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A Review of Adaptive Line Enhancers for Noise Cancellation

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Abstract: This paper provides a literature review on Adaptive Line Enhancer (ALE) methods based on adaptive noise cancellation systems. Such methods have been used in various applications, including communication systems, biomedical engineering, and industrial applications. Developments in ALE in noise cancellation are reviewed, including the principles, adaptive algorithms, and recent modifications on the filter design proposed to increase the convergence rate and reduce the computational complexity for future implementation. The advantages and drawbacks of various adaptive algorithms, such as the Least Mean Square, Recursive Least Square, Affine Projection Algorithm, and their variants, are discussed in this review. Design modifications of filter structures used in ALE are also evaluated. Such filters include Finite Impulse Response, Infinite Impulse Response, lattice, and nonlinear adaptive filters. These structural modifications aim to achieve better adaptive filter performance in ALE systems. Finally, a perspective of future research on ALE systems is presented for further consideration.

Key words: Adaptive filters, noise cancellation, adaptive line enhancer, non-stationary noise, adaptive algorithms.

INTRODUCTION

Noise cancellation has recently gained much attention as a method to eliminate noise contained in useful signals (Sambur 1978, Widrow *et al*. 1985). This technique has been applied in various communication and industrial appliances, such as hands-free phones, machineries, and transformers (Hernandez 2003, Wu *et al*. 2010). In addition, noise cancellation has been implemented in biomedical signal and image processing, echo cancellation, and speech enhancement (Sasaoka *et al*. 2009, Ahmad *et al*. 2011, Kim *et al*. 2011). In acoustics applications, noise from the surrounding environment severely reduces the quality of speech and audio signals. Therefore, an adaptive noise cancellation system is used to suppress noise and enhance speech and audio signal quality.

With a basic concept first introduced by Widrow, the Adaptive Noise Canceller (ANC) removes or suppresses noise from a signal using adaptive filters that automatically adjust their parameters (Widrow *et al*. 1975). The ANC uses a reference input derived from single or multiple sensors located at points in the noise field where the signal is weak or undetectable. Adaptive filters then determine the input signal and decrease the noise level in the system output. The parameters of the adaptive filter can be adjusted automatically and require almost neither prior signal information nor noise characteristics.

However, the computational requirements of adaptive filters are very high due to long impulse responses, especially during implementation on digital signal processors. Convergence becomes very slow if the adaptive filter receives a signal with high spectral dynamic range (Haykin 2002), such as in non-stationary environments and colored background noise. In the last few decades, numerous approaches have been proposed to overcome these issues. For example, the Wiener filter, Recursive-Least-Square (RLS) algorithm, and the Kalman filter were proposed to achieve the best performance of adaptive filters (Albert *et al*. 1991, Kazemi *et al*. 2008, Ding *et al*. 2009). Apart from these algorithms, the Least Mean Square (LMS) algorithm is most commonly used because of its robustness and simplicity. However, the LMS suffers from significant performance degradation with colored interference signals (Vaseghi 2008). Other algorithms, such as the Affine Projection algorithm (APA), became alternative approaches to track changes in background noise; but its computational complexity increases with the projection order, limiting its use in acoustical environments (Sergio Ramirez Diniz 2008).

An adaptive filtering system derived from the LMS algorithm, called Adaptive Line Enhancer (ALE), was proposed as a solution to the problems stated above. According to Widrow (Widrow *et al*. 1975, Widrow *et al*. 1976), ALE is an adaptive self-tuning filter capable of separating the periodic and stochastic components in a signal. The ALE detects extremely low-level sine waves in noise, and may be applied in speech with noisy environment. Different from other ANCs with multi-sensors, the ALE simply uses a single sensor and is therefore easier to control. Furthermore, unlike ANCs, ALEs do not require direct access to the noise nor a way of isolating noise from the useful signal. In literature, several ALE methods have been proposed for acoustics applications. These methods mainly focus on improving the convergence rate of the adaptive algorithms using

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modified filter designs, realized as transversal Finite Impulse Response (FIR), recursive Infinite Impulse Response (IIR), lattice, and sub-band filters (Widrow *et al*. 1985, Cho 1990, Abid Noor *et al*. 2008, Jing *et al*. 2008).

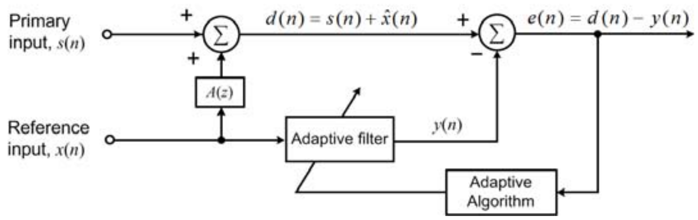


Fig. 1: Block diagram of adaptive noise cancellation system

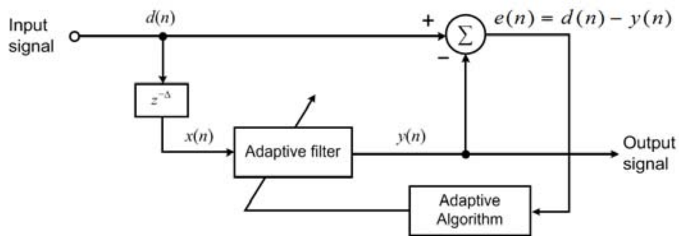


Fig. 2: Block diagram of adaptive line enhancer

The present paper critically reviews literature on ALE and the methods proposed in previous studies. Recent developments in adaptive algorithms are discussed together with structural modifications in adaptive filters used in ALE, which includes a detailed discussion about each method. Finally, a perspective on future research is suggested for further consideration.

Anc And Ale:

The ANC and the ALE are two adaptive filtering systems with similar mechanisms but slightly different filter designs. The original ANC uses two sensors to receive the target signal and noise separately, whereas the ALE uses only a single sensor to detect the target signal buried in noise, though it may use the same adaptive algorithm as the ANC.

