Real Time Lung Sound Separation from Cardiac Sounds by Adaptive Algorithm Technique

[1]K. Sathesh, [2]S. Rajasekaran, [3]P. Jayapal Reddy, [4]T. Manasa, [5]G. Mythresh

[1]Associate Professor, Department of ECE, Madanapalle Institute of technology and Science, Andhra Pradesh, India
[2]Head of the Department, Department of ECE, Madanapalle Institute of technology and Science, Andhra Pradesh, India
[3, 4, 5]Students, Department of ECE, Madanapalle Institute of technology and Science, Andhra Pradesh, India
E-mail
[1]drksathesh[at]gmail.com
[52]drrajasekarans[at]mits.ac.in
[3]jaypalreddy111[at]gmail.com
[4]tmanasa20[at]gmail.com
[5]gondhimallamythresh78[at]gmail.com

Abstract: ***For reliable voice acquisition, active noise control (ANC) can be a good option. Additionally, this method has the potential to reduce the Lombard effect. The well-known Filtered-x Least Mean Squares adaptive method is the most extensively employed in broadband active noise cancellation (FxLMS). We investigate an alternative to the FxLMS algorithm that aims to solve its occasionally delayed convergence without sacrificing cancelling capability. The ALE-FxLMS system is an option provided here, in which an Adaptive Line Enhancer (ALE) is utilised as a decorrelating step for the FxLMS algorithm. The single-channel example (one reference signal, one actuator, and one error sensor) is presented and analysed, as well as three potential system extensions to the multiple channel situation. Without decorrelating pre-processing, the suggested system has been shown to provide faster convergence with reference to a single FxLMS. Since no frequency component is weighted higher than the others when using a white reference signal, the FxLMS method is projected to be faster to convergence. The ALE-FxLMS system is described in this paper, in which an Adaptive Line Enhancer (ALE) is employed as a decorrelating pre-processing stage for the FxLMS algorithm. The ALE-FxLMS system intends to increase computational complexity while improving the convergence of the entire adaptive system. The single-channel scenario is investigated, as well as the system's expansion to the multiple-channel case, where strongly correlated reference signals can be established. Three possible generalisations of multiple channels are shown. The performance of these systems is evaluated without pre-processing, using the single FxLMS as a reference.***

Keywords: Heart sound signal, HSS, Lung sound signal, LSS, Adaptive line enhancer, ALE, Filtered Least mean square, FxLMS, Active noise control, ANC

1.Introduction

In medical equipment, a real-time sound signal separation approach is utilised to detect and observe disease using sound signals. The common doctor's stethoscope uses this technology to separate two sound signals, such as heart sound signals (HSS) and lung sound signals (LSS), by placing a flat sensor on the human body to receive and transmit the sounds of internal organs to the diagnostician's ears via headphones. As a result, the Stethoscope is important in medical signal analysis because physicians utilise it to detect symptoms of sickness in internal body organs by listening for irregularities in sound signals. A condenser microphone with preamplifier is used in a traditional stethoscope to receive sound signals from functional human body organs. The measured sound signal in this early model is a mix of sounds from the heart and lungs, as well as some internal and external interference or background noise, which is common in electronic equipment when observing sound signals. Electronics have become increasingly important in the healthcare system in recent years for disease early detection and diagnosis. In this way, many strategies were used to adapt the stethoscope and its output was computerised, but each system had significant drawbacks in terms of the distinctness and clarity of observed signals. Heart and lung sound signals are the most commonly detected input signals, and both organs emit a variety of sound signals. Because the heart sounds have a broad range but the lung sounds have a narrow spectrum, the lung sound signal is separated and isolated in order to detect and diagnose disease in the respiratory system. Lung illness has impacted 30 percent to 40 percent of persons worldwide in recent years.

