UNIVERSITI PUTRA MALAYSIA

ADAPTIVE INTERFERENCE CANCELLER USING ANALOG ALGORITHM WITH OFFSET VOLTAGE

ALAA HADI MOHAMMED

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By

ALAA HADI MOHAMMED

Thesis Submitted to the School of Graduate Studies, University Putra Malaysia, in Fulfillment of the Requirements for the Degree of Master of Science

January 2015

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DEDICATION

To my mother

Abstract of Thesis Presented to the Senate of University Putra Malaysia in Fulfillment of the Requirement for the Degree of Master of Science

ADAPTIVE INTERFERENCE CANCELLER USING ANALOG ALGORITHM WITH OFFSET VOLTAGE

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ALAA HADI MOHAMMED

January 2015

Chair: Azura Che Soh, PhD
Faculty: Engineering

The changes in signal characteristics of many interference cancellation applications could be quite fast. They require the utilization of the adaptive algorithms. Algorithms such as Least Mean Square (LMS), Normalized Least Mean Square (NLMS) and Recursive Least Square (RLS) algorithms often have poor numerical properties due to the practical implementation complexities. LMS and NLMS algorithms have been used in a wide range of signal processing applications because of their simplicity in computations compared to the RLS algorithm. The adaptation method of the LMS, NLMS and RLS algorithms quantizes the noise input signal during a limited period to track the error sample by sample. The output error signal is used for updating the weights processing the noise input signal. Since the quantization process is irreversible, an additive interference will be added to the input and output signals. This is to prevent losing the magnitude and sign information resulted from quantizing them within specific times. The output error signal used to update the weights causes an aliasing in the updated weights. This aliasing deviating the weights from their optimum values and increases the excess in the output Mean Square Error (MSE). This research describes a new approach for interference cancellation using an analog algorithm that adopts a new method to determine good tradeoff between the complexity and the convergence speed for optimum results. The proposed analog algorithm has been designed to deal directly with the continuous time domain of the input signal without quantizing it. Instead of using the error signal for updating the weights, the desired signal has been used to produce smooth weights to reduce the MSE output and to increase the convergence speed to the optimum output. In addition, the proposed algorithm has simple computational requirements that make it practically easy to be implemented. The experimental tests of the proposed algorithm have shown that the reduction percentage in the MSE output using the proposed algorithm is 51% compared to the NLMS algorithm and 61% compared to the RLS algorithm. In addition, the output Signal to

Interference Ratio (SIR) using the proposed algorithm has been doubled compared to NLMS and RLS algorithms.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Master Sains

PENYESUAIAN GANGGUAN PENGHALANG MENGGUNAKAN ANALOG ALGORITMA DENGAN OFFEST VOLTAN

Oleh

ALAA HADI MOHAMMED

January 2015

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Perubahan dalam ciri-ciri isyarat daripada banyak aplikasi pembatalan gangguan boleh dilakukan secara pantas. Mereka memerlukan penggunaan algoritma suai. Algoritma-algoritma seperti min kuasa dua terkecil (LMS), min kuasa dua terkecil ternormal (NLMS) dan kuasa dua terkecil jadi semula (RLS) sering mempunyai ciri-ciri berangka yang teruk kerana kerumitan pelaksanaan secara praktikal. LMS dan NLMS algoritma telah digunakan dalam pelbagai aplikasi pemprosesan isyarat kerana kesederhanaannya dalam pengiraan berbanding dengan algoritma RLS. Kaedah penyesuaian bagi algoritma LMS, NLMS dan RLS kuantum isyarat masukan hingar dalam tempoh terhad untuk mengesan ralat sampel dengan sampel. Isyarat ralat keluaran digunakan untuk mengemaskini pemberat yang memproses isyarat masukan hingar. Sejak pengkuantuman adalah proses tak boleh balik, gangguan tambahan akan ditambah kepada isyarat masukan dan keluaran. Ini adalah untuk mengelakkan kehilangan maklumat magnitud dan tanda akibat daripada pengkuantuman mereka dalam tempoh masa tertentu. Isyarat ralat keluaran digunakan untuk mengemaskini pemberat disebabkan pengkaitan pemberat yang telah dikemaskini. Pengkaitan ini akan menyimpang pemberat dari nilai-nilai optimum dan meningkatkan lebihan dalam keluaran ralat min kuasa dua (MSE). Kajian ini menerangkan pendekatan baru untuk pembatalan gangguan menggunakan algoritma analog yang menerima kaedah baru untuk menentukan perubahan baik antara kerumitan dan kelajuan penumpuan kepada keputusan yang optimum. Algoritma analog yang dicadangkan itu telah direka untuk berurusan secara langsung dengan domain masa yang berterusan kepada isyarat masukan tanpa pengkuantuman. Daripada menggunakan isyarat ralat untuk mengemaskini pemberat, isyarat yang dikehendaki telah digunakan untuk menghasilkan pemberat licin untuk mengurangkan keluaran MSE dan meningkatkan kelajuan penumpuan kepada keluaran yang optimum. Di samping itu, algoritma yang dicadangkan memerlukan pengiraan yang mudah dan senang dilaksanakan secara praktikal. Ujian eksperimen ke atas algoritma yang dicadangkan telah menunjukkan bahawa peratusan pengurangan dalam

