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گۆڤاری كوردستانیی بۆ لێكۆڵینەوەی ستراتیجیی

Active Noise Cancellation a New Horizon for Better Life

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Abstract

Modern life is accompanied by many kinds of noise signals. Equipment, devices, and tools are cheaper in price and more affordable today, but in many cases, they generate more noise. Competition between companies made them use cheaper materials and concentrate on electronics to make their products cheaper. In the end, the customer is the victim. For example, electric fans manufactured in the fifties and sixties of the previous century was much quieter than the ones manufactured after that. Also (in general), cars manufactured at that period were much quieter, especially for the inside cabin noise. Why is that? All due to competition and the run for using low-cost plastic materials to have a better end product price. Here we are trying to emphasize this issue and show how we can use electronic means to reduce environmental noise to have a better life. Using this approach is a key to solving this issue for budget limited people. Wealthier people usually have the option of using expensive products that are usually equipped with better sound insulation. Hence, this work is the cost-effective approach for reducing noise around us, and for sure this approach is the electronic one.

Keywords: Active Noise Cancellation, Digital Filtration, Environmental Noise, Noise Pollution, Adaptive Filter

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1. Introduction

Noise, our modern life fellow is affecting us in a bad way. A lot of stress and anxiety are related to it. Millions of cars on roads generate noise, even small equipment like Laptops and Computers have cooling fans that generate noise. It is hard to imagine a device that is not related to some kind of noise. Even small transformers (step-up and step-down ones) on printed circuit boards have some kind of related noise. How to get rid of these noises, one approach is to be wealthier. By being wealthier you can buy properly designed equipment, devices, etc., that usually generate the least amount of noise. But who doesn't like to be wealthier? And is that affordable for everyone? Of course not! The solution to this dilemma is to use the low-cost electronic devices that are partly responsible for noise generation to counteract these noises. This process is called active noise cancellation (ANC).

By active noise cancellation, we achieve a better quitter environment for all living creatures on this planet. The problem is that this cancellation process works well in a closed environment and not in open ones. It could be used inside cars, rooms, and halls, but not in the backyard of a house. In an open environment, many parameters need consideration. The first is the type of noise signal to be cancelled. As open environments contain different kinds of noise signals and a decision is required on which noise to cancel. The second is to find the source and direction of the noise signal which is hard to do in open environments, due to having many signals entrance paths. This is not the case in closed environments as the noise source and direction is indicated. Although research works continue in this direction and nothing is on the stop.

Two approaches are used for this purpose:

- Cancellation through a feedback control system.

- Cancellation by using filtration.

This paper provides a state-of-the-art review of this field and it also contains the various algorithms used in signal filtration and cancellation. It has been organized as follows: Section 2 describes feedback-based noise cancellation; Section 3 is about filtration-based signal cancellation and it contains a comparison between LMS, NLMS, and RLS. In the fourth section (4) we describe the metrics used for performance evaluation. The next section, five (5), is on the application of the adaptive filters. Section 6 is on the core issue of this paper, which is Active Noise Cancellation (ANC). The last section before the conclusion is on available products for noise cancellation on electronic trading platforms. We like to say that we do not go for or against any product, but it has been mentioned to give a broader topic view. The conclusion is provided in Section (8).

Table 1 shows the all-notation which is used throughout the paper. Readers who are not specialized in electronic engineering or signal processing can skip the equations and concentrate only on the textual description of the topic.

Table **1**: Notation

Symbol	**Description**
$\|\|.\|\|^2$	Squared Euclidean norm of a matrix
$(.)^T$	Transpose of matrix or vector
$(.)^*$	Complex conjugate
$(.)^H$	Hermitian matrix (conjugate transpose)
$(.)^{-1}$	Inverse matrix

2. Feedback based Cancellation

In feedback noise cancellation the processed signal is subtracted from the original one by counteracting it. The resulting surrounding environment should be less nosey with this process, and filtration could be used to concentrate on the signal or the frequency to be cancelled. Two main techniques are available to achieve this: the feed-forward and feedback schemes.

The feed-forward technique is more efficient with low environmental noise; however, the feedback technique is effective for high environmental noise (multi-directional noise). In 1953, Olson and May studied the feedback ANC headset, and a typical one is shown in Figure 1. From the figure, it is clear that a feedback ANC system consists of a control system (controller), a microphone (MIC), and a speaker (SPK) for cancelling or reducing noise signals. The controller could be analogue or digital and the former is more effective for broadband noise signals and less efficient for narrowband noise signals. In addition, the analogue feedback controller is fixed and cannot track noise variation. The digital ANC system uses the adaptive filter and it can adaptively update the filter coefficients to cancel or minimize undesired signals (Song, et al., 2005).

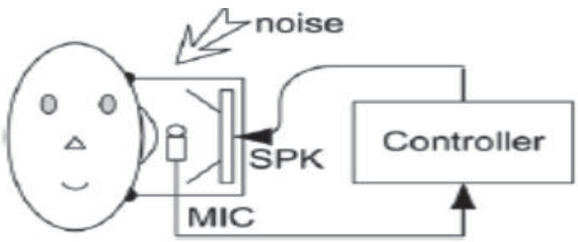

Figure 1: Feedback Control ANC (Song, et al., 2005)

3. Filtration based Cancellation

In filtration-based cancellation, two approaches are used. The old one is through using analogue filtration and the modern one is by using digital filtration. In the next subsections, both types are described, and as we are living in the digital age, the main concern will be the digital one.