To observe sound signals, many techniques based on computerised de-noising are utilised, such as Discrete Cosine Transforms (DCT), Fourier Transforms (FT), and Discrete Wavelet Transforms (DWT), however de-noising systems have not yet met biological real-time signal processing requirements. Adaptive noise cancellation (ANC) with an adaptive algorithm, on the other hand, is used to reduce noise and other interference from the stethoscope's input signal. The sound signals are extracted and computed using an adaptive filter and several adaptive algorithms such as LMS, RLS, and KF, but the technique processes both signals and does not separate the heart and lung signals. Using an Adaptive Line Enhancer (ALE) using adaptive algorithms, this flaw can be solved. The architecture is similar to that of the ANC, with the exception that the ANC's architecture has two input signals, the input sound signal and the reference signal, but the ALE's architecture considers the input signal to be the reference signal. That is, using adaptive FIR filters and adaptive filter algorithms, it isolates both sound streams while also reducing error (LMS, RLS, FxLMS and KF). The adaptive FIR filter co-efficient or weights update each iteration during the run duration of the ALE, thus the co-efficient values change in each tap from a feed back of adaptive filter tap output in each iteration, minimising

International Journal of Scientific Engineering and Research (IJSER)
ISSN (Online): 2347-3878
Impact Factor (2022): 7.741

mistakes and producing a better Signal-to-Noise ratio (SNR). Because if an internal body component is impacted by disease, the physician can only detect and diagnose it using the sound signal, respiratory sound analysis in a biomedical system requires better accuracy from input to output sound signal.

Adaptive Line Enhancer (ALE)

Biomedical signals are processed using a variety of ways, but these systems analyse the input signal, noise signal, and output signal. The ALE design is similar to the ANC architecture, however whereas ANC requires two input signals, the ALE employs the input signal as the reference signal, resulting in a nearly error-free output signal. As illustrated in Figure1, the suggested ALE-LMS architecture was used to process and separate signals at the same time in order to analyse real-time input signals.

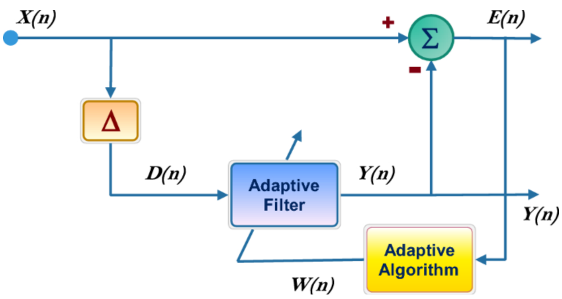

Figure 1: Adaptive Line Enhancer (ALE)

To acquire the lowest error rate of the output signal, the input signal is used as the reference signal in this architecture. The adaptive algorithms report back to the system, allowing the FIR filter coefficient to be updated. Least Mean Square (LMS), Recursive Least Square (RLS), and Kalman Filter (KF) are the three adaptive algorithms classified by Noor et al (2008). Different applications require different LMS algorithms. We presented two algorithms for noise cancellation: LMS and Normalised-LMS, which update the adaptive FIR filter coefficients. The suggested system iteratively processes the signals to achieve minimal error, and the adaptive filter output is segregated from the reference signals. In order to minimise errors, Signal-to-Noise Ratio (SNR), and Mean Square Error (MSE) in the quickest response time, the output can be analysed by adjusting the adaptive filter order, for example, N = 2, 4, 8, 16, and 32.

FxLMS Algorithm

The FxLMS (Filtered Least Mean Squared)filter is a system identification adaptive filter. The filter would provide an output that gradually reduces the erroneous signal fed into the filter's input. The difference between the desired response and the FxLMS filter output would be the error signal.

FxLMS is a gradient-based technique that can be used to identify an unknown system in the presence of a secondary path (e.g., a desired ANC controller). An FxLMS method for modifying an ANC controller is shown in a functional block diagram. An estimate model of the secondary path is shown in this diagram. The reference signal is filtered by $ before being used by the normal LMS algorithm, as can be seen. The compensation for the secondary path is the only difference between the LMS and FxLMS algorithms.

