Active noise cancellation of variable frequency narrow band noise using mixture of RLS and LMS algorithms

Hadi Sadoghi Yazdi*

Department of Computer Engineering,
Ferdowsi University of Mashhad,
Mashhad, Iran
E-mail: h-sadoghi@um.ac.ir
*Corresponding author

Ahmad Mardani Mehrabad

Telecommunication Co., Tehran, Iran
E-mail: Ahmad_mardani2002@yahoo.com

Saeed Mirghasemi

Department of Computer and IT Engineering,
Islamic Azad University Parand Branch,
Parand, Iran
E-mail: s.mirghasemi@gmail.com

Mojtaba Lotfizad

Department of Electronic Engineering,
Tarbiat Modares University of Tehran,
Iran, Tehran
E-mail: lotfizad@modares.ac.ir

Abstract: Due to the good tracking behaviour of the LMS adaptive filter in a noisy environment, the FX-LMS algorithm is proposed in the literature as a method of active noise control, ANC. But each of the LMS and RLS algorithms have their own advantages and disadvantages. In this paper, a new approach based on a mixture of the RLS and LMS algorithms, RLMS, is presented. The optimum weights of the mixture are derived and it is proved that the MMSE of the proposed system is reduced compared to those of the RLS and LMS algorithms. Then, the proposed RLMS algorithm is employed for active noise cancellation to form the FX-RLMS algorithm, in a duct. Experimental results show better performance of the RLMS algorithm compared to both the RLS and LMS algorithms of convergence and tracking behaviour in the system identification problem and noisy chirp tracking. The FX-RLMS algorithm shows better results in active noise cancellation compared to the FX-LMS algorithm.

Keywords: LMS; least mean square; RLSs; recursive least squares; FX-LMS algorithm; mixture of adaptive filter; ANC; active noise control.

Biographical notes: Hadi Sadoghi Yazdi received the BS Degree in Electrical Engineering from Ferdowsi Mashad University of Iran in 1994, and then he received to the MS and PhD Degrees in Electrical Engineering from Tarbiat Modarres University of Iran, Tehran, in 1996 and 2005, respectively. He works in the Department of Computer Engineering as Associate Professor at Ferdowsi University of Mashhad. His research interests include pattern recognition, and optimisation in signal processing.

Ahmad Mardani Mehrabad received the BS Degree in Electrical Engineering from Amir Kabir University of Technology, Tehran, Iran in 2000, and the MS Degrees in Electrical Engineering from Mazandaran University of Mazandaran, Iran in 2003. He is currently with Telecommunication Company of Tehran, Iran. His research interests include signal processing and networking.

Saeed Mirghasemi received the BS Degree in Electrical Engineering from Semnan University of Semnan, Iran in 2006, and his MS Degrees in Electrical Engineering from Malek Ashtar University of Tehran in 2009, Iran. He is currently with Islamic Azad University Parand branch, Parand, Iran. His research interests include adaptive filtering, intelligent image processing and fuzzy processing.

Mojtaba Lotfizad received the BS Degree in Electrical Engineering from Amir Kabir University, Iran, in 1980, and the MS and PhD Degrees from the University of Wales, UK, in 1985 and 1988, respectively. He then joined the Engineering Faculty Tarbiat Modarres University, Iran. He has also been a Consultant to several industrial and government organisations. His current research interests are signal processing, adaptive filtering, speech processing, and specialised processors.

1   Introduction

In recent years, acoustic noise cancelling by active methods, owing to its numerous applications, has been in the focus of interest of many researches. Contrary to the passive method, it is possible by using the active method to suppress or reduce the noise in a small space particularly in low frequencies (below 500 Hz) (Prandoni and Vetterli, 1998; Sadoghi Yazdi et al., 2004). ANC was introduced for the first time by Lveg (1936) for suppressing the noise in a duct (Elliott and Nelson, 1993). In the active control method by producing a sound with the same amplitude but with opposite phase, the noise is removed. For this purpose, the amplitude and phase of the noise must be detected and inverted. The developed system must have the adaptive noise control capability (Strauch and Mulgrew, 1998). In usual manner, an FIR filter is used in ANC whose weights are updated by a linear algorithm (Das and Panda, 2004; Das et al., 2006). Using the linear algorithm of the LMS is not possible owing to the non-linear environment of the duct and appearing the secondary path transfer function $H(z)$. Hence, the FX-LMS algorithm is presented in which the filtered input noise $x'(n)$ is used as an input to the algorithm (Tan and Jiang, 2001; Sicuranza and Carini, 2004). The notable points in the ANC are as follows:

- The duct length and the distance between the system elements are such that the system becomes causal (Prashanth et al., 2008).

- Regarding the speaker response, no decrease will be obtained in frequencies below 200 Hz (Sadoghi Yazdi et al., 2004). Also, passive techniques for reducing the noise in frequencies below 500 Hz have not been successful (Prandoni and Vetterli, 1998; Sadoghi Yazdi et al., 2004). Therefore, the ANC systems are used in the range of 200–500 Hz and above 500 Hz.

The existence of non-linear effects in the ANC environment complicates the use of the FX-LMS algorithm and similar algorithms. Divergence or slow convergence is among these difficulties. Some of research works in recent years (2008–2009) are reviewed in the next section.

