NOVEL DIGITAL TECHNIQUES FOR ECHO CANCELLATION APPLIED TO SPEECH SIGNALS

Noushin Karimian School of Electrical and Electronic Engineering, University of Manchester
Patrick Gaydecki School of Electrical and Electronic Engineering, University of Manchester

1. INTRODUCTION

Within the past five decades, the development and extensive use of digital channels[1] for communication have augmented awareness of the role of such systems in speech processing applications, such as speech enhancement. Speech enhancement algorithms have been used to solve problems in many various situations, such as correction of echo, rate modification, pitch alteration, reformation for the lost speech packets within a digital network, and also the hyperbaric speech correction[2]. Nonetheless, noise reduction is thought to remain the most frequent and significant challenge in speech enhancement.
Noise is generally referred to as the unwanted signals, in or outside the system, affecting the communication. Consequently, noise reduction has always been both challenging and interesting to the scientists. One of the most common cases where the noise shows great distortion is the unwanted echoes[3]. Echo is the repetition of a waveform either due to reflections (at points where the characteristics of the medium through which the wave propagates changes) or due to the acoustic feedback (between the speaker and the microphone) in the communication system. In telecommunications; echoes degrade the quality of service (QoS), which can be improved by two main methods of Echo Suppression and Echo Cancellation[2]. In this paper, Echo Cancellation methods have been used to illustrate how a communication can be improved by removing the echo. Amongst the existing types of echo (hybrid and acoustic), this paper is mainly concerned with the Acoustic Echo.

1.1. Acoustic Echo

Acoustic echo is generally constructed as a result of an acoustic feedback coupling path that is established between the receiving and transmitting devices (media). For instance, in microphone and speaker of a mobile phone handset, teleconference, hands-free phone or other hearing aid systems[3], the mechanism of acoustic echo is presented in Figure 1. In the same way, acoustic echo could be made through reflecting from a multitude of various surfaces including walls, ceilings and floors, and travelling in different paths. Similarly, the electrical echo may occur in hybrid connection of full duplex telephone wires[3].

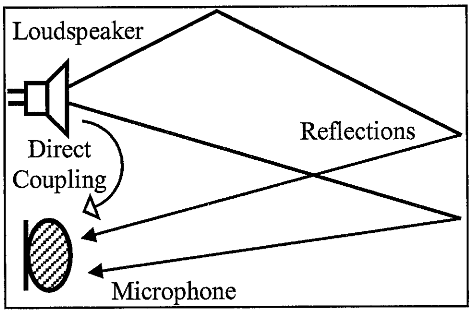

Figure 1. Acoustic echo mechanism[4]

As stated in the introduction, echo cancellation is used to improve the quality of the communication. Echo cancellers are sometimes referred to as adaptive linear filters. Adaptive filters are set of filters that repeatedly change their parameters in order to minimise the difference between the desired output and their own output[5].

The existing solution to the echo cancellation is the use of adaptive filter algorithms. Adaptive filter algorithms are often applied to systems for adjusting the coefficients of the filter, so as to minimise some function of the error, *e(n)*, between the desired response, *d(n)*, and the output of the adaptive filter, *y(n)*, given in Equation 1.

$$e(n) = d(n) - y(n) \tag{1}$$

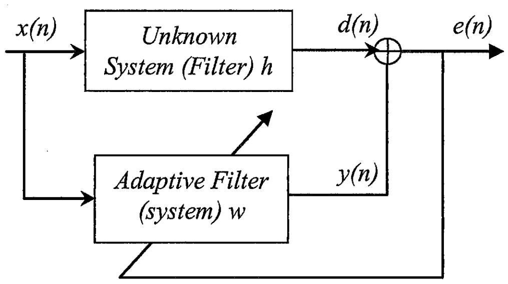

Figure 2. System identification structure[4]

The adaptation is a recursive process which has a general formula of[5]:

$$\textit{Next parameter estimate} = \textit{Previous parameter estimate} + \textit{Update (error)} \tag{2}$$

One of the main filtering methods i.e. Adaptive Filtering and its application to echo cancellation is studied, analysed and presented in this paper. It is worth mentioning that all the existing algorithms of the adaptive filtering have been studied and mathematically derived and implemented for this research. These algorithms include Least Mean Square (LMS), Normalised LMS (NLMS), Variable Step-size LMS (VSLMS), Variable Step-size Normalised LMS (VSNLMS), and Recursive Least Square (RLS).