A block diagram of a dual-input adaptive noise cancellation system with a primary sensor, a reference sensor, and an error junction is shown in Fig. 1. The primary sensor supplies a signal and a noise uncorrelated with the signal $s(n)+\hat{x}(n)$ as the primary input $d(n)$ to the canceller. A second sensor, the reference sensor, receives a noise $x(n)$, which is uncorrelated to $s(n)$ but correlated in some unknown way with the noise $\hat{x}(n)$, to provide the reference input to the adaptive filter. The $x(n)$ is transmitted over unknown channel $A(z)$ and received by the primary sensor, then filtered by the adaptive filter to produce an output $y(n)$ closely resembling $\hat{x}(n)$. $y(n)$ is subtracted from $d(n)$ to produce the system output known as error signal, or $e(n) = d(n) - y(n)$. The $e(n)$ provides the system control signal and updates the adaptive filter coefficients, which help minimize residual noise (Haykin 2002). Fig. 2 shows a block diagram of ALE with a single sensor to detect $s(n)+\hat{x}(n)$ or $d(n)$.

The ALE is in fact a degenerated form of ANC, consisting of a single sensor and delay $z^{-\Delta}$ to produce a delayed version of $d(n)$, denoted by $x(n)$, which de-correlates the noise while leaving the target signal component correlated. Ideally, the output $y(n)$ of the adaptive filter in the ALE is an estimate of the noise-free input signal. Hence, the ALE capability to extract the periodic and stochastic components of a signal can also be known as an adaptive self-tuning filter (Widrow *et al*. 1985, Campbell *et al*. 2002).

The ALE becomes an interesting application in noise reduction because of its simplicity and ease of implementation. However, to obtain the best performance in its computational process, the optimal approach is to execute ALE on a better convergence rate of adaptive algorithm with a less complex adaptive filter structure.

Adaptive Algorithms:

Attaining the best performance of an adaptive filter requires usage of the best adaptive algorithm with a fast convergence rate and low computational complexity. The LMS algorithm is the most commonly and widely used adaptive algorithm. Other adaptive algorithms that have been applied and developed to speed up the adaptive process include the Normalized LMS (NLMS), RLS, and the APA. This section discusses these algorithms and their developments to gain a better understanding of adaptive filtering techniques.

LMS Algorithm:

The most widely used adaptive filtering technique is a version of the LMS algorithm, initially proposed by Widrow and Hoff (Widrow *et al*. 1960). The LMS is based on the steepest descent method, a gradient search technique to determine filter coefficients that minimize the mean square prediction of a transversal filter.

The derivation of the LMS algorithm can be summarized as below.

$$y(n) = \mathbf{x}^T(n)\mathbf{w}(n), \tag{1}$$

$$e(n) = d(n) - \mathbf{x}^T(n)\mathbf{w}(n), \tag{2}$$

where the output of an adaptive transversal filter $y(n)$ and the error signal $e(n)$ are given by (1) and (2), respectively.

In these equations, $\mathbf{x}(n)$ is the input signal vector, and $\mathbf{w}(n)$ is the weight vector of the adaptive transversal filter. Here, the equations use the current estimate of the weight vector. The weight update recursion of the conventional LMS algorithm is given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}(n), \tag{3}$$

where μ is the step size parameter controlling the convergence rate within its suitable range. The step size value affects the convergence behavior of an LMS filter; a too low value of μ leads to extremely long convergence time of the algorithm, whereas a too high value of μ causes the algorithm to diverge, thus degrading the error performance of the adaptive filter. Therefore, choosing a suitable value for the step size is necessary when implementing the LMS algorithm as an adaptive filter. This concern has led to several attempts to control the step size, rather than choosing a fixed value or manually setting it in the LMS algorithm recursion. A good solution to this matter is time-varying step size, called Variable Step Size LMS algorithm (VSSLMS) (Aboulnasr 1997, Mader *et al*. 2000, Sasaoka *et al*. 2008, Mayyas *et al*. 2011).

Two types of VSSLMS algorithm have been proposed based on the method of obtaining the step size control equation. The first type adjusts the step size parameter according to the location of the adaptive filter coefficients compared with its optimum; larger step size values are chosen when the adaptive filter coefficients are far from optimal (Aboulnasr 1997). However, this algorithm type relies on certain criterion in adjusting the step size values; most of the time, the first type does not accurately reflect the adaptation process. Moreover, the step size equation parameters must be tuned to obtain the best performance, according to environmental conditions of the application. The second type of VSSLMS avoids the above problems by choosing step size values close to the optimum value at each time instant (Koike 2002).

The LMS algorithm has always been the ultimate choice in adaptive filtering because of its computational simplicity. LMS does not require off-line gradient estimations, repetition of data, or matrix inversion (Widrow *et al*. 1985, Haykin 2002, Sergio Ramirez Diniz 2008). Other features that attract usage of LMS algorithm are its proof of convergence in stationary environment, unbiased convergence to the Wiener solution, and stable behavior when implemented with finite-precision arithmetic. These advantages make the LMS the standard against other linear adaptive algorithms.

However, this type of algorithm suffers from significantly degraded performance with colored interfering signals (Vaseghi 2008). Likewise, computational complexity increases as the length of the adaptive filter increases. This becomes a problem in acoustics applications that require long adaptive filters to model path response, such as echo and noise cancellation. Therefore, improvements to this algorithm have been made to overcome such problems. Variants of the LMS have been developed by modifying the parameters involved in the performance of adaptive filters.

Numerous variants of LMS have been developed to best serve different applications. Well known variants are the NLMS, Leaky LMS, VSSLMS, and Filtered-X LMS (FXLMS) (Poularikas *et al*. 2006, Sergio Ramirez Diniz 2008). The weight update recursion of these versions and recent modifications of the LMS algorithm, such as the Frequency Response Shaped LMS (FRS LMS) and Hybrid LMS, are summarized in Table 1.