1.1   Recent works over ANC

ANC has gained a lot of significance in the recent past because of its potential use in low-frequency ANC applications (Elliott and Nelson, 1993). FX-LMS algorithm is one of the simplest methods for ANC applications. Because of the poor performance (Strauch and Mulgrew, 1998) of the FX-LMS algorithm in the case of non-linear noise processes, two non-linear adaptive algorithms, namely Filtered-S LMS (FSLMS) algorithm (Das and Panda, 2004; Das et al., 2006) and Volterra Filtered-X LMS (VFXLMS) algorithm (Tan and Jiang, 2001; Sicuranza and Carini, 2004), have been proposed. Computationally efficient fast implementation of these two algorithms is presented in Prashanth Reddy et al. (2008). The concept of reutilising a part of the computations performed for the first sample while computing the next sample, for a block length of two samples, is exploited to implement the fast and exact versions of the FSLMS and VFXLMS algorithms. Akhtar et al. (2009) investigate new methods for online Feedback Path Modelling and Neutralisation (FBPMN) in multichannel ANC systems for improving the degraded performance of strong acoustic feedback. The modification is to combine the role of the FBPM and FBPN filters into one FBPMN filter, which results in reduced computational complexity. Improved convergence performances with the ANC structure proposed in Akhtar et al. (2006) were obtained by introducing the delay compensation, and by removing the auxiliary noise from the error signal of the control filter. They used two adaptive filters, one for adapting the control filter and one for modelling the secondary path. Carini and Malatini (2008) introduce two improvements in the feedforward ANC system with online secondary path modelling developed by Akhtar et al. (2006). First, optimal variable step-size parameters are derived for the adaptation algorithms of the secondary path-modelling filter and of the control filter. Second, a self-tuning power scheduling for the auxiliary noise is introduced. A few papers like Flotte-Hernández et al. (2008) have worked on real constructed ANC systems where LMS algorithms were used to achieve noise suppression.

In this paper, the FX-LMS and FBFXLMS algorithms were implemented and tested to cancel noise over a prototype of a duct network using DSP processors.

In this work, a new structure is substituted to the LMS and the FX-LMS algorithm is improved to the FX-RLMS algorithm.

1.2 Related work in the adaptive filtering theory

Adaptive filtering is employed in a variety of applications to help modelling of time-variations of system parameters. In lack of a priori knowledge of the statistical model of the input signal, a wide range of algorithms has been developed. Among these, the LMS (Widrow and Stearns, 1984) algorithm is very attractive, as it provides an efficient, robust and low-complexity solution. Also, the simplicity of the LMS algorithm has made it an important benchmark for other algorithms. The ability of the LMS algorithm to operate in a non-stationary environment has been investigated by many authors (Widrow and Walach, 1984; Macchi, 1986; Farhang-Borojeny and Gazor, 1996). However, the slow convergence of the LMS algorithm for inputs with large eigenvalue spreads may lead to the use of the RLS algorithm (Haykin, 1996). On the other hand, the low tracking capability of the RLS algorithm in noisy environments (Haykin, 1996) makes it impractical to be used as a suitable adaptive filtering algorithm in low SNRs.

Historically, several methods have been developed to improve the performance of the LMS and RLS algorithms by combining both (Ysebaert et al., 2003; Yu and Chung Ko, 2003; Huang et al., 2008). Reduction of the complexity by combining RLS and LMS is considered in Ysebaert et al. (2003) wherein, a part of Kalman vector of RLS algorithm is updated with the LMS algorithm. Because of its application for per-tone equalisers, this method works in frequency domain and its implementation is too complicated. Owing to utilisation of Kalman filters, this method is restricted only to autoregressive signals. Yu and Chung Ko (2003) and Huang et al. (2008) are two different configurations of cascaded RLS and LMS. To solve the slow convergence problem of the LMS algorithm, a low-order RLS predictor is cascaded prior to the LMS predictor in Yu and Chung Ko (2003). Although Yu and Chung Ko (2003) is one of good research works on mixture of RLS and LMS for lossless compression but the tracking performance and reliability of the system are not considered. Huang et al. (2008) use cascaded RLS–LMS Predictor in MPEG-4 lossless audio coding. This research is constituted from several cascaded RLS, LMS and DPCM predictors. Therefore, the implementation complexity and amount of computations, owing to applying of high-order LMS and RLS predictors, are too much. In Oikawa and Tetsuya Shimamural (2006), a kind of parallelisation of RLS and LMS is discussed. It used two estimators. The first of which is the LMS and the second one is the RLS. This configuration is not really parallel, because the error signal of the first estimator is used as the desired signal for the

second estimator. Moreover, unlike our method, it does not have any combination of RLS and LMS at the end. Schober and Gerstacker (2001) are not talking about combination of RLS and LMS with each other. It has depicted the efficiency of separate combination of RLS and LMS with NSE against carrier phase variations in receivers. None of the above-mentioned works applied for automatic noise cancellation in a duct. Briefly, in this method, the input is decorrelated by using a suitable transformation before applying the LMS adaptation in the frequency domain (Haykin, 1996) or time domain (Oikawa and Tetsuya Shimamural, 2006; Schober and Gerstacker, 2001; Mboup et al., 1994). In Hansler (1990), the probability density function of the signal and error was utilised in the RLS algorithm. The MAP[1] estimator is cascaded to RLS and reduction of MSE[2] was obtained.

We proposed a new combination of RLS and LMS for ANC. Our three principles here are:

a When comparing the LMS and RLS algorithms individually, we have the LMS as a better tracker while the RLS has faster convergence speed. We are seeking for a combination that first we can benefit from the primary fast convergence speed of the RLS algorithm, and second, we can have the good tracking performance of the LMS algorithm after convergence.

b An efficient system is the one that is adjustable for different situations. So, we want to design a system that according to application, one of the RLS and LMS methods plays the dominant role in the ANC. In other words in systems with faster convergence, w_{RLS}, and for systems with more tracking ability, w_{RLS}, should be more pronounced.

c Increasing the reliability of the whole system is our last goal in mixture of the LMS and RLS algorithms. In a real constructed system, it is possible to have failure in one of RLS and LMS blocks, which means one of them is not working. In such a situation, we should have a system that is still workable.