To the authors' knowledge, the combination of the above mentioned adaptive filter algorithms, with another filter has not been experimented yet. In this research, for the first time, the Kalman Filter is used with the LMS algorithm of the adaptive filter, in an attempt to reduce the effect of echo in the communication channel. The above procedures involve acquisition and processing of both simulated and real data sets. The collected data have been imported to the computer for implementation and processing, using the codes that are written in MATLAB software.

Section 2 presents a study and analysis of the LMS adaptive algorithm and KF. In this section, the novel approach of using the KF with the LMS algorithm of the adaptive filter is also investigated. Results along with their analysis are presented in section 3, and section 4 provides conclusion remarks of the work presented in this paper.

2. KALMAN FILTER AND LMS ADAPTIVE ALGORITHM

2.1. Kalman Filter

The concept of KF dates back to 1960s, when R. E. Kalman published a paper on discrete data filtering[6]. In his famous paper, he provided a recursive solution[7] which since then has become the subject of extensive research on "assisted navigation and instrumentation" areas and applications such as aerospace, manufacturing, etc[8]. More detailed description about this filter including historical and theoretical background could be found in[9-14]. In technical terms, "the KF is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that it minimises the mean of the squared error"[7]. This filter has several advantages, one of which is its capability in supporting estimations of different states (past, present or even the future), regardless of existence of previous knowledge about the modelled system. KF uses some forms of feedback control mechanism in order to estimate its process. This is done through estimation of the process state at particular time intervals, measuring its feedback.

Consequently, KF equations should logically fall into two categories of *Time update* (used to foresee, in time, the present state and to obtain a priori estimate using the error covariance) and *measurement update* (used for feedback analysis, or sometimes referred to as the as corrector equations)[7].
Therefore, to summarise the behaviour of the KF, it could be said that following each "time and measurement" update, the iteration process is repeated with the previous a posterior estimates used to project or predict the new a priori estimates. The recursive conditioning nature of KF is what makes this filter different and more practically implementable compared to other types of filter such as Wiener filter that directly estimates all the data[14].

2.2. LMS Adaptive Algorithm

In 1959, Widrow and Hoff developed the Least Mean Square (LMS) algorithm through their studies of pattern recognition, which then, due to its computational simplicity[15], became one of the most commonly used algorithms. LMS uses the gradient vector of the w_i to obtain the optimal wiener solution, and consequently could be classified under the category of stochastic gradient algorithms[16].
The process of LMS algorithm involves an update of the filter tap weights with each iteration, as shown in Equation (3)[15]:

$$w(n+1) = w(n) + 2\mu e(n)x(n) \tag{3}$$

Where:

- $x(n)$ is the input vector of the time delayed input values
  $$x(n) = \left[x(n)x(n-1)x(n-2)x(n-N+1)^T\right]$$
- Vector $w(n) = [w_0(n)w_1(n)w_2(n)...w_{N-1}(n)]^T$ correspond to the adaptive FIR filter tap weight vector at time n, as Figure 3 depicts.
- Parameter μ is the step size, which is usually a small positive constant. This parameter affects the performance of the LMS algorithm. For instance, if:
  - μ = Too small, the time taken for the filter to converge to the optimal solution will be reasonably high
  - μ = Too large, causes the adaptive filter to be unstable and having a diverged output.

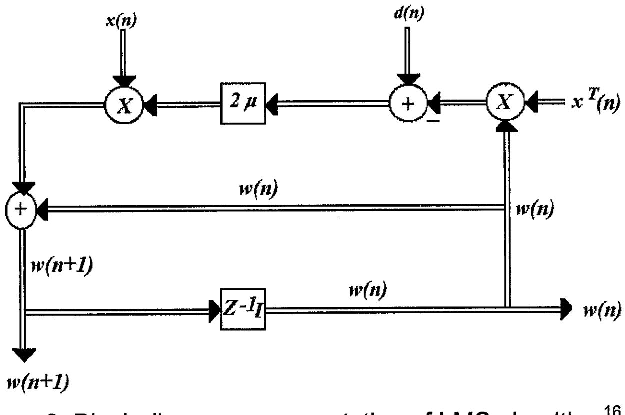

Figure 3. Block diagram representation of LMS algorithm[16]

2.2.1. Derivation of LMS Algorithm

The derivation of the LMS algorithm depends on both of the theories that were discussed earlier, the wiener solution and the steepest descent algorithm. Equation (4) is used to update the filter coefficients.