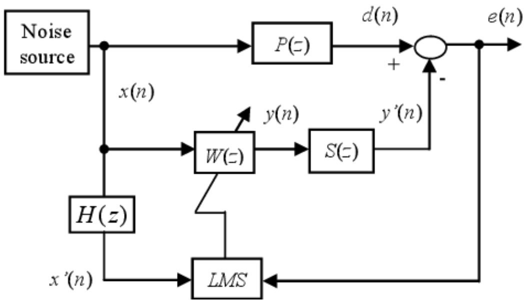

Figure 2: FxLMS algorithm

The standard least-mean-square (LMS) algorithm must be changed to account for the impacts of the secondary-path transfer function H (z). The input to the error correlator is filtered by a secondary-path estimate W to assure algorithm convergence (z). Morgan devised the filtered-X LMS (FxLMS) algorithm as a result of this. Burgess suggests that in ANC applications, this FxLMS algorithm be used to correct for the effects of the secondary path. Active noise cancellation can be achieved with the FxLMS filter. The noise to be cancelled will be referenced by the Reference input. The acoustic addition of anti-noise and the noise signal near the error microphone is the error(residual signal) input. The Filtered Reference is the reference signal that has gone through the secondary path and been filtered. Where the secondary path is the path from the FxLMS filter output to the FxLMS error input following the FxLMS filter output.

Derivation of FxLMS Algorithm

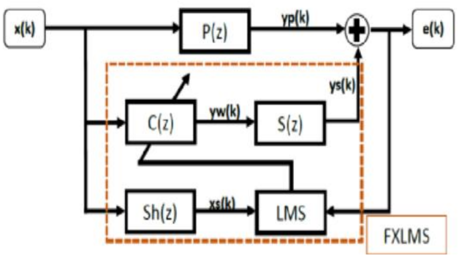

Figure 3: Block diagram of FxLMS algorithm

Symbols and Definitions for Figure 3

<u>**Symbol**</u> <u>**Definitions**</u>

x(k)-Noise Signal
xs(k)-Noise Signal Combined with assumed
Sh(z) based on S(z)
P(z) -Primary path transfer function
yp(k)-Primary noise signal at the error microphone
e(k) - Modified error signal
s(z) -Secondary path transfer function
C(z)& Sh(z)-Controller for the FxLMS algorithm
yw(k)-Generated noise based on C(z) controller
ys(k)-Output of adaptive filter

The FxLMS algorithm is a simple form of the LMS algorithm, which is why it was chosen based on the mean square error requirement minimization. There are two possible control systems for this adaptive filter: feedback and feed forward, which are distinguished by the reference signal x(n). The feedback employs a reference signal based on the feedback predictor, which can forecast and reduce the components of undesirable noise, making it less robust than feed forward but more compact and cost effective.

The FxLMS algorithm, which uses a similar way to the LMS algorithm but with steepest descent, can achieve this minimization using the following update equation.

$$W_{New} = W_{Old} + \mu \nabla J(n) \quad ...1$$

µ is an adaption step size (scalar),

∇ denotes the gradient operator (with respect to W parameters),

J(n) is the power of error signal.

The derivation of ∇J(n),

$$J(n) = E\{e^2(n)\}$$

Where E{.} denotes statistical expectation operator and

E{.} is a theoretical function. To avoid this operator, J(n) is approximated by

$$J(n) \approx e^2(n)$$

Then, estimate ∇J(n) as follows,

$$\nabla J(n) = \nabla e^2(n)$$
$$\nabla J(n) = 2e(n)\nabla e(n) \quad ...2$$

Now to estimate ∇e(n), the derivation is as follows based on the block diagram,

$$e(n) = d(n) + s(n) * y(n) \quad ...3$$

Where s(n) is the secondary path impulse response.