keluaran MSE dengan menggunakan algoritma yang dicadangkan adalah 51% dibandingkan dengan algoritma NLMS dan 61% dibandingkan dengan algoritma RLS. Di samping itu, output nisbah isyarat kepada gangguan (SIR) bagi algoritma yang dicadangkan adalah dua kali ganda dibandingkan dengan algoritma NLMS dan RLS.

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University Putra Malaysia
ALAA HADI MOHAMMED

I certify that a Thesis Examination Committee has met on (20-1-2015) to conduct the final examination of (ALAA HADI MOHAMMED MUSA) on his thesis entitled "ADAPTIVE INTERFERENCE CANCELLER USING ANALOG ALGORITHM WITH OFFSET VOLTAGE" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the University Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Master of Science.

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LIST OF ABBREVIATIONS AND SYMBOLS

AIC	Adaptive Interference Canceller
AM	Amplitude Modulation
CDMA	Code Division Multiple Access
DA	Distributed Arithmetic
DCD	Dichotomous Coordinate Descent
DR	Data Reusing
DSP	Digital Signal Processor
DTW	Dynamic Time Warping
FPGA	Field Programmable Gate Array
ISI	Inter-Symbol Interference
ISE	Instantaneous Square Error
KCL	Kirchhoff's Current Law
LMS	Least Mean Square
LTP	Long Tail Pair
MAC	Multiplier Accumulator
MIMO	Multi-input Multi-output
MSE	Mean Square Error
NDR	Normalized Data Reusing
NLMS	Normalized Least Mean Square
PSPICE	Personal computer Simulation Program with Integrated Circuit Emphasis
PSD	Power Spectral Density
RLS	Recursive Least Square
SIR	Signal to Interference Ratio
k	Boltzmann's constant = 1.38 x 10^{-23} Joules per K
T	Absolute temperature

B	Noise bandwidth measured in (Hz)
R	Resistance measured in (ohms)
C	Capacitor measured in (farad)
ω	Angular Velocity
f	Frequency
τ	Delay Time
$\bigtriangledown$	Partial Derivative Operator
μ	Step Size
$\bar{\mu}$	Fixed Step Size
$E\{.\}$	Expected Value Operator
$\mathcal{E}$	Mean Squared Error
e_{mini}	Minimum Mean Square Error
L	Filter Length
N	Number of Stages
G	Gain
ε	Very Small Positive Number
λ_i	Eigen Values
ξ_{ex}	Excess in Mean Square Error
$\xi_{ex}\|_{ss}$	Excess in Mean Square Error at the Steady-state
η	Attenuated Noise
σ_η^2	Attenuated Noise Power
M	Misadjustment
L	Number of Eigen Values
λ	Forgetting Factor
γ	Convergence Speed Parameter
α	$\mathrm{common-base\ current\ gain}$