3.1. Analog Filtration

In Analog filtration operational amplifiers (OP-Amps) are used to create active filters. Not many advances have been achieved in this direction particularly for noise cancellation, although some companies in the past manufactured some products, claiming it carries noise cancellation. There is no proof of whether they used Analog filtration (or how effective they are), but we classified them as Analog, based on the product manufacturing year. For example, in the pre-1990 era, it will be hard to find products that used digital filtration except for the military field, and if there was (although no evidence of that is found), they will be very expensive and not for public use.

3.2. Digital Filtration

In digital filtration, signal processor chips and digital algorithms are used for that process. In other words, a digital filter is a mathematical algorithm applied in software or hardware on a digital input signal to create a digital output signal for reaching filtering objectives. Digital filters can be categorized as time-variant or time-invariant, linear or nonlinear, casual or non-causal. A system is said to be linear if it satisfies the superposition principle. When the system remains unchanged over time the system is called a time-invariant system. The digital filter is causal if the output of the filter depends on only the present and past input signal however non-causal filter output relay on the present past and also future input. This is meaning the non-casual filter can predicate the future input that would be applied in the future (Lee & Kuo, 2001).

Two types of digital filters are available, the traditional one and the adaptive one. The traditional one has one input and output signal. The adaptive has many, and the concern here is adaptive filtration, as it plays an important role in Active Noise Cancellation (ANC). It adaptively updates the coefficient of the filter to minimize the noise signal. The desired signal is corrupted by the noise signal and reduces the performance of the wanted signal.

Various algorithms are implemented and developed by researchers to improve the quality of the signal. In this paper, the basic general algorithms such as Least Mean Square algorithm (LMS), Normalized Least Mean Square algorithm (NLMS), and Recursive Least Square algorithm (RLS) are compared in terms of different parameters such as input/output, computational complexity, hardware requirements, cost, etc. The goal is to help the reader to know how to design and select the algorithm.

In most electronic systems, a filtering technique is used to eliminate or minimize a noise signal. When the signal passes through a channel an unwanted signal is added to the desired signal. A filter is a system applied to a set of noisy data to extract the desired signal in a specified manner. The main objective of the filter is to improve signal quality and separate signal components that have been previously combined. The filters can be fixed or adaptive. The fixed filter can pass the frequencies contained in the signal and discards the frequencies occupied by the noise when the signal and unwanted signal are identified previously. However, adaptive filters are filters with the capability of adaptation to an unknown system (adjust their coefficient automatically), and their design requires no ***prior*** information on signal or noise characteristics. Adaptive filters have the advantages of versatility and low cost compared to fixed filters.

Inverse modelling, identification, prediction, and interference are the basic applications of adaptive filtering (Falcão, 2012). According to the frequency (low or high), the filter can be classified into four types:

1. Low Pass Filter passes only the frequencies below the cut-off frequency through the filter and attenuates the other contents.
2. High Pass Filter passes only the frequencies above the cut-off frequency and other frequencies are attenuated.
3. Band Pass Filter passes a certain band of frequencies, however attenuating all frequencies outside the band.
4. Band Stop Filter rejects only a band of frequencies while passing all frequencies outside the band (Porle, et al., 2015.).

There are two types of digital filters which are Finite Impulse Response (FIR) and Infinite Impulse Response (IIR). These systems are represented by differential equations and can be implemented in hardware/software. There are several ways to implement difference equations which are called digital filter structures. The structures are derived based on computational complexity, memory, finite word length effects, etc (Lee & Kuo, 2001).

3.2.1. Finite Impulse Response

An FIR system has a finite response and does not have feedback. The general Input/output difference equation of FIR is expressed as (Proakis & Manolakis, 1996):

$$y(n) = \sum_{k=0}^{M-1} b(k)x(n-k) \tag{1}$$

Where b(k), k=0,1,2,…, M-1 is the impulse response coefficients of the filter, and **M** is the filter's length. By taking the z-transform for the equation 1 becomes:

$$Y(z) = \sum_{k=0}^{M-1} b(k)X(z)z^{-k} \tag{2}$$

Thus, the system transfer function for FIR filter is:

$$H(z) = \sum_{k=0}^{M-1} b(k)z^{-k} \tag{3}$$

gure 2 shows the basic structure of the FIR filter. The main features of the FIR filters are always able because the output does not depend on the past output (non-recursive), linear phase response, w sensitivity to quantization noise, and simple to implement. The FIR filter can be realized in several ays such as direct form, cascade form, frequency sampling structure, and lattice structure (Proakis & [anolakis, 1996).

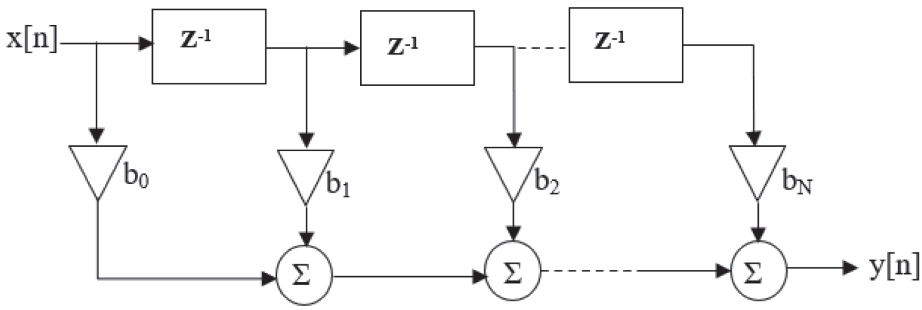

Figure 2: Finite Impulse Response (FIR)