Now to estimate ∇y(n), the derivation is as follows based on the block diagram,

$$y(n) = W^T x(n)$$

$$\nabla e(n) = s(n) * \nabla y(n)$$

Where W is the controller weight vector and x is the reference signal tap vector (of the same length as the controller length)
Now ∇y(n) can be expressed by,

$$\nabla y(n) = \delta y(n) / \delta W$$

$$\nabla y(n) = x(n) \quad ...4$$

$Substitute\ (4)\ into\ (3)$

$$\nabla e(n) = s(n) * x(n) \quad ...5$$

$Substitute\ (5)\ into\ (2)$

$$\nabla J(n) = 2e(n).s(n) * x(n) \quad ..6$$

$Substitute\ (6)\ into\ (1)$

$$W_{New} = W_{Old} + 2\mu e(n).s(n) * x(n) \quad ...7$$

The reference signal is filtered by ŝ(n) before passing through the standard LMS algorithm. Therefore resulting the compensation for secondary path. s(n) should be estimated through off-line or online secondary path techniques. If ŝ(n) denotes an estimate of s(n), then

$$W_{New} = W_{Old} + 2\mu e(n).s(n) * x(n)$$

$$OR$$

$$W_{New} = W_{Old} + 2\mu e(n).x_1(n)$$

The stability of the FxLMS algorithm is highly dependent on the x_f (n) power where the convergence rate is directly proportional to the step-size and this parameter is indirectly proportional to the steady state performance.

2.Simulation

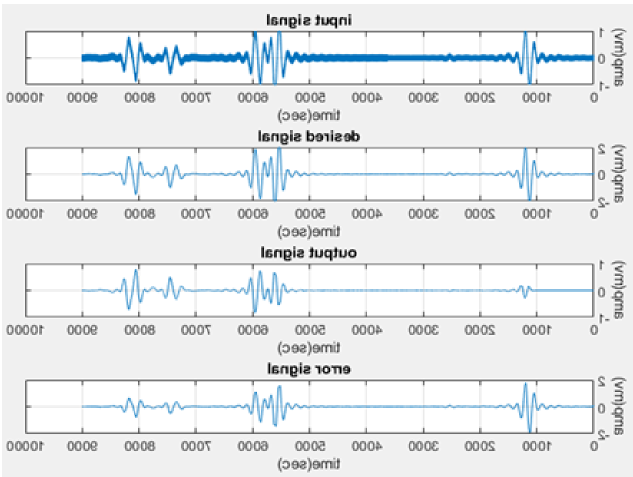

Figure 4: Input and Output Signals

Input signal is the combination of both heart sound and lung sound desired signal is the reference signal with delay output signal is the lung sound separated from the heart sound. error signal is the signal which came by minimizing the error from input signal.

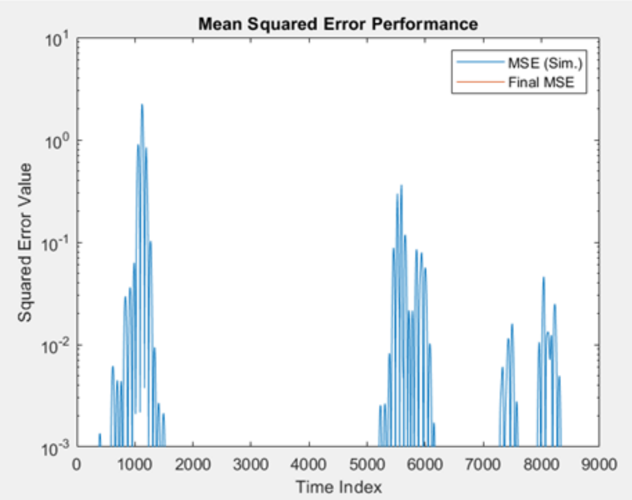

Figure 5: Mean Square Error Performance

Figure 5 represents the mean square error performance of input signal.

Graphical Representation

No.of coefficients	mmse	emse	r	MSE
2	7.14E-11	4.34E-15	4.253	1.07E-10
4	2.03E-07	2.49E-11	0.3658	0.0069
8	1.33E-07	3.47E-11	-2.2145	0.0038
16	1.70E-07	8.88E-11	-3.5316	1.16E-04
32	1.90E-07	1.99E-07	-4.1414	0.001