CHAPTER 1

INTRODUCTION

1.1 Background

Adaptive signal processing has developed widely due to increasingly availability of technology for the implementation of the emerging adaptive algorithms. These algorithms have utilized to solve a number of problems including noise or interference canceling, channel equalization, signal prediction as well as many others. Adaptive algorithms which achieve the adjusting mechanism of the system coefficients are closely related to optimization technique. In addition, the adaptive system, due to its real-time self-adjusting characteristics, is some time expected to track optimum behavior of the varying environment. In designing the adaptive system, many aspects must be taken into the account such as system structure, rate of convergence and tracking and computational aspects [1]. In the system structure, the input-output relationship of the adaptive system depends on its transfer function implementation. In the rate of convergence and tracking, the adaptive system can be made to converge fast or slowly to the optimum solution. In the computational aspects, the performance of the adaptive system must takes into the account the practical levels of computational complexity and limited-precision representation of the associated signals and coefficients.

One of these adaptive systems is the adaptive interference canceller. Interference is a general term used to describe an undesired signal affects a desired signal [2]. These undesired signals come from a variety of sources which could be considered in one of two main categories:-

- Interference that naturally comes from an internal source (random noise).
- Interference that comes from an external source.

Interference that naturally comes from an internal source is generated by all resistances such as resistors and semiconductors. This type of interference called thermal noise and it is due to the random motion of the electrons within the Conductive materials. Experimental and theoretical studies give the value of the root mean square voltage $\mathrm{V(rms)}$ of this thermal noise as

$$\mathrm{V(rms)} = \sqrt{4kTBR} \quad \text{(Volt)}, \tag{1.1}$$

Where

k - Boltzmann's constant = 1.38 x 10^{-23} Joules per K.

T - Absolute temperature.
B - Noise bandwidth measured in (Hz).
R - Resistance measured in (ohms).

Eq. (1.1) held for frequencies up to 10,000 GHz and at practical temperature [2]. Therefore, it is assumed to be valid in the practical communication systems. Thermal noise is often referred to as “band-limited white noise” because it has a uniform spectral density. Uniform spectral density means that if we have measured the thermal noise in any 1Hz bandwidth we would measure the same amount of noise. Fig. 1.1 shows the band-limited white noise.

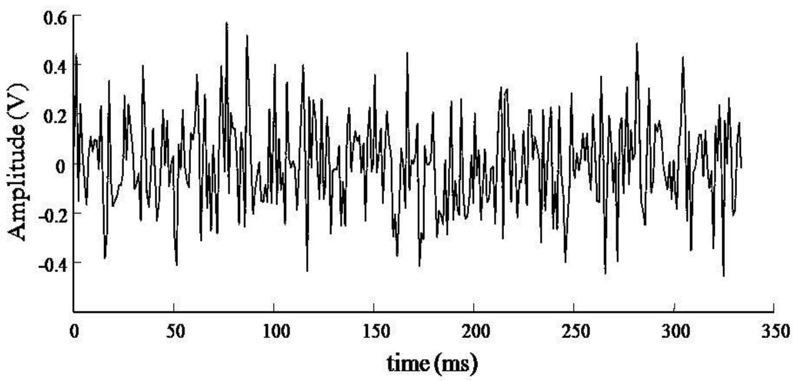

Fig. 1.1: Band-limited White Noise (Thermal Noise)

The power spectral density (PSD) of the band-limited white noise is constant over all frequencies and its unit is watt per Hz [2]. Interference that comes from an external source is due to communication systems (cross talk), harmonics, switched mode power supplies, rotating parts of power generators… etc.

1.2 Adaptation Algorithms

Adaptive algorithms are the algorithms that change their behavior according to desired information [1]. These algorithms are often used in the adaptive cancellers for achieving desired spectral characteristics to the signal and rejecting unwanted signals like noise or interference. The aim of designing these algorithms is for reducing the output mean square error and increasing the convergence speed to the optimal output. Adaptation algorithms could be summarized into two main categories; Least Mean Square (LMS) Algorithms category and Recursive Least Square (RLS) algorithms category. [1, 3].