2.2. Infinite Impulse Response

he IIR has infinite impulse response, and the filter output depends on the past output and the present ıd past input thus it's called a recursive filter. The general input/output difference equation of the R filter can be expressed as (Proakis & Manolakis, 1996):

$$y(n) = -\sum_{k=0}^{N} a(k)y(n-k) + \sum_{k=0}^{M} b(k)x(n-k) \tag{4}$$

'here a(k) and b(k) are the coefficients of the filter and x(n), y(n) is the input and output of the filter. y taking the z-transform for the equation 4 becomes:

$$Y(z) = -\sum_{k=0}^{N} a(k)Y(z)z^{-k} + \sum_{k=0}^{M} b(k)X(z)z^{-k} \tag{5}$$

hus, the system transfer function for FIR filter is:

$$H(z) = \frac{\sum_{k=0}^{M} b(k)z^{-k}}{1 + \sum_{k=0}^{N} a(k)z^{-k}} \tag{6}$$

gure 3 shows the basic structure of the IIR filter. The major advantages of the IIR filters are the edback, ease of design, and implementation as they require a smaller filter size, however, the IIR ter is an unstable and nonlinear phase. The IIR filter can be realized in several ways such as direct rm, cascade form, parallel structure, and lattice structure (Proakis & Manolakis, 1996).

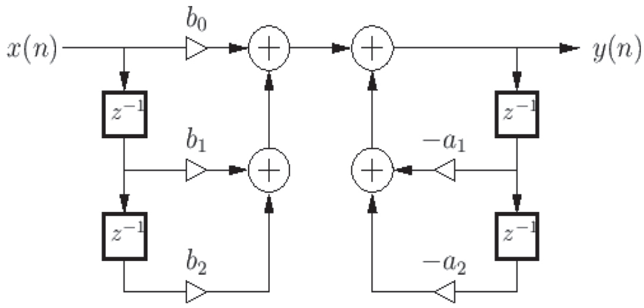

Figure 3: Infinite Impulse Response (IIR)

4. Metrics

The main Performance Function used in digital filters is the Mean-Square Error (MSE), which is used to measure the performance of the adaptive filter (Lee & Kuo, 2001). The filter updates the coefficients (in both FIR and IIR) to improve specifically determined performance criteria as shown in Figure 4.

MSE is expressed by:

$$\xi(n) = E[e^2(n)] \tag{7}$$

$\xi(n)$ depends on the length of the filter weight (L).

The output y(n) can be expressed as:

$$y(n) = w^T(n)x(n)x^T(n)w(n) \tag{8}$$

The error signal is determined by comparing the output signal y(n) with the desired signal d(n)

$$e(n) = d(n) - y(n) = d(n) - w^T(n)x(n) \tag{9}$$

The MSE can be determined by substituting equation 9 into equation 7.

$$\begin{aligned}\xi(n) &= E[e^2(n)] \\ &= E[d(n) - w^T(n)x(n)][d(n) - w(n)x^T(n)]\end{aligned} \tag{10}$$

Where:

$$\xi(n) = E[e^2(n)] = E] \tag{11}$$

$$\xi(n) = E[e^2(n)] = E] \tag{12}$$

$$\begin{aligned}\xi(n) &= E[e^2(n)] \\ &= E[|d(n)|^2] - 2p^T w(n) + w^T(n)Rw(n)\end{aligned} \tag{13}$$

P is the cross-correlation vector and expressed by:

And R is the input autocorrelation that can be expressed by:

$$p = E[d(n)x(n)] \quad (14)$$

$$R = E[x^T(n)x(n)] \quad (15)$$

By taking the derivative of equation 18 according to the w(n); it gives the minimum MSE (the optimum tap filter w^o):

$$\frac{\partial \xi(n)}{\partial w} = w^o = pR^{-1} \quad (16)$$

This equation is known as a Wiener filter, which defines the optimum tap weight in terms of autocorrelation and cross-correlation function. The autocorrelation is between the input of the system x(n), and cross-correlation is between the input x(n) and desired signal d(n).

Thus, the minimum MSE is achieved by substituting the optimum tap weight w^o in equation 13 is:

$$\xi(n) = E[e^2(n)] = E[d(n)^2] - p^T w^o \quad (17)$$

5. Adaptive Filtering Algorithms

Adaptive filters vary the frequency response and bandwidth with the time to get called a time-varying filter. Thus, based on incoming signals, the coefficients of the filter are automatically adjusted by an adaptive algorithm. In digital signal processing, the adaptive filter algorithm is utilized for channel equalization, interference cancellation, and channel estimation. Adaptive filter algorithms such as Least Mean Square, Normalized Least Mean Square, and Recursive Least Mean Square are described in the next sections. The adaptive filter algorithm consists of two parts (Lee & Kuo, 2001):

1. **Filtering process:** A process of calculating the output of the filter generated by a set of tap-inputs, which are similar to the input signals.

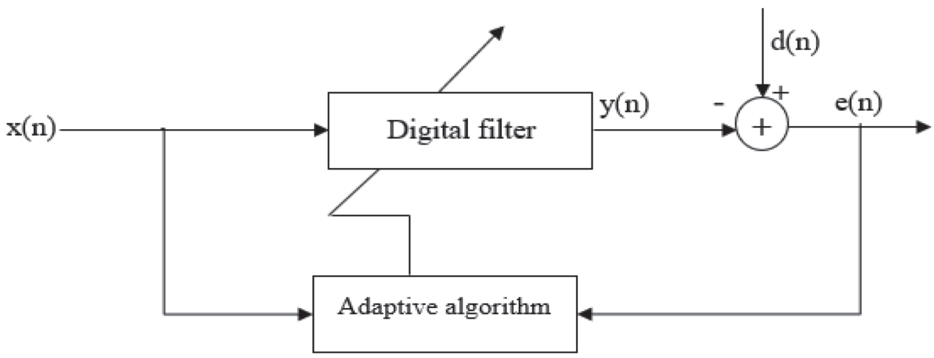

Figure 4: Adaptive filter algorithm

2. **Adaptive process:** A process to adjust the coefficients of the filter based on estimation error.