NLMS Algorithm:

The main drawback of the conventional LMS is the difficulty in choosing a suitable value for the step size parameter that guarantees stability. Therefore, the NLMS has been proposed to overcome this problem in controlling the convergence factor of LMS through modification into a time-varying step size parameter. The NLMS converges faster than the conventional LMS because it employs a variable step size parameter aimed at minimizing the instantaneous output error (Haykin 2002, Sergio Ramirez Diniz 2008).

The NLMS is defined as an extension of the LMS due to its step size parameter that is inversely proportional to the actual input signal energy. The second column of Table 1 shows the weight update recursion of NLMS. The value of μ has to be set within 0 and 2. A small value of γ is used to avoid possible division by zero. The NLMS has an advantage that exhibits potentially faster convergence speed than that of conventional LMS algorithm for both uncorrelated and correlated input data (Douglas *et al*. 1994).

Other developments have also been proposed to obtain even better convergence rate than that of the NLMS algorithm, such as the family of proportionate NLMS algorithm in echo cancellation system, which updates the gains proportional to current tap weights (Duttweiler 2000). This method provides tremendously fast convergence speed but still entails a modest increase in computational complexity. Apart from this development, (Vega *et al*. 2008) proposed a variable step-size NLMS algorithm by optimizing the square of the *a posteriori* error using a robust statistics approach. They tested this algorithm in system identification and acoustics echo cancelation application, and showed the algorithm's excellent performance even under severe conditions but with certain limitations.

Table1: Variations of the LMS algorithm

Algorithms	Weight update recursion	References
Conventional LMS	$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}(n)$	(Widrow *et al*. 1960, Haykin 2002)
Normalized LMS	$\mathbf{w}(n+1) = \mathbf{w}(n) + \dfrac{\mu}{\gamma + \mathbf{x}^T(n)\mathbf{x}(n)} e(n)\mathbf{x}(n),$ γ : small constant	(Haykin 2002, Sergio Ramirez Diniz 2008)
Leaky LMS	$\mathbf{w}(n+1) = (1-2\mu\gamma)\mathbf{w}(n) + \mu e(n)\mathbf{x}(n),$ γ : small constant	(Poularikas *et al*. 2006)
Variable Step Size LMS	$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)e(n)\mathbf{x}(n)$	(Aboulnasr 1997, Mader *et al*. 2000, Mayyas *et al*. 2011)
Filtered-X LMS	$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)e(n)\mathbf{x}'(n),$ $\mathbf{x}'(n) = \hat{s}(n)\mathbf{x}(n),$ $\hat{s}(n)$: the estimated response of the secondary path filter $s(n)$	(Kuo *et al*. 1999)
Frequency Response Shaped LMS	$\mathbf{h}(n+1) = [\mathbf{I} - \mu\mathbf{F}]\mathbf{w}(n) + \mu e(n)\mathbf{x}(n),$ $\mathbf{F}$ = □$\mathbf{F}_0$, where □ : constant	(Kukrer *et al*. 2006)
Hybrid LMS	$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu(n)e(n)\mathbf{x}^*(n)$ for $0 < n \le p$, $\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mathbf{R}^{-1}\mu(n)e(n)\mathbf{x}^*(n)$ for $n \ge p+1$, p : switching point from LMS to NLMS algorithm $\mathbf{R}^{-1} = E[\mathbf{x}^*(n)\mathbf{x}^T(n)]$	(Chern *et al*. 1995)

RLS Algorithm:

Another potential alternative to overcome slow convergence in colored environments is the RLS algorithm, which uses the least squares method to develop a recursive algorithm for the adaptive transversal filter. RLS tracks the time variation of the process to the optimal filter coefficient with relatively very fast convergence speed, which is practical in applications such as speech enhancement, channel equalization, echo cancelation, sound control and radar. However, RLS has stability problems and increased computational complexity compared with the LMS-based algorithms (Haykin 2002, Vaseghi 2008).

A summary of the RLS algorithm is shown as follows, which has been derived using the matrix inversion lemma from the Weighted Least-Squares algorithm (Sergio Ramirez Diniz 2008, Vaseghi 2008).

Initial value:
$$\mathbf{P}(0) = \delta^{-1}\mathbf{I},$$

Filter gain vector:
$$\mathbf{k}(n) = \frac{\mathbf{P}(n-1)\mathbf{x}(n)}{\lambda + \mathbf{x}^T(n)\mathbf{P}(n-1)\mathbf{x}(n)}, \tag{4}$$

Error signal equation:
$$e(n) = d(n) - \mathbf{w}^T(n-1)\mathbf{x}(n), \tag{5}$$

Filter coefficient adaptation:
$$\mathbf{w}(n) = \mathbf{w}(n-1) + \mathbf{k}(n)e(n), \tag{6}$$

Inverse correlation matrix:
$$\mathbf{P}(n) = \lambda^{-1}\mathbf{P}(n-1) - \lambda^{-1}\mathbf{k}(n)\mathbf{x}^T(n)\mathbf{P}(n-1). \tag{7}$$

The error signal equation in (5) describes the filtering operation of RLS, and the filter coefficient adaptation equation in (6) delineates the algorithm adaptive process, whereby the tap-weight vector $\mathbf{w}(n)$ is updated by incrementing its old value by an amount equal to the product of error signal $e(n)$ and the filter gain vector $\mathbf{k}(n)$.

Meanwhile, the filter gain vector and the inverse correlation matrix in (4) and (7), respectively, update the value of the gain vector itself.

The main problems with RLS are the potential divergence behavior in finite-precision environments and high computational complexity, which is of order of N^2, where N represents the filter length. The stability problems are usually caused by lost symmetry and positive definiteness of the matrix $\mathbf{P}(n)$. More robust implementations exist based on square-root factorization or QR decomposition of matrix $\mathbf{P}(n)$ (Vaseghi 2008). Variants of the so-called fast transversal algorithms with computational complexity of order N have been proposed for non-stationary environments (Peters *et al*. 1995, Papaodysseus 1999) and model systems for long impulse responses (Merched *et al*. 2001), but many of these variants suffer from stability problems when implemented in finite precision.