The least mean square algorithms category included Least Mean Square (LMS), Normalized Least Mean Square (NLMS), Data Reusing-LMS (DR-LMS) and Normalized DR-LMS (NDR-LMS) algorithms. The recursive least square algorithms category included standard Recursive Least Square (RLS) and QR decomposition-based RLS (QR-RLS) algorithms. In this research, the commonly used algorithms such as NLMS and RLS algorithms have been highlighted on during the test results, because these algorithms give better results in the field of interference cancellation comparing with the others.

1.2.1 Gradient Descent

Gradient descent is a method for finding a local minimum of a function [3]. It based on the observation that if the required variable of the multi-variable function $f(x, y, ..)$ is x, and if $f(x, y, ..)$ is defined and differentiable in a neighborhood of a point x_i then $f(x, y, ..)$ decreases from x_i in the direction of the negative gradient $-\triangledown_x f(x, y, ..)$ of $f(x, y, ..)$ with respect to x at x_i . It follows that, if

$$x_{i+1} = x_i - \mu \triangledown_x f(x, y, ..)|_{x_i} \; i \geq 0 \tag{1.2}$$

then

$$f(x_i) \geq f(x_{i+1}), \tag{1.3}$$

where: μ is the step size, it is small enough for increasing the convergence speed and $\triangledown$ is the partial derivative operator such that,

$$\triangledown_x f(x, y, ..) = \frac{\partial f(x, y, ..)}{\partial x} \tag{1.4}$$

This method is used in the adaptation algorithms for minimizing the error between the desired signal and the output signal to its minimum location for achieving the optimum case in the steady state.

1.2.2 Step Size ($\boldsymbol{\mu}$) and Misadjustment ($\boldsymbol{M}$)

The step size μ is a parameter used to control the convergence speed and the stability of the LMS algorithms. Practically, the range of the step size μ is $0 < \mu < 1$ [1]. Misadjustment M of the adaptive algorithms is defined as the ratio of the excess in the mean square error in the steady-state to the minimum mean square error. It regarded to be the standard of the adaptive algorithms quality and it should be kept as small as possible [1]. The relationship between the misadjustment M and the step size μ is given as

$$M = \frac{\mu L \sigma_x^2}{2}\,, \tag{1.5}$$

where L is the number of the Eigen values of the auto-correlation matrix of the inputs and σ_x^2 is the power of the input signal [1].

1.3 Problems Statement

The problems of the previous adaptation algorithms could be summarized into two of the following aspects: the additive interference due to quantizing the continues time domain of the noisy input signal within a specific intervals and the excess in the output Mean Square Error (MSE) due to using the output error signal for producing the weights that process the noisy input signal.

1.3.1 Additive Interference Due to Quantization Process

Quantization process involves sampling the continuous time domain of the signal for converting it to discrete time domain and holding the generated samples within specific intervals [4]. Hence, the input signal is quantized by a specific quantization level. Therefore, a significant loss in the instantaneous values of the original signal will be occurred. This significant will appear in the form of an additive interference to the original signal. as explained in Fig. 1.2.

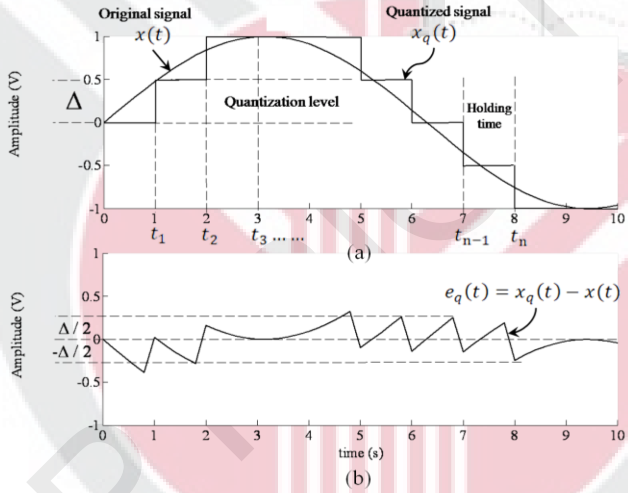

Fig. 1.2: (a) Original and Quantized Signals and (b) Error Due to the Quantization Process

From Fig. 1.2 (b), it is noticed that $e_q(t)$ is the error due to the quantization process. This error is an additive noise or interference and information loss from the original signal $x(t)$ due to the holding time $t_n - t_{n-1}$. Since $e_q(t)$ is a random variable uniformly distributed over the interval $[-\Delta/2, \Delta/2]$, the probability density function $P_e(e_q)$ of e_q is constant (flat) over this interval as shown in Fig. 1.3.

