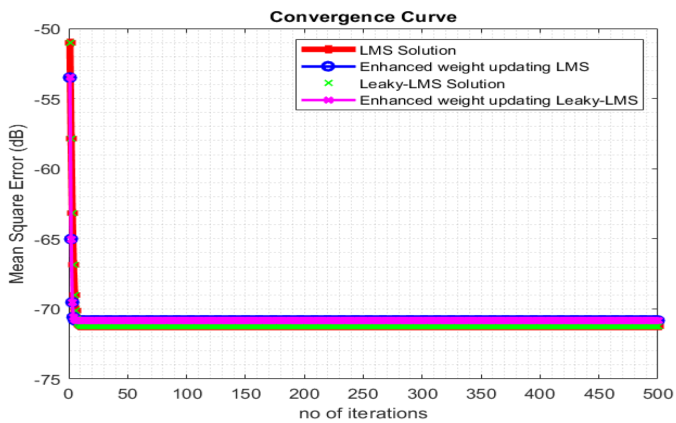


Fig.6 MSE for Conventional and proposed Modified Algorithms in Recorded Noise for LMS, Leaky-LMS, M=128, Step Size=0.001

Output for Pink Colored Noise:

Generally the color the power spectral density of noise is what defines it..In color noise signals Power spectral density is proportional to bandwidth unit to$\frac{1}{f^{\beta}}$. For pink noise, β=1, brown noise, and white noise, β=0, 1, and 2. In this experiment simulations were done using the colored noise like pink noise.

In figure 7 shows that the convergence performance of suggested algorithms enhanced by a factor 40% faster than conventional algorithms.

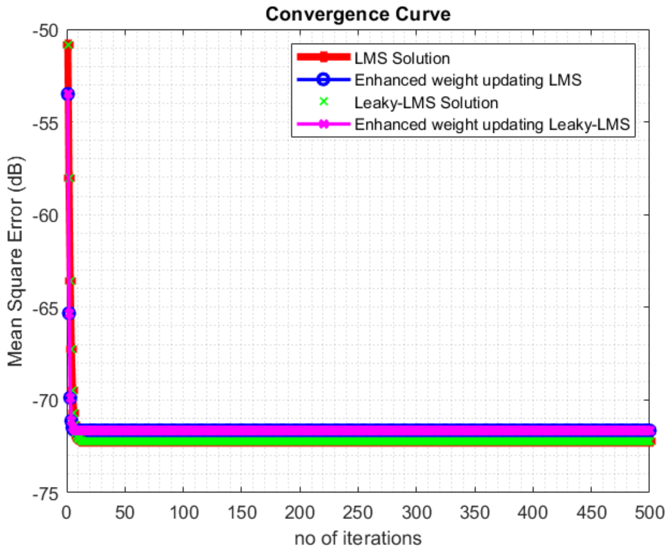


Fig.7 MSE for Conventional and proposed Modified Algorithms in Pink Colored Noise for LMS, Leaky-LMS, M=128, Step Size=0.01

Output for different Step size values for LMS:

In this experiment simulations were done using the LMS algorithm. Figure 8 shows that the convergence performance of proposed algorithms and enhanced weight updating LMS for different step size values like 0.005, 0.002, 0.01.

The step size value 0.01 have better MSE convergence than other step size values.

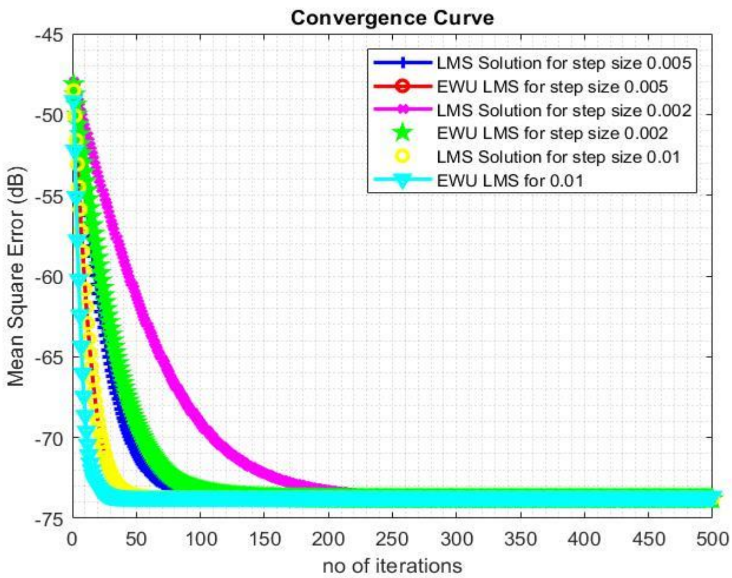


Fig.8 MSE for Conventional and proposed Modified Algorithms in Recorded Noise for LMS, Leaky-LMS, M=128, Step Size=0.005,0.002,0.01

Comparison Table of Proposed Modified and Conventional Algorithms:

Noise Source type	**Iteration**	**MSE in dB**			
		LMS	**EWU LMS**	**Leaky - LMS**	**EWU Leaky-LMS**
Recorded Audio Noise	50	-69.71	-76.04	-69.41	-72.54
	100	-69.84	-76.46	-72.57	-72.77
	200	-69.84	-76.47	-72.78	-72.78
	300	-69.84	-76.47	-72.78	-72.78
	400	-69.84	-76.47	-72.78	-72.78
	500	-69.84	-76.47	-72.78	-72.78
Pink Noise	50	-71.51	-77.63	-69.91	-72.54
	100	-71.62	-78.35	-71.76	-72.77
	200	-71.62	-78.44	-71.76	-72.78
	300	-71.62	-78.45	-71.76	-72.78
	400	-71.62	-78.45	-71.76	-72.78
	500	-71.62	-78.45	-71.76	-72.78

In the below table the comparison is done in between the LMS and Enhanced Weight Updated LMS, Leaky - LMS and Enhanced Weight Updated Leaky – LMS over the iterations 50, 100, 200, 300, 400, 500.

Table 1: Comparison Table of Proposed Methods

The LMS solution, and Leaky – LMS solution have better convergence performance than the Enhanced Weight Updating LMS (EWU LMS)

APPLICATIONS:

Here are some applications of utilizing the LMS for active noise cancellation and Leaky- LMS algorithm:

- Telecommunications
- Audio Systems
- Automotive Industry
- Aerospave and Aviation
- Industrial Settings
- Medical Applications
- Research and Laboratories
- Consumer Electronics
- Public Spaces

CONCLUSIONS:

In order to obtain good convergence rate and stability, the variant LMS algorithm's modified cost function is introduced here. The suggested modified LMS, Leaky-LMS algorithms yield a faster convergence rate and an acceptable MSE in comparison to standard methods.

In summary, while the LMS algorithm focuses on minimizing the Leaky LMS algorithm and the mean square error introduces a leaky term to provide memory effects and potentially improve convergence and stability in certain dynamic environments. The choice between LMS and Leaky LMS depends on the specific requirements and characteristics of the application at hand.

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