APA:

The APA can be viewed as an extension or generalization of the NLMS algorithm. In the coefficient update, APA reutilizes both past and present information, which is called data-reusing, whereas the NLMS algorithm uses only the current information. Ozeki and Umeda (Ozeki *et al*. 1984) initially studied this algorithm, and they proposed to reuse past multiple input vectors and update the weights of input vectors. The updating equations of standard APA for each iteration n are given by the following (Haykin 2002, Sergio Ramirez Diniz 2008):

$$e(n) = \mathbf{d}(n) - \mathbf{x}^T(n)\mathbf{w}(n), \tag{8}$$

$$t(n) = [\mathbf{x}^T(n)\mathbf{x}(n) + \delta\mathbf{I}]^{-1} e(n), \tag{9}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu\mathbf{x}(n)t(n), \tag{10}$$

where desired and input signal vectors are given in (11) and (12) respectively.

$$\mathbf{d}(n) = [d(n) \quad d(n-1) \quad \cdots \quad d(n-P+1)], \tag{11}$$

$$\mathbf{x}(n) = [x(n) \quad x(n-1) \quad \cdots \quad x(n-P+1)]. \tag{12}$$

Here, P is the projection order of APA, and μ is the step size parameter controlling the stability, convergence rate, and estimation error of the algorithm.

The APA has significantly improved convergence rate compared with that of the NLMS algorithm when highly correlated signals are used. However, the computational complexity of APA increases with higher projection order. This algorithm converges faster when using a higher projection order with large step-size value, but causes a large estimation error. On the other hand, low convergence rate with low estimation error are obtained when a lower projection order and smaller step size value are used (Sankaran *et al*. 2000). These problems have led to numerous new ideas in conducting APA by making the parameters variable.

An example is the Fast APA (FAPA), which increases the convergence rate when using a small step size with fixed projection order (Gay *et al*. 1995, Tanaka *et al*. 1999). Another version of APA with variable projection order has been proposed in (Kim *et al*. 2009), and called Evolutionary APA (E-APA). The projection order of the E-APA is automatically determined depending on the output error and a threshold. These two algorithms have recently been modified by applying the dichotomous coordinate descent (DCD) method, which has fewer multiplications and divisions (Zakharov *et al*. 2005, Albu *et al*. 2010). The DCD-FAPA has a similar performance with FAPA, whereas the DCD-E-APA has shown faster convergence speed with a smaller estimation error at reduced complexity compared with the standard APA.

As far as the APA step size is concerned, a few approaches of variable step size APA (VSS APA) have been proposed to develop the optimal step size for APA (Shin *et al*. 2004, Mayyas 2010, Rey Vega *et al*. 2010). Moreover, the Dynamic Selection APA (DS-APA) has been presented in which weight is updated by selecting the optimum input vectors derived by the largest mean-square deviation (MSD) decrease method (Kong *et al*. 2007). The DS-APA shows a relatively improved convergence performance, and small estimation error with low overall computational complexity compared with conventional APA. However, in terms of performance, most of these algorithms have only been compared with the standard APA, and still have relatively large estimation errors compared with the conventional NLMS.

The APA has been shown as a promising approach to balance convergence speed and computational complexity, and serves as a feasible alternative to RLS. Although many APA variations have been derived and proposed, these algorithms must be compared by looking for the best algorithm with faster convergence rate, lower computational complexity, and smaller estimation error compared with standard algorithms.

Structural Modifications Of Ale:

Widrow initially introduced the conventional ALE to eliminate noise based on the Widrow-Hoff LMS adaptive algorithm (Widrow *et al*. 1975). Since then, ALE structures have been developed using various methods to decrease its computational cost and achieve faster convergence rate. This section reviews and discusses ALE modifications using FIR, IIR, and sub-band filters, as well as other filter structures, such as cascade-form, parallel-form, and lattice-form.

Adaptive FIR filter:

For ALE design modification, the time domain FIR filter using adaptive filter weights and input has been initially proposed (Widrow *et al*. 1975, Zeidler *et al*. 1978) (McCool *et al*. 1980). The FIR filter is also known as the feedforward, non-recursive, or transversal filter in other literature, as numerous authors developed this filter type after its introduction.

The ALE structure is referred to as FIR-ALE in some literature to differentiate other structures implemented in the ALE scheme. FIR-ALE has advantages for its simplicity and stability during adaptation. However, its computational complexity increases when a large number of coefficients are required for higher SNR of input signal. Fig. 2 shows the construction of FIR-ALE using FIR filters as adaptive filter, and Fig. 3 shows the structure of the FIR filter, which is also called tap delay line filter. The structure in this figure is called direct form FIR, and can be specified by the following difference equation:

$$y(n) = \sum_{k=0}^{L-1} w_k(n)x(n-k-\Delta), \tag{13}$$

where Δ is the prediction distance of the filter, and any value Δ of delay can be chosen. The delay Δ de-correlates the noise components in the filter input with respect to those in the primary input, while introducing a simple phase shift between sufficiently large input sinusoidal components (Treichler 1979). Prediction distance Δ has been studied and shown to allow improved frequency estimation performance for multiple sinusoids in white noise for stationary inputs (Zeidler *et al*. 1978).