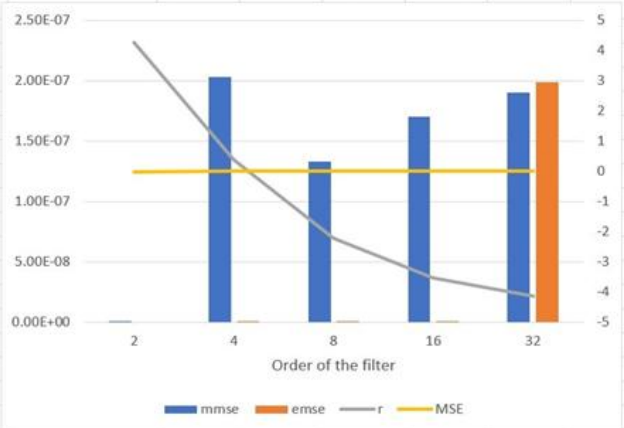

Figure 6: Graphical representation of N-coefficients

Figure 6 represents the MMSE, EMSE ,r ,MSE output values and represented in the form of graph in figure 6 different N co-efficient value consist of different values the values represents the quality of the signal.

Weights (Wsim)																	
N=2	-0.557851	-0.5512073															
N=4	-0.4077448	-0.4015686	-0.39476	-0.38734													
N=8	-0.2589136	-0.2532473	-0.24716	-0.24068	-0.233817	-0.226586	-0.21901	-0.2111									
N=16	-0.1658393	-0.1613072	-0.15648	-0.15137	-0.14599	-0.140354	-0.13448	-0.12838	-0.12208	-0.115589	-0.108923	-0.102099	-0.09513	-0.08805	-0.08085	-0.073562	
N=32	-0.1029805	-0.1021432	-0.10112	-0.0999	-0.098489	-0.096892	-0.0951	-0.09313	-0.09097	-0.088627	-0.086104	-0.083401	-0.08052	-0.07749	-0.074295	-0.070964	-0.0675
	-0.0639175	-0.0602238	-0.05643	-0.05255	-0.048603	-0.044589	-0.04053	-0.03642	-0.03229	-0.028144	-0.023989	-0.019835	-0.01569	-0.01157	-0.007477		

Figure 7: Weights of the filter

Weights of the different N coefficients are represented in figure7.

References

[1] **K.Sathesh, N.J.R.Muniraj (2014)**"Real Time Heart and Lung Sound Separation Using Adaptive Line Enhancer With NLMS", Journal of Theoretical and Applied Information Technology, Vol. 65 No.2.

[2] **G. Charbonneau et al (2000)** provides a detailed discussion and guidelines for the application of basic analysis techniques to respiratory sounds.

[3] **Christian McMechan et al (2011)** The duo developed a microcontroller and DSP based low-cost digital stethoscope which produced excellent sound quality using a condenser phone as well as recording, playback, and Bluetooth capability.

[4] **Shing Chow Chan, Yijing Chu March (2012)** Performance analysis and design of FxLMS algorithm in Broadband ANC system with online Secondary-Path modelling VOL. 20, NO. 3.

[5] **Jafar Ramadhan Mohammed May(2007)** A new simple adaptive noise cancellation scheme based on ALE and NLMS filter.

[6] **Zahra M.K. Moussavi et al (2007)** presented "Separating Heart Sounds from Lung Sounds" In a respiratory sound analysis, various methods were applied for separating the heart sound from the lung sound.

[7] Roshahliza M. Ramli et al (2012) and Veena N. Hegde et al (2012) presented an ALE based on adaptive noise cancellation systems and its application.

[8] **I. Hossain; Z. Moussavi (2004)** An overview of heart-noise reduction of lung sound using wavelet transform based filter.

[9] **Thato Tsalaile, Saeid Sanei(2007)**Separation of Heart Sound Signal From Lung Sound Signal By Adaptive Line Enhancement.

[10] **M. Kompis and E. Russi,** "Adaptive heart-noise reduction of lung sounds recorded by a single microphone," in Proc. 14th Ann. Int. Conf. IEEE EMBS, pp. 2416-2419, 2003.

[11] **J. Gnitecki, Z. Moussavi, and H. Pasterkamp,** "Recursive least squares adaptive noise cancellation filtering for heart sound reduction in lung sounds recordings," in Proc. 25th Ann. Int. Conf. IEEE E MBS, vol.3 pp.2416-2419, 2003