Figure 4 shows the general block diagram of adaptive filter algorithms.

Where:

x(n): reference input signal

y(n): digital filter output signal

d(n): desired signal

e(n): error signal, and e(n)= d(n)-y(n)

As mentioned earlier, there are two types of digital filters FIR and IIR filters. The FIR filter is linear phase response and stable in comparison to the IIR filter which is unstable. Since the filter need adaptation, the stability problem is much more complex to handle. Therefore, for real-time applications, the FIR adaptive filter is broadly used.

The output of the FIR filter with the length M is:

$$y(n) = \sum_{k=0}^{M-1} w_k(n)x(n-k) \quad (18)$$

Where $b_k(n)$ is the time-varying filter coefficients and adjusted by the adaptive algorithm. The input vector a time n is:

$$x(n) = [x(n)x(n-1) \dots \dots \dots x(n-M+1)]^T \quad (19)$$

The weight vector at a time n is:

$$w(n) = [w_0(n)w_1(n) \dots \dots w_{M-1}(n)]^T \quad (20)$$

By using the vector operation, the output y(n) can be expressed as:

$$y(n) = w^T(n)x(n)x^T(n)w(n) \quad (21)$$

The error signal is determined by comparing the output signal y(n) with the desired signal d(n)

$$e(n) = d(n) - y(n) = d(n) - w^T(n)x(n) \quad (22)$$

5.1. Steepest Descent

Each algorithm has the corresponding cost function to operate and is required to be improved. In the steepest descent, the cost function is Mean Square Error (MSE). Mean Square Error is a quadratic function of the weights and is represented by a positive bowl-shaped surface shown in Figure 5. The proper algorithm is selected based on the complexity, convergence, and steady-state performance. Steepest descent (SD) is an iterative method, in the beginning, and it uses some initial weight vector. The filter taps are updated at each iteration in the direction of the negative gradient of the error surface. When the performance surface has the greatest rate of decrease, the steepest descent reached the optimum point. The steepest descent can be expressed by (Falcão, 2012) (Sahoo, 2012):

$$w(n+1) = w(n) - \frac{\mu}{2}\nabla\xi(n) \tag{23}$$

Where:

μ: is the step size

$\nabla\xi(n)$: is the gradient of the error function e(n) concerning w(n).

$$\nabla\xi(n) = \frac{\partial[e(n)^2]}{\partial w} = E[|d(n)|^2] - 2p^T w(n) + w^T(n)Rw(n) = -2p + 2Rw(n) \tag{24}$$

Thus, the new filter weight is:

$$w(n+1) = w(n) - \frac{\mu}{2} = w(n) + \mu \tag{25}$$

Substituting $p = E[d(n)x(n)]$; and $R = E[x^T(n)x(n)]$ in equation 25, the update weight vector is:

$$w(n+1) = w(n) + \mu x(n)[d(n) - y(n)] \\ = w(n) + \mu x(n)e(n) \tag{26}$$

The resulting filter is called Least Mean Square Algorithm (LMS). LMS algorithm is generally used in various applications and it is discussed in the next section.

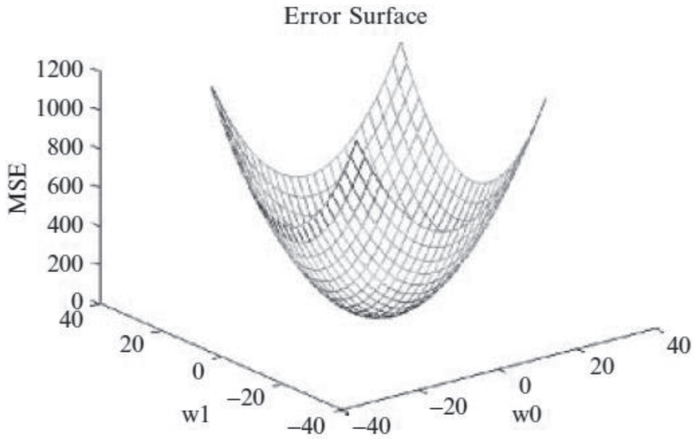

Figure 5: Performance surface

5.2. Least Mean Square Algorithm

The Least Mean Square algorithm (LMS) is designed by windrow Hoff in 1959 and it is based on the random gradient steepest descent to determine filter weight which minimizes the MSE. It is the simplest algorithm in designing adaptive filter structures (Hayes, 1996) (Dewasthale & Kharadkar, 2014). The main advantages of the LMS algorithm are strength and simplicity. The simplicity of the LMS algorithm is due to using fewer numbers of additions and multiplications. As MSE depends on the convergence factor (⊠), the strength of the LMS algorithm is related to the fast convergence rate. This fast convergence works well with large MSE values, however, with small step size (small MSE values) the convergence rate tends to be slow (Mon, et al., 2016) (Olyaee, et al., 2010). Figure 6 shows the general block diagram of the LMS algorithm.