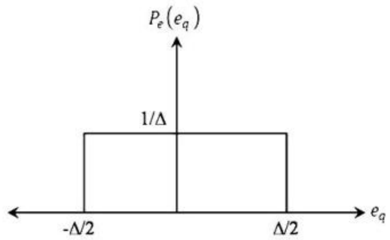

Fig. 1.3: Probability Density Function of the Quantization Error e_q

Hence, the probability density function $P_e(e_q)$ of the error e_q over the interval $[-\Delta/2\,,\ \Delta/2\,]$ is defined as

$$P_e(e_q) = \begin{cases} 1/\Delta & for \ \ -\Delta/2 < e_q \leq \Delta/2 \\ \\ 0 & otherwise \end{cases} \tag{1.6}$$

And thus, the mean square value of the quantization error $E\{e_q^2(t)\}$, by means of the probability density function $P_e(e_q)$ is

$$E\{e_q^2(t)\} = \int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} e_q^2 \ P_e(e_q)\, de_q \ = \frac{1}{\Delta}\int_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}} e_q^2\, de_q = \ \frac{1}{\Delta}\, \frac{e_q^3}{3}\bigg|_{-\frac{\Delta}{2}}^{\frac{\Delta}{2}}$$

$$= \frac{\Delta^2}{12} \tag{1.7}$$

This effective error (interference) is added to the orginal signal $x(t)$ as an information loss [4]. This means that it must be added an interference $e_q(t)$ to the original signal $x(t)$ so that the quantized signal $x_q(t)$ is generated as shown in Fig. 1.4.

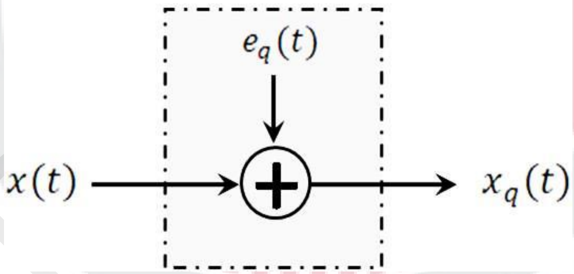

Fig. 1.4: Quantizer Representation

In conclusion, using the quantization process means an additive interference to the original signal. This additive interference is represented by the error $e_q(t)$ which is produced during the quantization process.

1.3.2 Excess in the Mean Square Error (MSE)

The previous algorithms are based on assuming that the weights w converge to their optimal values w_{op} so that the error between the desired and output signals is at its minimum value. But in fact this is not so, because the noisy gradient resulted from using the error signal for producing these weights causes an instantaneous deviation in the weights from its optimal values, this deviation in the weights could be expressed as $\Delta w = w - w_{op}$. Hence, the instantaneous deviation in the weights will generate an excess in the MSE [1]. The value of this excess in the MSE can be calculated as following:

The adaptive systems that use the previous algorithms consist of a linear combiner, i.e., the output signal $y(n)$ at instant $'n'$ is composed by a linear combination of the signals coming from an array of delayed inputs $\mathbf{X}$ weighted by array of weights $\mathbf{W}$. In this case,

$$y(n) = \sum_{i=0}^{\mathrm{N}} w_i(n)\, x_i(n) = \mathbf{W}^T(n)\, \mathbf{X}(n), \tag{1.8}$$

where, N is the length of the adaptive canceller (number of delay stages), $\mathbf{W}^T(n) = [\, w_0 \;\; w_1 \;\; . \;.\; . \;\; w_{\mathrm{N}}\,]$ and $\mathbf{X}(n) = [\, x_0 \;\; x_1 \;\; . \;.\; . \;\; x_{\mathrm{N}}\,]^T$. The output error at instant $'n'$ is given by