$$w(n+1)=w(n)-\mu\nabla\xi(n) \tag{4}$$
$$\xi(n)=E[e^2(n)]$$

Where:

- $w(n)$: Current tap weight vector
- $\nabla\zeta(n)$: The current gradient of the cost function with respect to the filter tap weight coefficient vector

Since the LMS algorithm operates based on the "random process implementation of the steepest descent algorithm – seen in Equation (5)"[17], the error signal cannot be extracted. Therefore the immediate obtained value is used as an estimate.

$$w(n+1)=w(n)-\mu\nabla\xi(n) \tag{5}$$

Where $\xi(n)=e^2(n)$

By re-arrange Equation (4), and substituting it in Equation (4):

$$\begin{aligned}\nabla\xi(n) &= \nabla(e^2(n)) \\ &= \frac{\partial e^2(n)}{\partial w} = 2e(n)\,\frac{\partial e(n)}{\partial w} \\ &= 2e(n)\,\frac{\partial(d(n)-y(n))}{\partial w} \\ &= -\,2e(n)\frac{\partial e w^T(n)x(n)}{\partial w} = -\,2e(n)\,x(n)\end{aligned} \tag{6}$$

Substituting (6) into (4) results in (7) which is the recursion of the LMS adaptive algorithm.

$$w(n+1)=w(n)+2\,\mu\,e(n)\,x(n) \tag{7}$$

2.2.2. Implementation of the LMS Algorithm

LMS algorithm contains iterations, each of which has 3 different steps. These steps are outlined below[17].

A. The output of the FIR filter, $y(n)$ is calculated:

$$y(n)=\sum_{i=0}^{N-1} w(n)\,x(n-i)=w^T(n)\,x(n)$$

B. The value of error is computed:

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

C. The tap weights of the FIR vector are updated and prepared for the next iteration:

$$w(n+1)=w(n)+2\,\mu\,e(n)\,x(n)$$

As it was previously pointed out, due to the computational simplicity of the LMS algorithm, it is known to be one of the most popular adaptive algorithms. It is important to note that *2N* addition, *2N+1* multiplication (*N* for calculating the output *y(n)* and one for *2μe(n)* and additional *N* for the scalar by vector multiplication) are required for each iteration of the LMS algorithm[18].

3. LMS ALGORITHM COMBINED WITH KALMAN FILTER FOR ECHO CANCELLATION

As it was mentioned in the earlier section, Kalman Filter is regarded as "a set of mathematical equations that provide an efficient computational (recursive) means to estimate the state of a process, in a way that it minimises the mean of the squared error"[7]. This means that the minimised squared error will cause the filter output to be closer to the desired signal.

In order to take advantage of this desirable behaviour of the Kalman filter; for the first time, it has been combined with the simplest and most commonly used algorithm of adaptive filter (LMS algorithm) to create a hybrid filter, in an attempt to reduce the effect of the echo in communication channel. By using KF, the minimised squared error will cause the filter output to be closer to the desired signal. Figure 4 depicts the flow diagram of how the code for the combination of LMS and KF in echo cancellation operates.

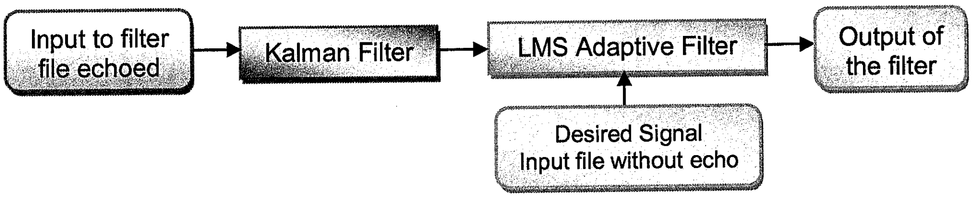

Figure 4. Process of KF combined with LMS adaptive filter algorithm

As shown in Figure 4, initially an echoed file is used as an input to the Kalman filter; the signal of this echoed input is depicted in figure 5.