The proposed method in this paper, mixture of RLS and LMS, namely the RLMS[3] algorithm has a better tracking performance and a lower MMSE[4] compared with the RLS and LMS algorithms. The proposed RLMS algorithm is configured for the ANC problem.

Section 2 is devoted to the proposed RLMS algorithm. Section 3 of the paper concerns the investigation of the ANC in a duct. In Section 4, application of the proposed RLMS algorithm is presented in the system identification problem, the noisy sinusoidal chirp tracking and ANC and finally, conclusions are derived in the final.

2 RLMS algorithm

We combine the LMS and RLS algorithms in a parallel form. At first, we briefly review the LMS and RLS algorithms.

2.1   The LMS algorithm

The LMS algorithm is an important member of the family of gradient algorithms. A significant feature of the LMS algorithm is its simplicity and good tracking properties in identification problem at low SNRs. The LMS is a linear adaptive filtering algorithm that consists of a filtering process and an adaptation process according to the following equations:

Filtering process:

$$y_k = X_k^T W_k. \tag{1}$$

Adaptation process:

$$W_{k+1} = W_k + \mu e_k X_k,$$

where

$$e_k = d_k - y_k. \tag{2}$$

The weight vector of the estimator at time index k is $W_k = [W_1,\ldots,W_L]^T$ and $X_k = [x_1,\ldots,x_L]^T$ the L element vector of the samples of a buffered data sequence, which is a stationary random process, and L is the number of filter taps and e_k is the estimation error and d_k represents the desired response and μ is the step size.

2.2   The RLS algorithm

The RLS filter is an adaptive, time-update version of the Wiener filter. Its goal is to minimise the weighted sum of the squared error, i.e., the error function in the time domain obtained from equation (3)

$$\varepsilon_k = \sum_{i=1}^{k} \lambda^{k-i} e_i^2, \tag{3}$$

where e_k is the error signal, $e_k = d_k - X_k^T W_k$ and λ is the forgetting factor. The filter weights are obtained as,

$$W_{k+1} = W_k + R_k^{-1} X_k e_k, \tag{4}$$

where R_k is the input autocorrelation matrix and its inverse, R_k^{-1} is obtained recursively from the following equation (Haykin, 1996),

$$R_k^{-1} = \lambda^{-1} R_{k-1}^{-1} - \frac{\lambda^{-2} R_{k-1}^{-1} X_k X_k^T \left(R_{k-1}^{-1} \right)^T}{1 + \lambda^{-1} X_k^T R_{k-1}^{-1} X_k}. \tag{5}$$

2.3   The proposed RLMS algorithm

We combine the LMS and RLS algorithms in a parallel form, as shown in Figure 1. In a system identification configuration, the outputs are fed to an adaptive linear combiner.

As depicted in Figure 1, we have increased the reliability of the whole system with parallelisation of the LMS and RLS. In real constructed systems, with failure in one of the RLS and LMS blocks, the whole system is still workable in the noise cancellation configuration, although with a reduced efficiency.

Figure 1   The configuration for RLMS algorithm, in system identification problem
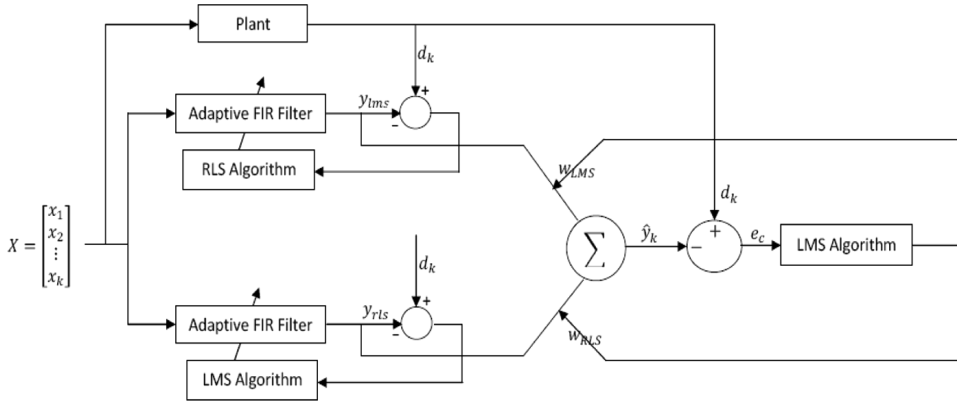
In the following equations, the optimum weights of the combiner are derived and it is proved thopat the MMSE of the RLMS is decreased compared with those of the RLS and LMS algorithms.

$$e_c = d - (w_{LMS} y_{LMS} + w_{RLS} y_{RLS}) \tag{6}$$

where e_c is the error output of the proposed system and d is the desired signal and w_{LMS} and w_{RLS} are weights by which the outputs of the LMS and RLS algorithms are weighted, respectively.

y_{LMS} and y_{RLS} are outputs of the LMS and RLS filters, respectively.

$$y_{LMS} = d - e_{LMS} \tag{7}$$

$$y_{RLS} = d - e_{RLS}. \tag{8}$$

e_{LMS} and e_{RLS} are the output errors of the LMS and RLS algorithms, respectively. By substitution of equations (7) and (8) into equation (6), we obtain:

$$e_c = d - w_{LMS}(d - e_{LMS}) - w_{RLS}(d - e_{RLS})$$
$$= d(1 - w_{LMS} - w_{RLS}) + w_{LMS} e_{LMS} + w_{RLS} e_{RLS}. \tag{9}$$