$$e(n) = d(n) - y(n), \tag{1.9}$$

where $d(n)$ is the desired signal. Hence, because of the instantaneous deviation in the weights, w is given as

$$w(n) = w_{op} + \Delta w(n) \tag{1.10}$$

By vectors form,

$$\mathbf{W}(n) = \mathbf{W}_{op} + \Delta\mathbf{W}(n), \tag{1.11}$$

$$\mathbf{W}^T(n) = \mathbf{W}_{op}^T + \Delta\mathbf{W}^T(n) \tag{1.12}$$

By substituting Eq. (1.12) into Eq. (1.8) yield

$$y(n) = \mathbf{W}_{op}^T\, \mathbf{X}(n) + \Delta\mathbf{W}^T(n)\, \mathbf{X}(n) \tag{1.13}$$

Therefore, the output error at instant $'n'$ (Eq. (1.9)) will be

$$e(n) = d(n) - \mathbf{W}_{op}^T\, \mathbf{X}(n) - \Delta\mathbf{W}^T(n)\, \mathbf{X}(n) \tag{1.14}$$

But $d(n) - \mathbf{W}_{op}^T\mathbf{X}(n) = e_{op}$, where e_{op} is the minimum value of $e(n)$ at the optimal weights w_{op}. Thus,

$$e(n) = e_{op} - \Delta\mathbf{W}^T(n)\, \mathbf{X}(n) \tag{1.15}$$

$$[e(n)]^2 = e_{op}^2 - 2e_{op}\, \Delta\mathbf{W}^T(n)\, \mathbf{X}(n) + \Delta\mathbf{W}^T(n)\, \Delta\mathbf{W}(n)\, \mathbf{X}^T(n)\, \mathbf{X}(n) \tag{1.16}$$

By applying the expected value operator $E\{.\}$ to Eq. (1.16), the MSE, $E\{e^2(n)\}$, at instant $'n'$ will be obtained as

$$E\{e^2(n)\} = e_{mini} - 2E\{\Delta\mathbf{W}^T(n)\}E\{e_{op}\,\mathbf{X}(n)\}$$

$$+E\{\Delta\mathbf{W}^T(n)\,\Delta\mathbf{W}(n)\,\mathbf{X}^T(n)\,\mathbf{X}(n)\} \qquad (1.17)$$

where e_{mini} is the minimum MSE $E\{e_{op}^2\}$. By the orthogonality principle $E\{e_{op}\,\mathbf{X}(n)\} = 0$ and thus, Eq. (1.17) will be

$$E\{e^2(n)\} = e_{mini} + E\{\Delta\mathbf{W}^T(n)\,\Delta\mathbf{W}(n)\,\mathbf{X}^T(n)\mathbf{X}(n)\} \qquad (1.18)$$

Therefore, the excess in the MSE, $\Delta E\{e^2(n)\}$, is

$$\Delta E\{e^2(n)\} = E\{e^2(n)\} - e_{mini} = E\{\Delta\mathbf{W}^T(n)\,\Delta\mathbf{W}(n)\,\mathbf{X}^T(n)\mathbf{X}(n)\} \qquad (1.19)$$

This excess in the MES will lead to noisy adaptation process which restricts the reaching to the desired output.

1.4 Research Objectives and Scopes

1.4.1 Research Objectives

The aim of this thesis is to improve the process of cancellation the interference associated with the analog signal by using a new algorithm that deals directly with the analog signal without quantizing it within a limited intervals. The specific objectives are:

- To produce smooth and stable weights for reducing the output MSE and increasing the convergence speed to the optimum output.
- To improve the output signal to interference ratio (SIR) with a limited number of the adaptation stages and investigating the controllability feature on the output by using an offset voltage.
- To investigate the practical implementation simplicity of the proposed analog algorithm.