Obtaining the optimal value of Δ has also been studied in several studies to achieve better performance for high SNR with multiple sinusoids embedded in the input signal (Zeidler *et al*. 1978, Egardt *et al*. 1983, Yoganandam *et al*. 1988). The FIR-ALE filter is also implemented using other methods of adaptive algorithms instead of the famous LMS. An example is the Linear Approximation Method (LAM) for real time implementation purpose (Yamamoto *et al*. 2003), which uses triangular approximation to obtain a high speed coefficient estimation of FIR filter for input signals with high SNR. However, this method is employed only for cases with a single sinusoid in white noise. Meanwhile, a detailed study was done by Ziedler (Zeidler 1990) to implement real-time ALE that considers the effect of signal bandwidth, input SNR, noise correlation, and noise non-stationarity restricted to the FIR filter using the LMS algorithm (Zeidler 1990). Another approach by Said (Said 2008) employed two FIR filters to form an adaptive feedback cross-coupled line enhancer in which the output of each filter becomes the input of the other. Said tested this structure using signals with white Gaussian noise and colored noise; the study showed this structure to have better SNR performance compared with other algorithms, such as the standard LMS and transfer domain adaptive filter. An advantage of this method is that no transformation process is required in the time domain adaptive filter. However, this method has only showed results using simulation and not real noisy signals.

Adaptive IIR filter:

Subsequently, the IIR filter has been proposed as an alternative to the FIR filter-based ALE to decrease computational complexity. The IIR, also called recursive, is a filter in which the zeros and poles can be adapted. If the FIR and IIR filters utilize the same number of coefficients, the frequency response of the IIR filter can better approximate a desired characteristic. This filter requires fewer coefficients in most cases, especially when the desired model has poles and zeros (Diniz *et al*. 2010). Therefore, implementing the IIR filter is highly desirable compared with hundreds of taps in the FIR filter for some applications. However, the IIR filters are seldom used since they come with a number of difficulties, such as instability of the adaptive filter, slow convergence, error surface with local minima, and phase distortion (Diniz 2008).

The IIR-ALE is constructed using the IIR filter as the adaptive filter of ALE. Fig. 4 shows the conventional structure of the adaptive IIR filter. This structure is called the direct-form IIR filter and can be determined by the following difference equation:

$$y(n) = \sum_{m=1}^{M} a_m y[n-m] + \sum_{m=0}^{N} b_m x[n-m] \tag{14}$$

where N and M are the adaptive filter numerator and denominator orders, respectively. The main drawbacks of this structure are instability during adaptation and high coefficient sensitivities to quantization noise (Diniz

2008). Various attempts have been made to overcome these issues and the slow convergence speed mentioned earlier.

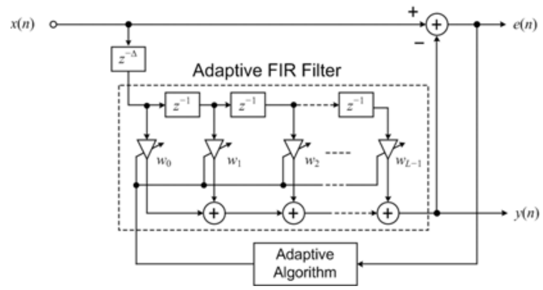


Fig. 3: Block diagram of FIR-ALE filter.

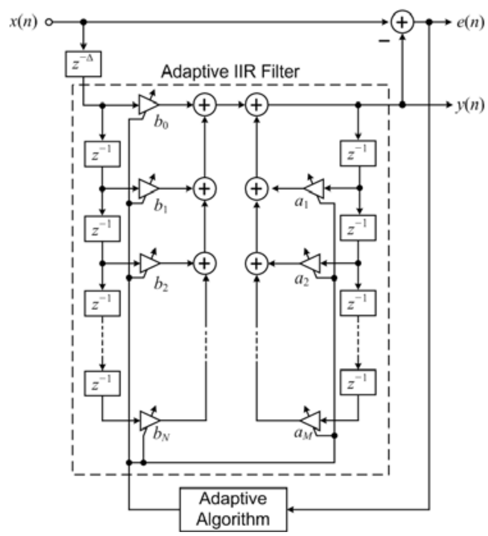


Fig. 4: Structure of ALE with direct-form adaptive IIR filter.

Rao and Kung (Rao *et al*. 1984) initially developed the adaptive IIR filter using an adaptive notch filter to enhance and track sinusoids in additive, colored, or white noise. The developed filter requires a smaller filter length, which reduces adaptation error. However, the computational complexity of the coefficient update is relatively larger compared with that of the FIR-ALE. In addition, the developed filter requires half the number of parameters compared with the autoregressive moving average model, and also requires no additional order to handle more colored noise environments. Meanwhile, Fan and Jenkin (Fan *et al*. 1988) observed that the adaptive IIR filter can provide superior performance after convergence, but that it requires longer convergence time and is also more sensitive to the proper selection of filter order for echo cancellation application. Li *et al*. (Li *et al*. 1993) proposed a realization of high stability and high convergence speed adaptive IIR filter using second-order bandpass or notch filter for single sinusoid detection. Furthermore, IIR-ALE has showed a high convergence speed when applying a variable step size to update the filter coefficient and uncorrelated noise with maximum values of the filter Q-factor and input SNR. The second-order IIR filter has become a solution for transversal filters, which require a large number of taps to achieve sharp bandpass characteristic. Belt *et al*. (Belt *et al*. 1995) considered this approach to obtain sharp bandpass characteristics with only few parameters for faster convergence speed and accuracy in frequency estimation. Belt derived two separate optimization algorithms that perform simultaneously during ALE operation, showing that fast frequency tracking is possible and the IIR filter bandwidth is automatically adjusted to the bandwidth of the uninterrupted input signal. On the other hand, Bruno *et al*. (Bruno *et al*. 2005) presented a reduced complexity IIR filter based on the Steiglitz-McBride method to avoid the local minima problem and allow a better compromise between filter order and modeling performance.

The interference sinusoidal signal may be composed of a fundamental frequency as well as any harmonic frequencies. Simple second-order notch filters and higher order IIR notch filters can be used to filter out these frequencies. However, the second-order notch filter is insufficient because it contains only one deep notch in its magnitude response, and a higher-order IIR notch filter is inefficient as it utilizes multiple adaptive filter coefficients. Therefore, an adaptive harmonic IIR notch filter has been proposed for efficient frequency estimation application in a multi harmonic frequency environment (Tan *et al*. 2009). This filter has been combined with an algorithm using a single adaptive coefficient to simultaneously estimate fundamental and harmonic frequencies. This kind of filter has been implemented on digital signal processors using a different structure of harmonic IIR notch filter (Guan *et al*. 2010).