Assuming $w_{LMS} + w_{RLS} = 1$ and for convenience, we let $w = w_{LMS}$ then,

$$e_c = we_{LMS} + (1-w)e_{RLS}. \tag{10}$$

Assuming $E\{e_{LMS}e_{RLS}\} = 0$ and taking expectation from squares of both sides of equation (10), we have,

$$E\{e_c^2\} = w^2 E\{e_{LMS}^2\} + (1-w)^2 E\{e_{RLS}^2\} \tag{11}$$

or equivalently,

$$\xi_c = w^2 \xi_{LMS} + (1-w)^2 \xi_{RLS}. \tag{12}$$

For finding the optimum weights, we take the derivative of the above-mentioned equation,

$$\frac{\partial}{\partial w} \xi_c = 0$$

$$w_{opt} = \frac{\xi_{RLS}}{\xi_{RLS} + \xi_{LMS}}, \quad \xi_{c\min} = \frac{\xi_{LMS}\xi_{RLS}}{\xi_{RLS} + \xi_{LMS}}. \tag{13}$$

In the above-mentioned formulae, the MMSE of the proposed approach is lower than those of both the LMS and the RLS algorithms. In practice, combination of the RLS and LMS may be done dynamically with LMS method according to the following equation (14):

$$\begin{bmatrix} w_{LMS} \\ w_{RLS} \end{bmatrix}_k = \begin{bmatrix} w_{LMS} \\ w_{RLS} \end{bmatrix}_{k-1} + \mu_c \begin{bmatrix} y_{lms} \\ y_{rls} \end{bmatrix}_k e_{ck}, \tag{14}$$

where μ_c is the step size and e_{ck} is the output error in kth sample.

Because of automatic tuning of the weighting system according to equation (14), it is possible to design a system where one of the RLS and LMS methods plays the dominant role in the ANC. For systems with faster convergence, w_{RLS} and for systems with more tracking ability w_{LMS}, are more pronounced.

We utilise the proposed RLMS algorithm in the ANC application but, before explaining the proposed FX-RLMS algorithm, the FX-LMS algorithm is introduced in the next section.

3 Principle of active noise control in a duct

If we assume that the noise propagates in a one-dimensional form, then it is possible to use a single channel ANC for noise cancellation. For simulation and implementation of this system, a narrow duct is used as in Figure 1. According to Figure 1, the primary noise before reaching to the speaker is picked up by the input microphone. The system uses the input signal for generating the noise cancelling signal $y(n)$. The generated sound by the speaker gives rise to a reduction in the primary noise. The error microphone measures the residual signal, $e(n)$, which can be minimised using an adaptive filter, which is used for identifying the duct's transfer function. Because of using the input and error microphones, we must take into account some functions, which are known as the secondary path effects. In such a system, usually for cancelling the noise, the FX-LMS algorithm, Figure 2, and equation (1) are considered

(Prandoni and Vetterli, 1998; Elliott and Nelson, 1993; Akhtar et al., 2006, 2009). The vector $x'(n)$ is a filtered version of the vector $x(n)$ using LMS adaptive filter (equation (2)).

Figure 2 Using the FX-LMS algorithm in a single channel ANC system
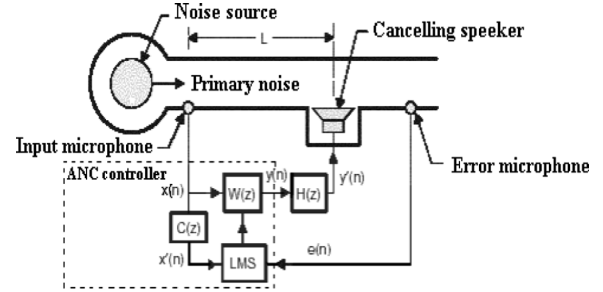
In the above-mentioned figure, $C(z)$ is an estimation of $H(z)$, which can be obtained by some off-line techniques (Flotte-Hernández et al., 2008). The considerable points in the execution of the FX-LMS are as follows

- cancelling the broadband noise needs a filter of high order, which increases the duct length (Flotte-Hernández et al., 2008)

- to choose the proper step size, we need knowledge of statistical properties of the input data (Kuo and Morgan, 1999; Eriksson et al., 1987)

- to ensure the convergence, the step size is chosen small; hence, the convergence speed will be low and the performance will be weak

- for executing the above-mentioned algorithm, we need to estimate the secondary path

- non-linear behaviour of this system stimulated new researches on developing algorithms in ANC.

Increasing the speed of convergence of the LMS algorithm is the main concern in ANC. So, we increase the convergence speed of the LMS algorithm by mixing it with the RLS algorithm and substitute in filtered input LMS algorithm. We proceed to applying the mixture of the RLS and LMS algorithms in system identification, noisy chirp tracking and ANC in the next section.

4 Applications of the RLMS algorithm

We use the RLMS algorithm in identification and in noise reduction from noisy chirp sinusoid problem and, finally, FX-RLMS algorithm is proposed for ANC application.

4.1 Using the RLMS algorithm in identification and noisy chirp tracking

In simulation of RLMS for identification and noise reduction problems, the forgetting factor of the RLS algorithm, λ, is set to 0.5 for increasing the tracking ability

and the step size of LMS algorithm is set to 0.06 and μ_c in equation (14) is 0.02.