1.4.2 Research Scopes

The scope of this thesis covers the adaptive algorithms which are used in the adaptive interference cancellers such as Normalized Least Mean Square (NLMS) algorithm and Recursive Least Square (RLS) algorithm. In this work, the main problems of the of these algorithms such as the excess in the output MSE due to using the output error signal for updating the weights and the additive interference due to the quantization process have been highlighted on.

1.5 New Proposed Methodology

The proposed method for minimizing the output MSE and increasing the convergence speed to the optimum output treats two aspects: the additive interference due to the quantization process and the excess in the MSE due to using the output error signal for updating the weights used in processing the noisy input signal. The additive interference due to the quantization process will be canceled by using an analog algorithm which has been designed to deals directly with the continues time domain of the input signal without quantizing it. The excess in the MSE will be reduced by using the desired signal for updating the weights instead of using the output error signal as long as the output error signal is a random process. The proposed canceller that adopts utilizing the new proposed method is named as Adaptive Interference Canceller (AIC). Fig. 1.5 shows the block diagram of the proposed AIC.

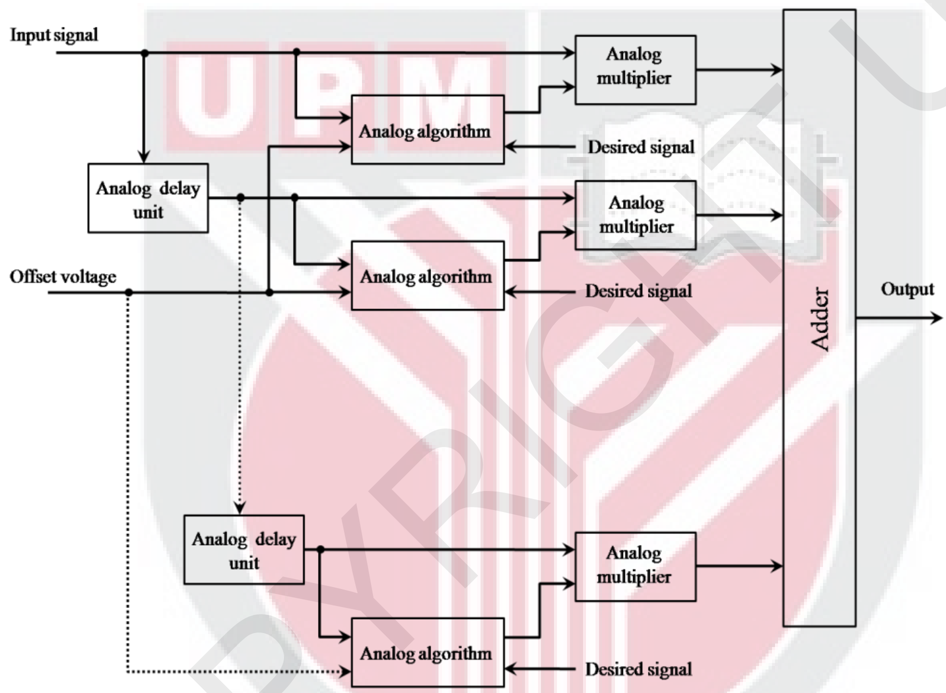

Fig. 1.5: The Block Diagram of the Proposed AIC

1.6 Outline of Thesis

The thesis is divided into five chapters:

- Chapter 1 introduces some background information on the Adaptive algorithms which are used in the adaptive cancellers and the mathematical concepts that these algorithms are based on. It also consists of the scope and objectives of the research and the new proposed methodology.
- Chapter 2 contains a literature review which present the methods used in the field of adaptive interference cancellation. In this chapter, many

methods in this field of study and the summary achievement of other researchers have been reviewed.

- Chapter 3 describes the method used in design the Adaptive Interference Canceller (AIC) which includes design the proposed analog algorithm, controllability feature on the output using an offset voltage and the practical implementation simplicity of the proposed AIC.
- Chapter 4 discusses the results obtained from the proposed method. It also presents a comparison between the obtained results and the results obtained from the previous algorithms such as Normalized Least Mean Square (NLMS) algorithm and Recursive Least Square (RLS) algorithm.
- Chapter 5 summarizes what has been achieved in this research and suggests the future work that could be carried on this thesis.

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