Other adaptive filter structures:

IIR filters have also been implemented as adaptive filter on ALE systems to increase the convergence speed and decrease computational complexity. These filters have been structured using direct form, which is the simplest and easiest to realize. Instead of this structure, the adaptive filter has been developed and modified using other methods to improve its performance and meet application requirements, as well as to overcome the drawbacks of the previously discussed methods.

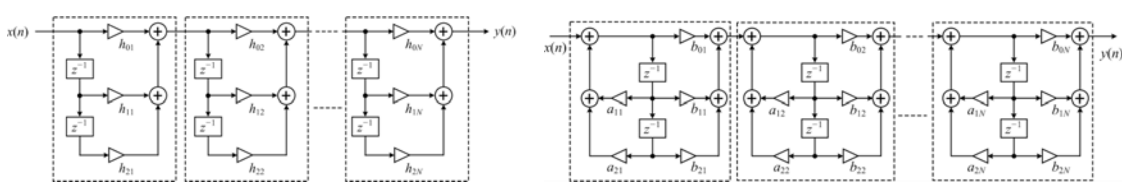
In previous subsections, the direct form of IIR filters have been reviewed, but these structures have some difficulties in terms of stability, coefficient sensitivity, and output quantization noise (Diniz 2008). Therefore, alternate solutions have been proposed in the development of adaptive filters, such as implementation using cascade structure, parallel realization, and lattice structures to overcome these issues (David 1984, Kwan *et al*. 1989, Cho 1990). All these structures allow easy stability monitoring, whereas the parallel form appears to be the most efficient in gradient computation. However, the standard parallel form may slowly converge when two poles approach each other (Diniz *et al*. 1993). These structures have been implemented using Field Programmable Gate Array and digital signal processors for various applications (Cousseau *et al*. 1996, Martinez-Peiro *et al*. 1999, Xiaojuan *et al*. 2007). In this subsection, the common alternate structures of adaptive filters, such as the cascade, parallel, and lattice form based on FIR and IIR filters, are presented and reviewed. Detailed descriptions on these structures can be found in text books about digital signal processing (Antoniou 2006, Diniz *et al*. 2010, O'Shea *et al*. 2011).

Cascade structure:

The *N*th order of the cascade form can be constructed by connecting several first- or second-order FIR or IIR filters in a series as shown in Fig. 5. The transfer function of the structure can be defined as follows for the cascade FIR filter and cascade IIR filter, respectively.

$$H(z) = \prod_{k=1}^{N} h_{0k} + h_{1k} z^{-1} + h_{2k} z^{-2}, \tag{15}$$

$$H(z) = \prod_{k=1}^{N} \frac{b_{0k} + b_{1k} z^{-1} + b_{2k} z^{-2}}{1 - a_{1k} z^{-1} - a_{2k} z^{-2}} \tag{16}$$



(a) Cascade IIR filter (b) Cascade FIR filter

Fig. 5: The second-order filter sections of (a) cascade FIR filter and (b) cascade IIR filter.

N denotes the number of sections as $N = M/2$ for even-order filters, and $N = (M+1)/2$ for odd-order filter. The structures of cascade form filters have been developed and explored using various methods to improve their performances.

The cascade FIR filter has been considered as an adaptive filter in early works, which aimed to achieve low complexity and low sensitivity (Yoshikawa *et al*. 1992, Dong *et al*. 2010). Forssen analyzed the behavior of the FIR filter with cascaded form using the gradient and normalized gradient algorithm (Forssen 1994). Meanwhile, the linear phase of the cascade FIR filter has been designed with discrete coefficients recently, and these have showed competence in achieving remarkable reduction in implementation cost and number of adders (Dong *et al*. 2011). However, realization using IIR filter is more advantageous, because it uses a lower filter order than the FIR filter to produce the same transfer function characteristics. Moreover, using the cascade form for adaptive IIR filters provides an attractive realization because the stability of filter parameterization is easily monitored, and filter pole locations are readily obtained from adapted parameters.

Williamson *et al*. discussed the structures of cascade IIR filters (Williamson *et al*. 1995) and classified them based on each of their methods. The typical cascade form of the IIR filter uses second-order sections, each with two poles and two zeros; this is referred as the standard cascade. This structure is used to simplify sensitivity and lower complexity, but has stability problems (Rao 1993). Another structure utilizes an all-pole cascade of second-order sections in a series, followed by a tapped delay line to realize the numerator, which is named all-pole based cascade. Similar to the standard cascade, this structure also possesses stability problems and is of lowest complexity. Williamson suggested two structures of cascade-form realization using an all-pole section. Williamson constructed the first structure of the all-pole section, called tapped cascade, with the filter output from weighted taps taken from the structure interior. The second structure expands the tapped cascade to create orthogonal signals at the taps. Therefore, such structures are called orthogonal tapped cascades, and these have been compared using two algorithms, namely, the NLMS and Gauss-Newton algorithms. According to analysis, the standard cascade is poor in sensitivity complexity and error surface geometry, as well as possesses the lowest convergence speed. Meanwhile, the tapped cascade indicates superior performances in all aspects with only $3N+1$ multiplications of computational complexity.

Parallel structure:

The parallel form can be constructed using the first or second-order filter sections of the FIR or IIR filter, as shown in Figs. 5(a) and (b), respectively, based on the parallel configuration shown in Fig. 6. The transfer function of this structure can be represented by the following equation:

$$H(z) = \sum_{i=1}^{M} H_i(z) \tag{17}$$

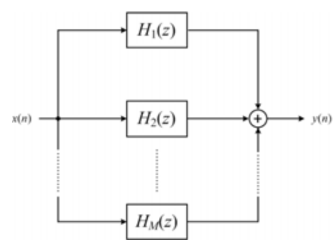


Fig. 6: The parallel structure of $H(z)$.

where $H_i(z)$ indicates the transfer function of each filter section, similar to those in Equations (15) and (16).