4.1.1 The system identification problem

We study the behaviour of the proposed algorithm in two different conditions, stationary and non-stationary environments. For the stationary environment, the error-performance surface is fixed and the essential requirement is to seek the minimum point of that surface. But, in a non-stationary environment, minimum point of the error surface changes with statistical variations of the input. Therefore, adaptive filter must track these variations and optimum weights of filters must be changed in adaptation process as well. It is assumed that optimum weights of the plant change according to a first-order Markov process as (Haykin, 1996),

$$W_{\text{opt}(k+1)} = aW_{\text{opt}(k)} + \eta \qquad (15)$$

where a is a constant and η is an AWGN.[5]

We expect contribution of RLS algorithm be higher than LMS algorithm in seeking optimum weights at convergence phase in RLMS algorithm, because of slow convergence of the LMS algorithm and fast convergence of the RLS algorithm. Results of the simulation for an identification problem are plotted in Figure 3 at convergence phase. Figure 3 shows the time evolution of the respective weightings for outputs of the LMS (i.e., w_{LMS}) and RLS (i.e., w_{RLS}) filters. From Figure 3, we can conclude that during the convergence phase, w_{RLS} begins to increase while w_{LMS} decreases.

Figure 3 LMS and RLS weightings during the convergence phase (see online version for colours)
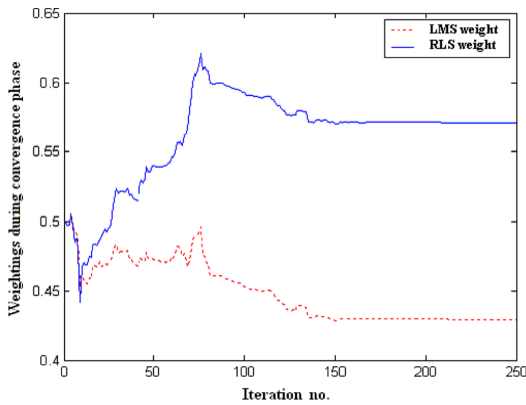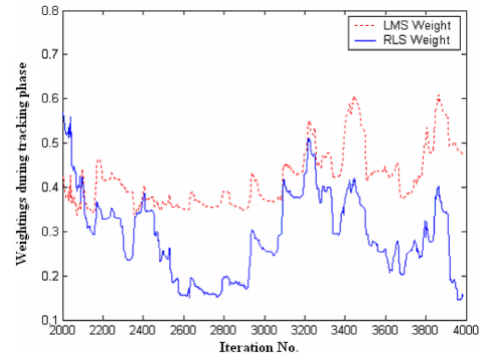

In the tracking phase of the RLMS algorithm, we expect $w_{RLS} < w_{LMS}$ in finding optimum weights, because of good tracking of LMS algorithm in low SNR (Haykin, 1996). To check the tracking behaviour of the proposed system, optimum weights of the plant are changed according to equation (15). As seen in Figure 4, in tracking phase w_{LMS} is bigger than w_{RLS}.

We conclude from the above-mentioned observations that the mixture of the LMS and RLS, i.e., RLMS, according to the proposed scheme has two notable advantages:

a   In the convergence phase, the RLS weight (w_{RLS}) is greater than the LMS weight (w_{LMS}), so we expect that the convergence speed to be higher than that of the LMS algorithm (Figure 5).

b   In the tracking phase for the system identification problem, w_{LMS} is greater than w_{RLS} (Figure 4). Also in a different SNR, the MSE of RLMS is less than both the LMS and the RLS algorithms (Figure 6).
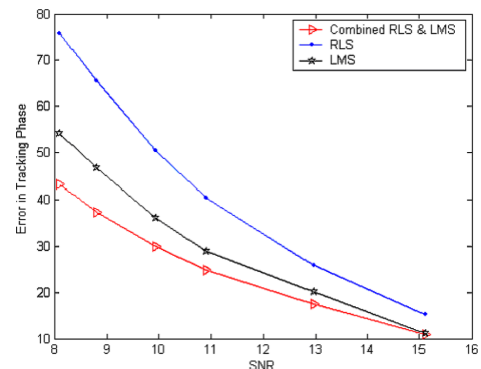
Figure 4 LMS and RLS weightings during the tracking phase (see online version for colours)

Figure 5 Learning curve of the proposed and LMS algorithms (see online version for colours)
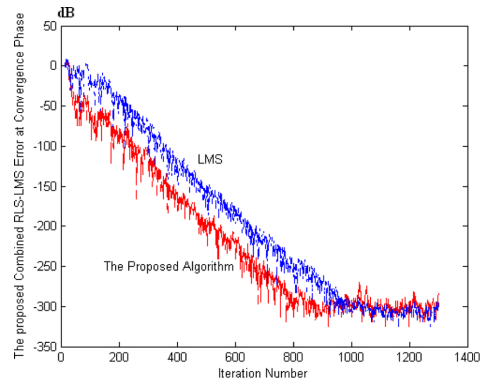
Figure 6 MSE vs. SNR in the tracking phase (see online version for colours)

4.1.2 Noisy chirp tracking

We used a dynamic mixture of RLS and LMS in a noise reduction application. Adaptive recovery of a chirp sinusoid buried in noise is a standard method because the chirp sinusoid represents a well-defined form of non-stationarity.

In this experiment, we consider the tracking of a chirped sinusoid. The chirped input signal is given by:

$$S(k) = \sqrt{P_s} \exp(j[(2\pi f_c + \psi k / 2)k + \varphi]) \qquad (16)$$

where $\sqrt{P_s}$ denotes the signal amplitude, f_c is the centre frequency, ψ is the chirp rate and φ is an arbitrary phase shift. The signal $S(k)$ is deterministic but non-stationary because of the chirping. $S(k)$ is added with noise $n(k)$, then tracking of the noisy chirp is a benchmark for testing the RLMS and LMS and RLS algorithms. The SNR is denoted by:

$$SNR = 10 \log\left(\frac{\sqrt{P_s}}{A_n}\right) \qquad (17)$$

where A_n is the amplitude of the noise.