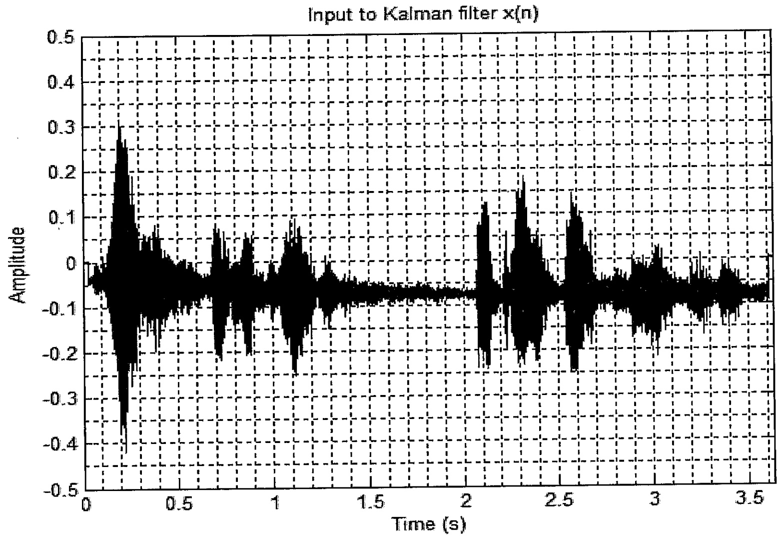

Figure 5. Input to the KF x(n)

Figure 6 shows the desired signal (i.e. signal without echo) superimposed on to the Kalman Filter output. As it is clear from this figure, the output of the Kalman filter is not completely matching to the desired non echo signal and therefore the output of the Kalman filter is acting as an input to the LMS adaptive algorithm; result of which is presented in Figure 7.

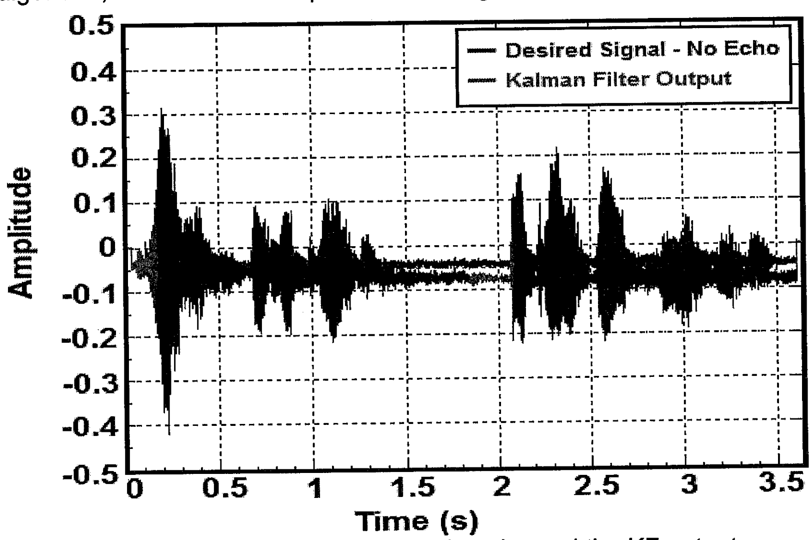

Figure 6. The desired .wav file - No echo and the KF output

Figure 7 presents the superimposed signal of the desired signal (with no echo) and the output of the LMS adaptive filter. As expected, the combination of the Kalman Filter and the LMS adaptive filter resulted in a very good response in terms of echo cancellation, which is evident from the output signals shown in Figures 7.

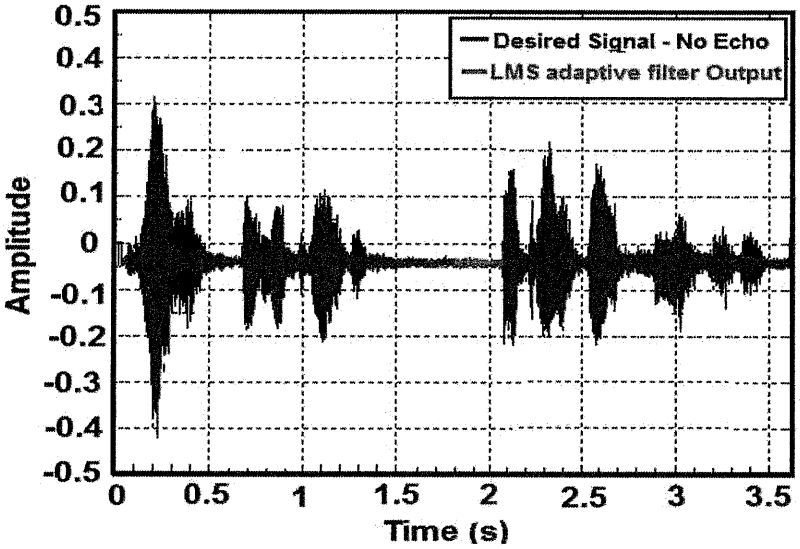

Figure 7. Comparison of the desired signal and the hybrid filter output

As well as the graphical illustration of the hybrid filter outputs, numerical comparison of this filter outputs with that of desired has also been considered and presented in Table 1.