In previous works, this structure has been realized with FIR and IIR filters to overcome the problems associated with computational costs, convergence speed, and filter stability. The realization of parallel-form FIR filter has been examined to improve the FIR filter efficiency, because it can be used to reduce power consumption. The design quality of the parallel-form FIR filter has been discussed in (Shang *et al*. 1998) using several algorithms based on LMS. Later, parallel FIR filter implementation with low hardware complexity has been proposed in (Chao *et al*. 2007) using two stages of parallel FIR filter structures. Apparently this method could efficiently reduce the number of required multiplications and additions at the cost of delay elements. In addition, the proposed method also has small structures and simple control signals which facilitate VLSI implementation. On the other hand, this form has been proposed for the implementation on ALE with second-order IIR filters to enable applications involving detection and enhancement of multiple narrowband signals (David 1984). However, the selection of the number of sections, M, and initial condition to the adaptive coefficients must be considered to provide rapid convergence rate.

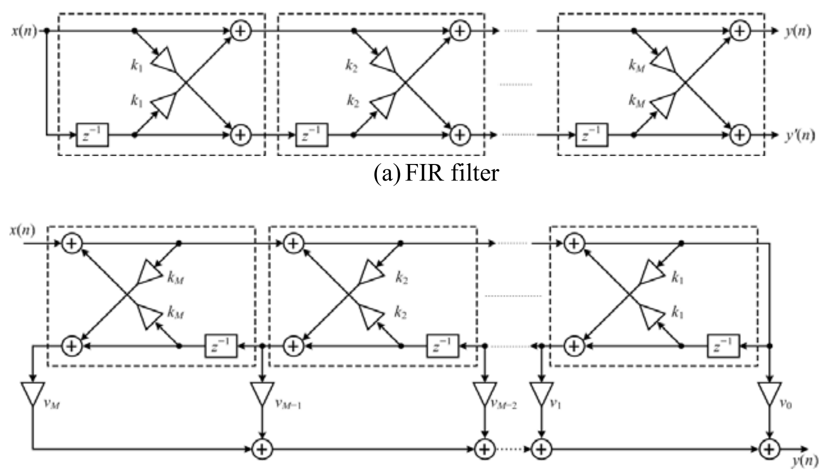
Lattice structure:

Another method in adaptive filter realization is the lattice structure developed in detail by Gary and Markel (Gray *et al*. 1973) for digital filter realization. Fig. 7 illustrates the configuration of this structure, which is constructed using single or two multipliers and delays. In the adaptive filtering method, the value of multipliers is chosen using an adaptive algorithm instead of a fixed value. This structure has several advantages: it is easy to develop and program as a recursive procedure for filter design, extremely efficient, and requires no simultaneous equation solution for tap gains.

Equations of the two-multiplier lattice-form FIR filter can be expressed as shown in (18) and (19), with its configuration shown in Fig. 7(a).

(a) FIR lattice filter (b) IIR lattice filter

Fig. 7: Basic block of two-multiplier and a delay of (a) FIR lattice filter and (b) IIR lattice filter.



(a) FIR filter

(b) IIR filter

Fig. 8: Lattice form realization of M-th (a) FIR lattice filter and (b) IIR lattice filter.

$$f_M[n] = f_{M-1}[n] + k_i b_{M-1}[n-1], \tag{18}$$

$$b_M[n] = b_{M-1}[n-1] + k_i f_{M-1}[n], \tag{19}$$

M is the filter order, k is the filter coefficient, and i = 1, 2, …, M, with $f_0 = b_0 = k_0 x[n]$ and $f_M = y[n]$. Meanwhile, Fig. 7(b) shows the lattice-form IIR filter, also called the lattice inverse filter, using two-multipliers. The equations derived from this form are represented as follows:

$$f_M[n] = f_{M-1}[n] + k_i b_{M-1}[n-1], \tag{20}$$

$$b_M[n] = k_i f_{M-1}[n] + b_{M-1}[n-1]. \tag{21}$$

Figs. 8(a) and (b) show the structures of the Mth-order lattice-form FIR and IIR filter, respectively. These structures have been implemented as adaptive filters in ALE, as shown in Fig. 2. Stability of the lattice-form IIR filter can be ensured if the coefficients fulfill the condition below.

$$|k_i| < 1, \text{ where } i = 1, 2, \dots, M. \tag{22}$$

The lattice realization has been developed for its superior transient properties and ability to reduce sensitivity to quantization errors (Leib *et al*. 1987). Apart from that, the filter coefficients can be adjusted independently without changing the rest of the filter, if additional sections must be added when the lattice filter order increases (Friedlander 1980). For ALE implementation, Reddy *et al*. (Reddy *et al*. 1981) derived the lattice-form FIR filter using RLS algorithm in ALE system for a single sinusoidal signal in broadband noise, showing the method's superiority compared with conventional FIR filters via LMS implementation using a suitable delay parameter Δ value rather than the standard choice. The same method has also been used to analyze the ALE steady-state response for a single sinusoidal signal in lowpass noise, with a suitable value of delay parameter (Reddy *et al*. 1981). However, both previous works by Reddy only used single sinusoidal signals buried in noise on the lattice structure of FIR-ALE.