The estimation error for 1001 samples for 2 s with 1 kHz sample rate of chirp is shown in Figure 7. In low SNR, the proposed method is better than the RLS and LMS algorithms, while in SNR bigger than 20dB, RLS is slightly better than the proposed method. Thus, we propose that for low SNR environment, a dynamic mixture of RLS and LMS is used for noise reduction.

Figure 7   Estimation error vs. SNR (see online version for colours)
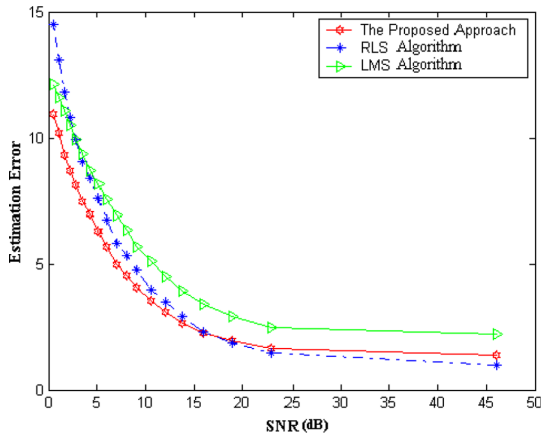

4.2   Using the RLMS algorithm in ANC

The present network is used to actively cancel the noise as in Figure 8. Two points are interested in the proposed system as

a   increasing the convergence speed

b   increasing the tracking ability of the RLMS algorithm compared with the RLS and LMS algorithms.

For precise simulation of the proposed algorithm and comparison with the conventional FX-LMS method,

the transfer function of the primary path (the duct transfer function) and the secondary path must be available, which for this purpose, the information given in Lveg (1936), which is obtained practically is utilised.

Figure 8   A structure for cancelling noise in a duct with the proposed method (see online version for colours)
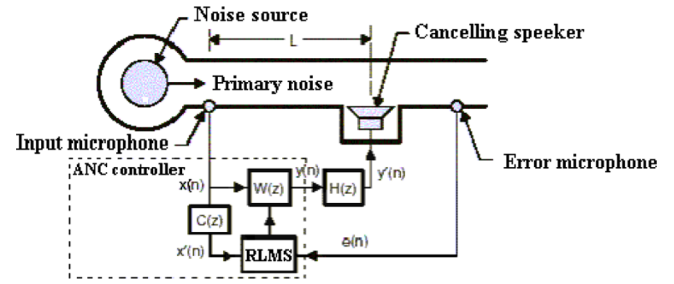

Higher convergence speed and lower error for the proposed algorithm in comparison with the FX-LMS algorithm in Figure 9 is observed. On average, the convergence speed increased 1.6 times and the final MSE minimum error decreased by 16%. Figure 10 shows the convergence and tracking phases of FX-LMS and FX-RLMS proposed algorithms, respectively. This figure shows increasing speed of convergence in the proposed algorithm compared with FX-LMS algorithms and also it shows reducing error in tracking phase for RLMS and FX-LMS algorithms.

Figure 9   Learning curves to sinusoidal chirp with a variable frequency of 300–305 Hz in ANC in the duct for the FX-LMS (see online version for colours)
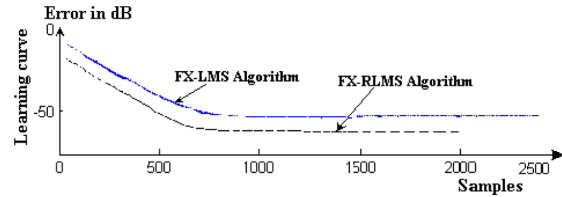
Figure 10   Learning curves for convergence and tracking phases, convergence for frequency of 300 Hz and tracking for sinusoidal chirp with a variable frequency of 300–305 Hz (see online version for colours)
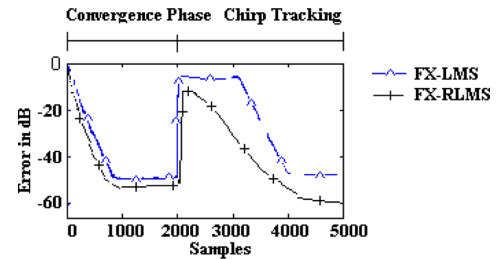
4.3   Active noise cancellation of variable frequency narrow band noise using FX-RLMS algorithm

For best mixing of LMS and RLS algorithms in the FX-RLMS algorithm, suitable μ_c in equation (14) is required in wide range frequency 200–500 Hz. We employed a novel approach based on frequency estimation

and a look-up table, which is obtained in learning phase. We know which ANC algorithms have different behaviour in variety of frequencies so we find optimum μ_c (μ_{opt}) in each frequency. For this purpose, a novel system is

proposed as shown in Figure 11. The proposed system contains three main parts

a   ANC algorithm

b   best step size calculation for fusion of RLS and LMS outputs in ANC

c   frequency estimation.

The FX-RLMS algorithms shown structure in Figure 8 are used for ANC algorithm. Best step size of ANC algorithm, μ_{opt}, is obtained in range 200–500 Hz, by changing of step size for reaching to minimum error in Figure 8. μ_{opt} is obtained by step 25 Hz in range 200–500 Hz. Table 1 shows μ_{opt} vs. frequency in ANC application.