Table 1. Numerical comparison of the hybrid filter outputs with that of desired at different times

	Amplitude of the input, output and the desired signal at different time			
Time (s)	Input to Kalman Filter	Desired Signal	Output of Kalman Filter	Output of LMS adaptive filter
0.4	0.3	0.2	0.07	0.05
1.1	0.35	0.3	0.25	0.23
1.3	0.17	0.12	0.05	0.03
3	0.3	0.25	0.25	0.25
3.25	0.2	0.15	0.15	0.15

Graphical and numerical illustration of the LMS adaptive filter output signal and the desired signal demonstrates that the LMS adaptive filter and the desired signal display similar profile, proving that the echo has been successfully removed.

4. CONCLUSION

In this research, all the existing algorithms of the adaptive filter have been studied, mathematically derived and implemented; out of which, the LMS algorithm was chosen due to the computational simplicity of this adaptive algorithm.

In this paper, a novel approach of using the Kalman Filter and the LMS adaptive algorithm to build a hybrid filter, in an attempt to reduce the effect of echoes over the channel, has been demonstrated. As expected, this merger produced a very good response in terms of echo cancellation. The

success of this combination was confirmed by both graphical and numerical analysis as well as the output sound.
The above procedures involved acquisition and processing of both simulated and real data sets (recorded voices). Having considered the examined algorithm and filter, and results obtained, it could be said that this paper has met the specified goals and could act as a stepping stone towards further research in speech enhancement for the communication based applications.

REFERENCES

1. N. Pavlidou, A. J. Han Vinck, J. Yazdani, and B. Honary. Power Line Communications: State of the Art and Future Trends. IEEE Communications Magazine. 41(4) pp. 34-40. (April 2003)
2. A. Spanias and M. E. Diesher, "Speech Enhancement", Arizona State University. (1997)
3. S. V. Vaseghi, Multimedia Signal Processing Theory and Application in Speech, Music and Communication, John Wiley & Sons, Ltd. (2007)
4. S. Raghavendran, Implementation of an Acoustic Echo Canceller Using Matlab®, University of South Florida, p. 12. (2003)
5. S. Haykin, Adaptive Filter Theory. 1st Edition, Prentice-Hall Inc., pp. 1-31. (1986)
6. R.E. Kalman, A New Approach to Linear Filtering and Prediction Problems, Transaction of the ASME - Journal of Basic Engineering. (March 1960)
7. G. Welch, and G. Bishop, An Introduction to the Kalman Filter, University of North Carolina. (July 2006)
8. Peter S. Maybeck, Stochastic Models, Estimation, and Control, Volume 1, Academic Press, Inc. (1979)
9. Sorenson, H. W. 1970. "Least-Squares estimation: from Gauss to Kalman," IEEE Spectrum, vol. 7, pp. 63-68. (July 1970)
10. A. Gelb. Applied Optimal Estimation, MIT Press, Cambridge. (1974)
11. Grewal, S. Mohinder, and P. Andrews Angus, Kalman Filtering Theory and Practice. Upper Saddle River, NJ USA, Prentice Hall. (1993)
12. Lewis, Richard. Optimal Estimation with an Introduction to Stochastic Control Theory, John Wiley & Sons, Inc. (1986)
13. R. G. Brown and P. Y. C. Hwang., Introduction to Random Signals and Applied Kalman Filtering, Second Edition, John Wiley & Sons, Inc. (1992)
14. O.L.R. Jacobs. Introduction to Control Theory, 2nd Edition. Oxford University Press. (1993)
15. S. Haykin., Adaptive Filter Theory. 2nd Edition, Prentice-Hall Inc., New Jersey. (1991)
16. A.D. Poularikas and Z.M. Ramadan, Adaptive Filtering Premier with MATLAB®, Taylor & Francis Group LLC. (2006)
17. M. Hutson, Acoustic echo cancellation using digital signal processing, The University of Queensland. (2003)
18. B. Farhang-Boroujeny., Adaptive Filters, Theory and Applications. John Wiley & Sons. (1999)