Meanwhile, Cho proposed a simple and efficient means to retrieve single sinusoidal signals corrupted with noise using ALE through a second-order lattice-form IIR filter with section coefficients adapted using the variation of the Burg algorithm to maintain the poles of the IIR filter in the unit circle, satisfying the filter stability condition when parameters have been converged (Cho *et al*. 1989). This approach requires less computational burden compared with the direct-form IIR filter (Rao *et al*. 1984) and less sensitive to variation of input SNR and input frequencies. Cho also analyzed the method performance in (Cho *et al*. 1990), and investigated the same method using multiple sinusoids. The method requires computational complexity of $O(N)$ compared with $O(N^2)$ in other earlier works (Kwan *et al*. 1989), and the adaptation algorithm is simpler. Watanabe *et al*. (Watanabe *et al*. 1985) studied the second-order lattice filter to develop a low sensitivity lattice filter using minimum multipliers for a single sinusoid signal corrupted by noise. This method is implemented in the realization of a fourth-order ALE using two components of the second-order lattice filter (Watanabe *et al*. 1994). The center frequency of this fourth-order lattice ALE can be operated using the same adaptive algorithm, i.e., LMS as the second-order lattice ALE. However, these early works have only focused on using single sinusoidal signals interfered by noise as input signal to the system; certain applications, such as harmonics, involve various components in an input signal and cannot benefit from these results. Thus, Leib *et al*. (Leib *et al*. 1987) presented an analytical study of the lattice filter for ALE, but the input signals they used consisted of multiple sinusoid signals in white noise. They showed comparable results to conventional transversal ALE filter when stochastic gradient is used as adaptive algorithm. Recently, the lattice-form FIR filter has also been implemented as a component of noise reduction system in speech enhancement applications presented by Takemoto (Takemoto *et al*. 2010) to improve noisy speech quality and suppress background noise.

Nonlinear adaptive filters:

The adaptive filters elaborated in previous subsections are mainly categorized to be linear, which estimates a desired response using a linear combination of an available set of observables applied to the filter input. Other than that, the adaptive filter is considered as nonlinear.

Gabor (Gabor 1954) first introduced the idea of a nonlinear adaptive filter using a Volterra series. Examples of nonlinear adaptive filters are extended Kalman, Volterra, and neural filters. Nonlinear adaptive filters can produce better results than conventional linear adaptive filters in noise reduction (Stella *et al*. 2006). Recently, the artificial neural network (ANN) has been widely utilized as a nonlinear adaptive filter in system identification (Gupta *et al*. 1999, Prasad *et al*. 2003), pattern recognition (Anagun 1998), speech enhancement (Knecht *et al*. 1995, Fah *et al*. 2000), image processing (Kong *et al*. 1996, Egmont-Petersen *et al*. 2002), and adaptive beam-former for antenna array applications (Du *et al*. 2002). A neural network is a massive parallel distributed processor made by simple processing units known as neurons. The network has a natural propensity for storing experiential knowledge and making it available for use (Vapnik 1998). The basic theory of ANN can be found in (Gurney 1997).

The neural network has also been proposed as an adaptive filter in noise cancellation and adaptive line enhancement (Ramli *et al*. 2012). Magotra *et al*. (Magotra *et al*. 1991) used a neural network system for seismic discrimination where the network input consists of the ALE filter coefficient. The ALE used is known as the adaptive correlation enhancer, which suppresses noise between several distinct polarized phases of the seismic signal and enhances the phase onset. In another study, Choi *et al*. (Choi *et al*. 2000) used the neural network as an adaptive filter in conventional ALE, named as Neural Network-based ALE (NALE) for biomedical application, as shown in Fig. 2. ANN is capable of processing nonlinear signals and learning from its environment, thus NALE is believed able to cope with the nonlinearity inherent in background noise. This system is effective in extracting and enhancing the weak QRS complex from the electrocardiography signal corrupted with background noise. Later, Patra *et al*. (Patra *et al*. 2005) utilized this system to detect and track dim objects in forward-looking infrared imagery. NALE development has also been studied to compare its performance with the common linear adaptive filter structure, showing improved noise reduction performance (Ramli *et al*. 2012). Despite its capacity as an alternative method in adaptive filtering, the neural network depends largely on the amount of training time and its structural size, ruling it out from many real-time applications.

Perspective Of Future Research:

Widrow *et al*. (Widrow *et al*. 1975, McCool *et al*. 1980) first presented an ALE implementation using the LMS to provide real-time potential for many applications. Sinusoids have been separated from broadband noise with a relatively simple algorithm, faster convergence speed, and low computational complexity. Consequently, the ALE has been investigated and applied for a wide range of applications, including frequency estimation (Ramli *et al*. 2010), speech enhancement (Sasaoka *et al*. 2009, Takemoto *et al*. 2010), mobile communication (Varma *et al*. 2004, Wu *et al*. 2005), biomedical applications (Madhavan 1992, Mitchell 1999, Choi *et al*. 2000), automobiles (HernÃ¡ndez 2003), and image processing (Youlal *et al*. 1992, Fahmy *et al*. 2003). Extending the use of this system in various other potential applications using better performance adaptive algorithms and elegant adaptive filter structures to reduce or eliminate noise contained in the signal would be interesting future research. Each algorithm has operational limitations; an intelligent system could be developed whereby the parameters describing variations in noise signals may be utilized to select a suitable adaptive algorithm to reduce noise in the target signals. Hence, an optimal algorithm can be selected and used to reduce the noise in different signal segments.

Conclusion:

This paper reviewed existing literature related to adaptive filtering in noise reduction using an adaptive line enhancer (ALE) instead of an adaptive noise canceller (ANC). ALE was developed based on the ANC concept, whereby both systems may use similar adaptive algorithms and adaptive filter structures. ALE has the advantage of employing only a single input signal compared with conventional ANC; therefore, using ALE in parameter control and manipulation to obtain a clean output signal is easier than using ANC. The widely used adaptive algorithm of ALE is the LMS because of its fast convergence speed and low computational complexity. However, various adaptive algorithms have also been developed to obtain better performance compared with those of conventional LMS for various applications that need to be relatively faster and low-cost. The review discussed structures of adaptive filters that have been implemented to execute adaptive algorithms. Utilizing the adaptive filter and adaptive algorithm with low computational complexity, fast convergence speed, and elegant filter structural design, alongside intelligent adaptation algorithms, is desirable for future implementation.

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