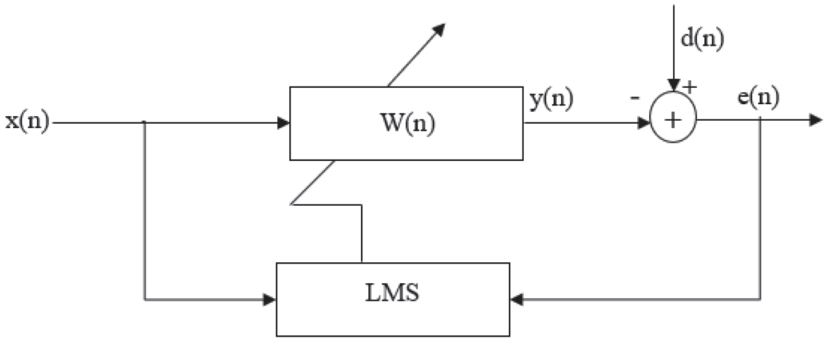

Figure 6: Adaptive filter with LMS algorithm

The output of the FIR filter y(n) is expressed by:

$$y(n) = w(n) * x(n) = \sum_{l=0}^{L-1} w_l(n)x(n-l) \tag{27}$$

Where n is the number of iterations. The error signal can be calculated by:

$$e(n) = d(n) - y(n) \tag{28}$$

Where:

d(n) is the desired output

y(n) is the output of the FIR filter

In the steepest descent adaptive filter, the updated filter equation is given by:

$$w(n+1) = w(n) + \mu E[e(n)x^*(n)] \tag{29}$$

The expectation [e(n)x*(n)] is usually unknown thus there is a practical limitation with this algorithm. Hence, the expectation [e(n)x*(n)] was replaced by an estimated sample mean.

$$\hat{E}[e(n)x^*(n)] = \frac{1}{L}\sum_{l=0}^{L-1} e(n-l)x^*(n-l) \tag{30}$$

Therefore, the update tap vector becomes:

$$w(n+1) = w(n) + \frac{\mu}{L}\sum_{l=0}^{L-1} e(n-l)x^*(n-l) \tag{31}$$

If it utilizes only one sample mean (L=1), which is a special case, the sample mean will change to:

$$\hat{E}[e(n)x^*(n)] = e(n)x^*(n) \tag{32}$$

By substituting the equation (32) into equation (29) the update weight vector for the LMS algorithm is:

$$w(n+1) = w(n) + \mu[e(n)x^*(n)] \tag{33}$$

The adaptive filter based on the LMS algorithm has 2L+2 multiplications and 2L additions per output value.

5.3. Normalized Least Mean Square Algorithm

The Least Mean Square algorithm uses a fixed convergence factor μ, when the step size is large. This algorithm experiences a gradient noise amplification problem which is solved by using the Normalized Least Mean Square algorithm (NLMS). NLMS uses a time-varying convergence factor μ(n), thus this algorithm increases the convergence speed compared to the LMS algorithm (Thenua & Agarwal, 2010). The update weight vector for the NLMS algorithm is (Poularikas, 2017):

$$w(n+1) = w(n) + \mu(n)[e(n)x(n)] \tag{34}$$

After that, we will define the Posterior error $e_{ps}(n)$, as:

$$e_{ps}(n) = d(n) - w(n+1)x^T(n) \tag{35}$$

And the Error can be calculated by

$$e(n) = d(n) - w^T(n)x(n) \tag{36}$$

By substituting equation 34 and equation 36 in equation 35, the Posterior error $e_{ps}(n)$ becomes:

$$e_{ps}(n) = [1 - \mu(n)x^T(n)x(n)]e(n), \text{ and } x^T(n)x(n) = \|x(n)\|^2 = \sum_{i=0}^{M-1}|x(n-i)|^2 \tag{37}$$

Reducing e_{ps} for □(n) is:

$$\mu(n) = \frac{1}{\|x(n)\|^2} \tag{38}$$

Substituting equation 38 into equation 34, the updating weight filter becomes:

$$w(n+1) = w(n) + \frac{1}{\|x(n)\|^2}[e(n)x(n)] \tag{39}$$

But the general updating weight vector for the NLMS algorithm is:

$$w(n+1) = w(n) + \frac{\mu}{\|x(n)\|^2}[e(n)x(n)] \tag{40}$$

Note that the □-NLMS is the improved version of the NLMS algorithm and it can be expressed by:

$$w(n+1) = w(n) + \frac{\mu}{\varepsilon + \|x(n)\|^2}[e(n)x(n)] \tag{41}$$

Where □ is a small positive number? Introduced to avoid updating the weight vector to infinity when the input signal x(n) becomes very small or zero.

5.4. Recursive Least Square Algorithm

In time-varying environments, the Recursive Least Square algorithm has super performance. However, this algorithm has stability and computational complexity problem. The main advantage of the RLS algorithm over the LMS and NLMS algorithm is a faster convergence. The purpose of the LMS algorithm is to minimize mean square error which is the sum of the squares of the difference between the desired signal d(n) and the filter output y(n). Conversely, the objective of the RLS algorithm is to reduce the weighted least-squares cost function directly from the input signal x(n) and desired signal d(n). To minimize the weighted least squares error, the RLS algorithm yields a set of filter coefficients $w_n(k)$ at sample (n) (Thenua & Agarwal, 2010) (Lampl, 2020). The weighted least-squares cost function WLS of the RLS can be expressed by (Falcão, 2012):

$$J(n) = \sum_{i=0}^{k} \lambda^{n-i} e^2(n) \tag{42}$$

Where:

□ : is the forgetting factor (0□□□1) which gives exponentially decay weight to older error samples.