Figure 11   The proposed system for cancellation of variable narrow band frequency
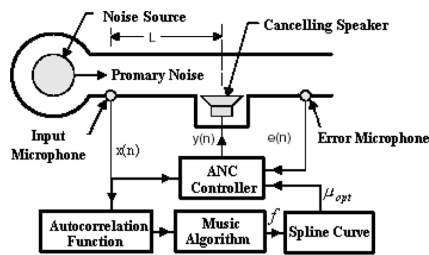
Table 1   Obtained μ_{opt} vs. frequency in ANC application

f	200	237.5	275	300	312	325
μ_{opt}	0.025	0.009	0.025	0.029	0.030	0.03
f	350	375	400	425	475	500
μ_{opt}	0.026	0.017	0.011	0.022	0.031	0.03

For selecting of μ_{opt}, frequency is required. So, we used MUSIC algorithm for frequency estimation (Eriksson and Allie, 1988; Bouchard and Yu, 2001). Using MUSIC algorithm, frequency of signal is estimated by extracting of Eigenvalues of autocorrelation function.

In the above-mentioned figure, a spline curve has been fitted over the μ_{opt} vs. frequency.

5   Conclusions

For increasing the convergence speed and decreasing the MSE in the tracking mode, combining of the adaptive filters is a suitable method. A new approach based on a mixture of the RLS and LMS algorithms was presented, namely the RLMS algorithm. We proved that the MMSE of the proposed algorithm is reduced compared with those of the RLS and LMS algorithms. The RLMS algorithm was employed for active noise cancellation to form of the FX-RLMS algorithm, in a duct. Our new approach has several superiorities to the above-mentioned works, namely:

• our work is presenting a new configuration for combining of RLS and LMS methods in a real parallel form, considering convergence speed, tracking performance and error reduction

• applying the final system for ANC in a duct

• increasing the reliability of the whole system, which is not considered in previous research works.

Obtained results showed increasing performance of the RLMS algorithm in system identification, noisy chirp tracking and active noise cancellation.

References

Akhtar, M.T., Abe, M. and Kawamata, M. (2006) 'A new variable step size LMS algorithm-based method for improved online secondary path modeling in active noise control systems', *IEEE Trans. Audio, Speech Lang. Process.*, Vol. 12, No. 2, March, pp.720–726.

Akhtar, M.T., Abe, M., Kawamata, M. and Mitsuhashi, W. (2009) 'A simplified method for online acoustic feedback path modeling and neutralization in multichannel active noise control systems', *Elsevier Signal Processing*, Vol. 89, pp.1090–1099.

Bouchard, M. and Yu, F. (2001) 'Inverse structure for active noise control and combined active control sound reproduction systems', *IEEE Trans. Speech and Audio Processing*, Vol. 9, No. 2, February, pp.141–151.

Carini, A. and Malatini, S. (2008) 'Optimal variable step-size NLMS algorithms with auxiliary noise power scheduling for feedforward active noise control', *IEEE Trans. Audio, Speech and Language Process*, Vol. 16, No. 8, November, pp.1383–1395.

Das, D.P. and Panda, G. (2004) 'Active mitigation of nonlinear noise processes using a novel filtered-s LMS algorithm', *IEEE Trans. Speech Audio Process.*, Vol. 12, No. 3, May, pp.313–322.

Das, D.P., Mohapatra, S.R., Routray, A. and Basu, T.K. (2006) 'Filtered-S LMS algorithm for multichannel active noise control of nonlinear noise processes', *IEEE Trans. Speech Audio Process*, Vol. 14, No. 3, September, pp.1875–1880.

Elliott, S.J. and Nelson, P.A. (1993) 'Active noise control', *IEEE Signal Process. Mag.*, Vol. 10, No. 4, October, pp.12–35.

Eriksson, L.J. and Allie, M.C. (1988) 'System considerations for adaptive modeling applied to active noise control', *IEEE*, Vol. 3, June, pp.2387–2390.

Eriksson, L.J., Allie, M.C. and Greiner, R.A. (1987) 'The selection and application of an IIR adaptive filter for use in active sound attenuation', *IEEE Trans. Acoustics, Speech and Signal Processing, ASSP-35*, April, pp.433–437.

Farhang-Borojeny, B. and Gazor, S. (1996) 'Performance of LMS-based adaptive filters in tracking a time-varying plant', *IEEE Trans. Signal Processing*, Vol. 44, November, pp.2868–2871.

Flotte-Hernández, O.R., Pineda-Olivares, A., Dieck-Assad, G., Avila-Ortega, A., Martínez Chapa, S.O. and Bouchereau-Lara, F. (2008) 'On the performance of active noise control FX-LMS and FBFX-LMS algorithms for duct network noise attenuation', *Electronics, Robotics and Automotive Mechanics Conference*, Cuernavaca, Morelos, Mexico, pp.575–581.

Hansler, E. (1990) 'Adaptive echo compensation applied to the hands-free telephone problem', *Proc. ISCAS 1990*, Vol. 1, pp.279–282.

Haykin, S. (1996) *Adaptive Filter Theory*, 3rd ed., Prentice-Hall, Englewood Cliffs, NJ.

Huang, H., Fränti, P., Huang, D. and Rahardja, S. (2008) 'Cascaded RLS–LMS prediction in MPEG-4 lossless audio coding', *IEEE Trans. Audio, Speech, and Language Processing*, Vol. 16, No. 3, March, pp.554–562.

Kuo, S.M. and Morgan, D.R. (1999) 'Active noise control: a tutorial review', *Proceedings of IEEE*, Vol. 87, No. 6, June, pp.943–973.

Lveg, P. (1936) *Process of Silencing Sound Oscillations*, US Patent 2043416, 9 June.

Macchi, O. (1986) 'Optimization of adaptive identification for time-varying filters', *IEEE Trans. Automat. Contr.*, Vol. AC-31, pp.283–287.