e(n): is the error signal (difference between desired signal and output signal generates by a transversal filter) and can be expressed by:

$$e(n) = d(n) - y(n) = d(n) - w^T(n-1)x(n) \tag{43}$$

The tap-input vector x(n) is given by:

$$x(n) = [x(n), x(n-1), \ldots\ldots, x(n-M+1)]^T \tag{44}$$

The tap-weight vector w(n) is given by:

$$w(n) = [w_0(n), w_1(n), \ldots\ldots, w_{M-1}(n)]^T \tag{45}$$

When the tap-weights have optimum value, the value of the cost function becomes minimum. The optimum value of the tap-weights is described by the normal equation in matrix form as:

$$\emptyset(n)\hat{w}(n) = z(n) \tag{46}$$

Where $\emptyset(n)$ is the square correlated matrix and it can be expressed by:

$$\emptyset(n) = \sum_{i=0}^{k} \lambda^{n-i} x(n) x^T(n) \tag{47}$$

The z(n) is the M-by-1 cross-correlated matrix, and it can be written as:

$$z(n) = \sum_{i=0}^{k} \lambda^{n-i} x(n) d^*(n) \tag{48}$$

Where:

x(n): is the tap inputs of the transversal filters
d(n): is the desired signal

	LMS	NLMS	RLS
Input parameters	1. Initial vector w(n)=0 2. Input vector x(n) 3. Desired output d(n) 4. Step size μ	1. Initial vector w(n)=0 2. Input vector x(n) 3. Desired output d(n) 4. Step size μ, constant ε	1. Tap-weight vector $\hat{w}(n-1)$, 2. Input x(n) 3. Desired output d(n) 4. Correlated matrix $\emptyset_A{}^{-1}(n-1)$
Output parameters	1. Output of the filter y(n) 2. Tap vector w(n+1)	1. Output of the filter y(n) 2. Tap vector w(n+1)	1. Filter output $y_{n-1}(n)$ 2. Update tap-weight vector w(n) 3. Update of the Correlated matrix $\emptyset_A{}^{-1}(n)$
Computation procedure (for real function)	1. $y(n)=w^T(n)x(n)$ 2. e(n)=d(n)-y(n) 3. $w(n+1)=w(n)+\mu e(n)x^*(n)$	1. $y(n)=w^T(n)x(n)$ 2. e(n)=d(n)-y(n) 3. $w(n+1)=w(n)+\frac{\mu}{\varepsilon+x^T(n)x(n)}[e(n)x(n)]$	
Computation procedure (for complex function)	1. $y(n)=w^H(n)x(n)$ 2. $e(n)=d(n)-w^H(n)x(n)$ 3. $w(n+1)=w(n)+\mu e(n)x^*(n)$	1. $y(n)=w^H(n)x(n)$ 2. $e(n)=d(n)-w^H(n)x(n)$ 3. $w(n+1)=w(n)+\frac{\mu}{\varepsilon+x^H(n)x(n)}[e(n)^*x(n)$	1. Gain vector $k(n)=\frac{\lambda^{-1}\emptyset_A{}^{-1}(n-1)x(n}{1+\lambda^{-1}x^T(n)\emptyset_A{}^{-1}(n-}$ 2. Filtering $y(n)=w^T(n)x(n)$ 3. Error estimation e(n)=d(n)-y(n) 4. Update tap-weight vector $w(n)=w(n-1)+k(n)e^*(n)$ 5. Update of the correlated matrix $\emptyset_A{}^{-1}(n)=\lambda^{-1}\emptyset_A{}^{-1}(n-1)-\lambda^{-1}k(n)x^T(n)\emptyset_A{}^{-1}(n-1)$
Addition or subtraction	2L	3L	$2L^2+2L$
Multiplication	2L+2	3L+2	$3L^2+4L$
Division	0	1	1
Convergence (Sujathakumari, 2018)	Slow	Faster than LMS (medium)	Faster than LMS and NLMS (high)
Stability	more stable	Stable	Less stable
SNR (Hadei & Lotfizad, 2010)	Low	Better than LMS	High
Complexity (Sujathakumari, 2018)	Simple	More complex	Most complex
Cost	Low	Medium	High cost

To calculate the RLS we need to apply the matrix inversion lemma, and then we have:

$$\emptyset_A{}^{-1}(n) = \lambda^{-1}\emptyset_A{}^{-1}(n-1) - \lambda^{-1}k(n)x^T(n)\emptyset_A{}^{-1}(n-1) \quad (49)$$

Where:

$\emptyset_A{}^{-1}(n)$: is the invert correlated matrix

λ^{-1}: is the inverse forgetting factor

K(n): is the (M-by-1) gain vector

The gain vector k(n) is calculated by:

$$k(n) = \frac{\lambda^{-1}\emptyset_A{}^{-1}(n-1)x(n)}{1+\lambda^{-1}x^T(n)\emptyset_A{}^{-1}(n-1)x(n)} \quad (50)$$

Thus, the update weight vector w(n) can be calculated by:

$$w(n) = w(n-1) + k(n)e^*(n) \quad (51)$$

Table 2 show comparisons among LMS, NLMS, and RLS in term of various parameters such as input, output, computation procedure (for real and complex function), addition/subtraction, multiplication/division, stability, cost, convergence, complexity, and SNR (signal to noise ratio).

Table 2: Shows the comparison among LMS, NLMS, and RLS algorithms.

Important things that could be extracted from the table is that the least computation-intensive algorithm is the LMS and the most is the RLS. Stability-wise, the most suitable algorithm is the LMS, and the least is the RLS. NLMS algorithm is between the two. Concerning the convergence which is an important factor in digital filtration algorithms as it describes how fast the error signal is reduced, the RLS is the best and the LMS is the worst (NLMS is in-between).

6. Application of Adaptive Filtration

Adaptive filters are used in several applications such as noise reduction, telecommunication, radar, video and signal processing (audio is part of it). The performances of the adaptive filters rely on the algorithms and the design method. Adaptive filters are implemented in three ways: analogue, digital and mixed. Each has its own advantages and disadvantages. In addition, many types of filtrations are possible with adaptive filters, linear, nonlinear, FIR, and IIR (other types are also available).

Adaptive filters have four conventional applications such as noise cancellation, inverse modelling, system identification, and linear prediction (Morales, 2011). As our concern here is noise cancellation, other applications are not described in this work.

6.1. Noise Cancellation

Figure 7 shows the noise cancellation system which is consist of two microphones, the first microphone is used to measure the noise signal (r'(n)), and the second microphone is used to measure the desired signal which is corrupted by the noise signal (d(n)+r(n)). To cancel out the unwanted signal from the desired signal d(n), the adaptive filter processes the noise signal to make it equal to the noise that corrupted the signal and subtract it. Noise cancellation can be effective in many places, like cars, aircraft, headphones, medical devices, and industrial processes (Morales, 2011).

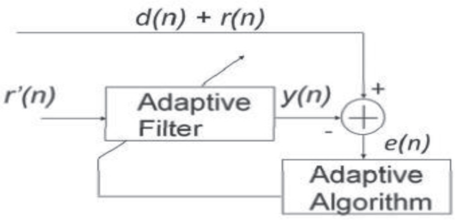

Figure 7: Adaptive noise cancellation system

Figure 8 shows the feedback ANC system inside a room. The system consists of a two-sensor, which includes an input sensor (MIC), adaptive filter, and cancelling source speaker (SPK). The input sensor is used to measure the annoying noise and provides the input to the adaptive filter.

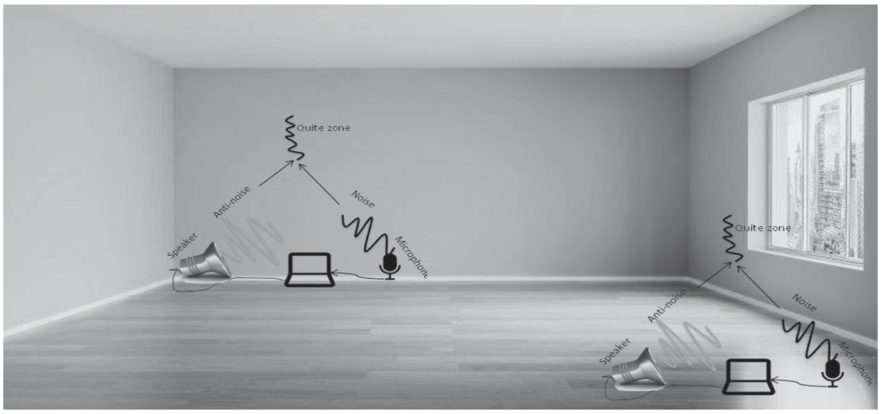

Figure 8: Feedback ANC system inside a room

7. Available ANC Systems

In this section, we list some products manufactured by companies claiming that they cancel annoying noises or are embedded with active noise cancellation. Although we have no feedback on how effective these systems are, we address them based on the company's advertisements.

Many professional headphones are labelled that it has noise cancellations. As it has been mentioned before sound cancellation should work well for headphones because the surrounding environment is very small, as headphones are directly attached to the ear.

For headphones, and if someone visits any electronic trading platforms like Amazon or Ali-express, and type "Noise Cancellation Headphones", a list of products will be shown. Here we list a sample manufactured by Sony cooperation, although mentioning that product should not be taken as pros or cons for it, but Sony is selected as it is an old company in the field of electronic products manufacturing. We choose Ali-express and the product name is "Used, Sony WH-XB900N Hi-Res Noise Canceling Wireless Headphone". The price is around 120 USD for the used one, and as the name is referring to, it has noise cancellation.

In the case of open environments, a company manufactured a product named Muzo and the advertisement for this product is: Your Personal Zone Creator with Noise Blocking Tech (Kickstarter, 2017). The cost is around 500 USD. We tried to check the availability of the product on Amazon.com, but at the time of this writing, it was not. Although, the availability of the product on Amazon should not be taken as pros or cons, as we wittiness sometimes products on that link but they are not good (not only on Amazon but on all trading platforms).

8. Conclusion

One of the goals behind this paper is to help researchers properly select the most suitable algorithm for applications-wise noise cancellation. The main techniques used for noise cancellation are described in this paper, the noise feedback control system, and the adaptive filtration algorithms. For the adaptive one, many algorithms were developed by researchers where each algorithm has different parameters based on the input/output and the update of weight coefficients. Hence, this paper review and compare the most common algorithm such as LMS, NLMS, and RLS algorithm. The LMS algorithm is more stable with less SNR (signal to noise ratio) compared to the NLMS and RLS algorithms. The RLS has higher convergence rates and signal to noise ratios, in addition to being less stable and costly.

Active noise cancellation is opening many horizons for humanity to have a better surrounding environment. It starts with the cancellation of unwanted noise signals that are annoying to humans, creates stress and anxieties, to embedding certain kinds of sounds or melodies in sound playing systems to enhance the surrounding environment. For example, in a living room these systems can reduce modern lifestyle companion noises like air-conditioner systems noises; it can also embed some nature-related sounds to please the room's occupants.

As it has been mentioned before, one of the challenges that face ANC is that it works well in closed environments and not open ones. Although, there has been some penetration by a small number of companies claiming that they manufactured systems that work for open environments, after testing it was found that they are not effective, but the pace is continuing.