Mboup, M., Bonnet, M. and Bershad, N. (1994) 'LMS coupled adaptive prediction and system identification: a statistical model and transient mean analysis', *IEEE Trans. Signal Processing*, Vol. 42, October, pp.2607–2615.

Oikawa, S. and Tetsuya Shimamural, T.Y. (2006) 'A parallel estimator with LMS and RLS adaptation for fast fading channels', *International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, Japan, 12–15 December, pp.845–848.

Prandoni, P. and Vetterli, M. (1998) 'An FIR cascade structure for adaptive linear prediction', *IEEE Trans. Signal Processing*, Vol. 46, September, pp.2566–2571.

Prashanth Reddy, E., Das, D.P. and Prabhu, K.M.M. (2008) 'Fast adaptive algorithms for active control of nonlinear noise processes', *IEEE Trans. Signal Process*, Vol. 56, No. 9, September, pp.4530–4536.

Sadoghi Yazdi, H., Fathy, M. and Lotfizad, M. (2004) 'Vehicle tracking at traffic scene with modified RLS', *Int. Conf. Image Analysis and Recognition*, LNCS.3212, Porto, October, pp.623–632.

Schober, R. and Gerstacker, W.H. (2001) 'Noncoherent adaptive channel identification algorithms for noncoherent sequence estimation', *IEEE Trans. Communications*, Vol. 49, No. 2, February, pp.229–234.

Sicuranza, G.L. and Carini, A.C. (2004) 'Filtered-X affine projection algorithm for multichannel active noise control using second-order Volterra filters', *IEEE Signal. Process. Let.*, Vol. 11, No. 11, November, pp.853–857.

Strauch, P. and Mulgrew, B. (1998) 'Active control of nonlinear noise processes in a linear duct', *IEEE Trans. Signal Process.*, Vol. 46, No. 9, September, pp.2404–2412.

Tan, L. and Jiang, J. (2001) 'Adaptive volterra filters for active control of nonlinear noise processes', *IEEE Trans. Signal Process.*, Vol. 49, No. 8, August, pp.1667–1676.

Widrow, B. and Stearns, S.D. (1984) *Adaptive Signal Processing*, Prentice-Hall, Englewood Cliffs, NJ.

Widrow, B. and Walach, E. (1984) 'On the statistical efficiency of the LMS algorithm with nonstationary inputs', *IEEE Trans. Inform. Theory, Special Issue on Adaptive Filtering*, Vol. IT-30, March, pp.211–221.

Ysebaert, G., Vanblue, K., Cuypers, G., Moonen, M. and Pollet, T. (2003) 'Combined RLS-LMS initialization for per tone equalizers in DMT-Receivers', *IEEE Trans. on Signal Processing*, Vol. 51, No. 7, July, pp.1916–1927.

Yu, R. and Chung Ko, C. (2003) 'Lossless compression of digital audio using cascaded RLS-LMS prediction', *IEEE Trans. Speech and Audio Processing*, Vol. 11, No. 6, November, pp.532–537.

Notes

[1]Maximum A Posteriori.

[2]Mean Square Error.

[3]Recursive Least Mean Square.

[4]Minimum Mean Square Error.

[5]Additive White Gaussian Noise.

Bibliography

Besson, O. and Stocia, P. (1996) 'Analysis of MUSIC and ESPRIT frequency estimations for sinusoidal signal with low pass envelopes', *IEEE Trans. Signal Processing*, Vol. 44, No. 9, September, pp.2359–2364.

Bjarnason, E. (1995) 'Analysis of the filtered-X LMS algorithm', *IEEE Trans. Speech and Audio Processing*, Vol. 3, November, pp.504–514.

Burgess, J.C. (1981) 'Active adaptive sound control in a duct: a computer simulation', *J. Acoustical Society America*, Vol. 70, No. 3, September, pp.715–726.

Cartes, D.A., Ray, L.R. and Collier, R.D. (2003) 'Lyapunov turning of the leaky LMS algorithm for single-source, single-point noise cancellation', *Mechanical System and Signal Processing*, Vol. 17, No. 5, pp.925–944.

Kuo, S.M., Panahi, I., Chung, K.M., Horner, T., Nadeski, M. and Chyan, J. (1996) *Design of Active Noise Control Systems with the TMS320 Family*, Texas Instruments.

Morgan, D.R. (1980) 'Analysis of multiple correlation cancellation loop with a filter in the auxiliary path', *IEEE Trans. ASSP*, Vol. ASSP-28, No. 4, August, pp.454–467.

Phooi, S.K., Zhihong, M. and Wu, H.R. (2000) 'Nonlinear active noise control using LYAPUNOV theory, and RBF network', *IEEE, Neural Networks for Signal Processing*, Vol. 2, 11–13 December, pp.916–925.

Rafaely, B., Carrilho, J. and Gardonio, P. (2002) 'Novel active noise-reducing headset using earshell vibration control', *The Journal of the Acoustical Society of America*, Vol. 4, No. 112, October, pp.1471–1481.

Rupp, M. (1997) 'Saving complexity of modified filtered-X-LMS and delayed update LMS algorithms', *IEEE Trans. Circuits and System II*, Vol. 44, January, pp.57–60.

Sayyarradsari, B., How, J.P., Hassibi, B. and Carrier, A. (1998) 'An estimation-based approach to the design of adaptive IIR filters', *Proceeding of the American Control Conference*, Philadelphia, Pennsylvania, June, Vol. 5, pp.3148–3152.

Stoica, P. and Soderstrom, Torsten (1991) 'Statistical analysis of music and subspace rotation estimates of sinusoidal frequencies', *IEEE Trans. Signal Processing*, Vol. 39, No. 8, August, pp.1836–1847.