الألغاء الفعال للضوضاء، أفاق جديدة لحياة أفضل

الملخص:

الحياة العصرية مصحوبة بالكثيرمن الضوضاء الأتية من استخدام الكثير من الأجهزة والمعدات. التقدم التكنولوجي والمنافسة جعلت هذهِ الأدوات أرخص سعرًا و متوفرة للجميع، و ذلك يعني توليد المزيد من الضوضاء. المنافسة بين الشركات دفعتهم إلى استخدام مواد أرخص والتركيز على الإلكترونيات لجعل منتجاتهم أرخص في النهاية، والزبون هو الضحية في النهاية. على سبيل المثال، كانت المراوح الكهربائية المصنعة في الخمسينيات والستينيات من القرن الماضي أكثر هدوأً من المراوح التي تم تصنيعها بعد ذلك .أيضًا (وبشكل عام)، كانت السيارات المصنعة في تلك الفترة أكثر هدوءًا من السيارات الحالية، وخاصة بالنسبة لضوضاء المقصورة الداخلية. لماذا كل هذا؟ السبب يعود الى المنافسة المحتدمة بين الشركات والتوجهه لاستخدام مواد بلاستيكية منخفضة التكلفة للحصول على منتج نهائي ذات سعر أرخص. نحاول هنا التأكيد على هذه المسألة وإظهار كيفية استخدام الوسائل الإلكترونية لتقليل الضوضاء البيئية للحصول على حياة أفضل. يعد استخدام هذا النهج مفتاحًا لحل هذه المشكلة خصوصآ للأشخاص ذوي الدخل المحدود. عادة ما يكون لدى الأشخاص الأثرياء خيار استخدام منتجات باهظة الثمن, تكون في العادة مجهزة بعزل صوت جيد وذلك غير متوفر لعامة الناس. ولذلك فإن هذا العمل هوالنهج الفعال من حيث التكلفة للحد من الضوضاء من حولنا، وبالتأكيد ان هذا النهج، هو النهج الإلكتروني.

الكلمات الدالة : إلغاء الضوضاء النشطة، التصفيه الرقمية، الضوضاء البيئية، التلوث الضوضائي، التصفيه التكيفه نەهێشتنی

نەهێشتنی کاریگەر بۆ ژاوەژاو، ئاسۆیەکی نوێ بۆ ژیانێکی باشترئوختة:

ژیانی مۆدێرن هاوەڵە لەگەڵ ژمارەیەکی زۆر لە ژاوەژاو. بە هۆی پێشکەوتنی تەکنۆلوجیا، ئامێر و کەڵو پەل و ئامراز هەرزانترن لە نرخدا، و بەئاسانتر دەست دەکەون، بەڵام لە زۆر کاتدا دەبنە هۆی دروستبونی رێژەیەکی زۆر لە ژاوەژاو. ڕکابەری نێوان کۆمپانیاکان بۆتە هۆکاری بەکارهێنانی کە رە ستە ی هەرزانتر، و تیشک بخنە سەر پێشکەوتنە ئەلکترۆنیەکان، بۆی بەرهەمەکانیان بە نرخیکی گونجاوتر بخەنە ڕوو و لە کۆتایدا بەکاربەر بۆتە قووربانی. بۆنمونە پانکەی کارەبایی کە لە پەنجاکان و شەستەکانی سەدەی پێشوو دروست دەکران، زۆر بێدەنگترن لەوانەی کە لە سەردەمەکانی دواتر دروست کراون. هەروەها بە شیوەیەکی گشتی ئەو ئوتۆمۆبێلانەی کەلەو سەردەمەدا دروست دەکران بێدەنگتر بوون، بەتایبەتی لە رووی ژاوەژاوی ناو ئوتۆمبێلەکە. بۆچی؟ هەمووی دەگەڕێتەوە بۆ ڕکابەری نێوان کۆمپانیاکان و بەکارهێنانی موادی پلاستکی هەرزان (کواڵتی نزم) بۆ خستنەڕووی بەرهەمێکی هەرزانتر. لێرەدا دەمانەوێت ئاماژە بەو کێشانەی سەرەوە بکەین و پیشانی دەین کە چۆن دەتوانین بە بەکار هێنانی ئامێری ئەلکترۆنی دەتوانین ژاوەژاوە کەم کەینەوە. کەمکردنەوە ژاوەژاوە دەبێتە هۆکاری باشکردنی ژینگە بەتایبەتی بۆ کەسانی کەم دەرامەت کە توانای کرینی ئامێری گرانبەهایان نیە. ئەو ئامێرانە مەوادی باشتر بەکاردەهێنرێت تیایدا و کۆمپانیاکان بە وردتر دیزانیان (design) دەکەن کە ئەمە دەبیتە هۆکاری کەمکردنەوەی ژاوەژاوەیان. زۆرینەی کات ئامێری گرانبەها درووست دەکرێن لە لایەن کۆمپانیا خاوەن ئەزموونەکان، و لە ڕووی ژاوەژاوە باشن(ژاوەژاویان کەمە)، بەڵام ئەم ئامێرانە تەنها بەردستن بۆ خەڵکانی دەوڵەمەند. ئەو رێگەیەی کە لەم تۆژینەوەیەدا خراوەتە ڕوو گونجاوە لە ڕووی تێچوونەوە بۆ کەمکردنەوەی ژاوەژاوەیەی دەوروبەرمان وە بە دڵنیایەوە لە ڕێگەی بەکارهێنانی ئامێرە ئەلکترۆنیەکانە کە لەرووکی دیکەوە خۆیان هۆکارێکی بوونیانن.

کلیلـی ووشـەکان: نەهێشـتنی ژاوەژاو، پاڵێـوەری دیجیتاڵـی، ژاوەژاوی ژینگەیـی، پیسـبوونی ژینگـەی بەهـۆی ژاوەژاوەوە ، پاڵێـوەری گونجانـدن

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