Noise Reduction for L-3 Nautronix Receivers

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Abstract

L-3 Nautronix provides a variety of underwater acoustic communication systems products which all stem from the same technological base. To improve range and reliability performance, there is a continuous desire to increase the signal to noise ratio of an incoming signal. Often, a limiting factor of the signal to noise ratio (SNR) is the proximity of the receiving hydrophone to a noisy platform, such as the engine of a boat from which the hydrophone is deployed.

The desired outcome of this project is to determine the benefits of local boat noise reduction on system performance. Adaptive filtering techniques were used to determine the amount of performance increase obtained by reducing boat noise interference in both model and real world environments. Using popular adaptive filtering setups, the processed model data demonstrates that a theoretical improvement in SNR of 12 dB can be achieved using an ideal setup. The processed trial data achieves an improvement of 3dB, which demonstrates the potential of this approach to form the basis for future extension to a real time system.

1. Introduction

1.1 Noise Reduction

The topic of noise reduction has long been the concern of a wide variety of industries. Significant advances have been made in noise reduction theory, with abundant literature available on both active and passive noise reduction techniques (Elliott et al 1993; Haykin 2000; Veen et al 1988). Some popular approaches in the realm of passive noise reduction include non-classical adaptive systems (Zaknich 2005), blind source separation (Haykin 2000), beamforming (Veen et al 1988), and adaptive filter theory (Zaknich 2005; Haykin 2000; Haykin 2002). After a feasibility analysis that considered relevance, cost, available literature and likelihood to succeed, it was found that adaptive filter (AF) theory is the most attractive solution for this application.

1.2 The Local Noise Problem

L3-Nautronix develops acoustic communication systems used for communication between vessels through the underwater channel. A large amount of local noise may be introduced to an incoming information signal (in particular, an L-3 Nautronix information signal) if it is received on a noisy platform, such as a boat with a running motor. The local boat noise scenario is further complicated by the non-static fixture (shown in Figure 1), which creates a time varying channel between the Receiver (Rx) hydrophone and the noise source.

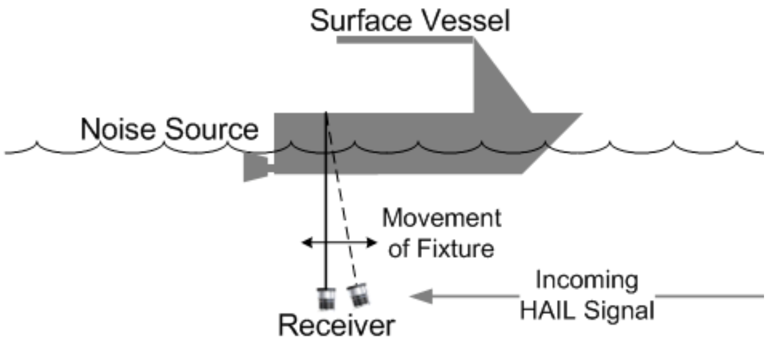

Figure 1 Local boat noise scenario

1.3 Problem Formulation

To express the project aim, consider the following definitions for describing the system:

$s(t)$ = The HAIL signal at Rx
$n(t)$ = The noise signal at the motor
$r(t)$ = The total signal at Rx (the contaminated signal)
$\hat{s}(t)$ = The estimate of the HAIL signal
$h(t,\tau)$ = Impulse response of the channel (time varying)
$g(t,\tau)$ = Impulse response of the AF (time varying)
c = Speed of sound in water *(~1500m/s)*

These definitions are shown on the following figure which represents a typical scenario where the boat motor interferes with an incoming HAIL signal.

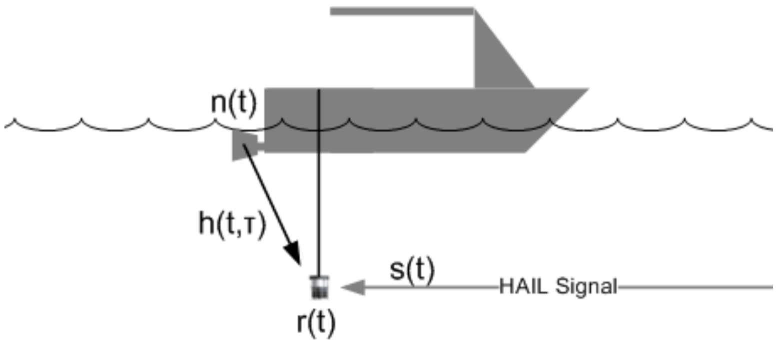

Figure 2 Local boat noise scenario

The overall received signal at the Rx will be a combination of the information signal, and the noise signal (after travelling through the channel). The signal at the Rx is then:

$$r(t) = s(t) + n(t) * h(t) \tag{1}$$

The purpose of this project is to use noise reduction techniques to develop a system that given the values of $r(t)$ and $n(t)$, produces an output signal, $\hat{s}(t)$, with a better SNR than the received signal, $r(t)$. This will be done by processing model and trial data using adaptive filtering techniques, and assessing improvement in Rx performance. Increase in SNR and decoding improvement will be used as criteria for success.

2. Adaptive Filtering Primer

An adaptive filter is one that updates its parameters to minimise the value of an error signal (Zaknich 2005). This is done with a particular adaptation algorithm, such as one from the least mean squares (LMS) or recursive least squares (RLS) families of algorithms. Adaptive filters can be used in four different topologies. The topology used for this application is the *interference cancellation topology*, shown in Figure 3.

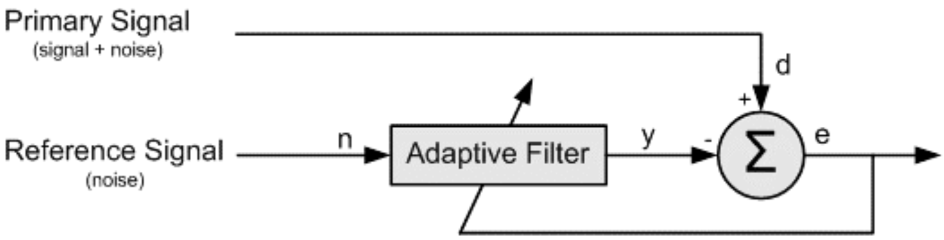

Figure 3 Adaptive filter used in the interference cancellation topology

With this topology, the error signal is an estimate of the information signal, *s(t)*. The adaptive filter will output a successful estimate of *s(t)* when *g(t)* approaches *h(t)*, which can be seen from the flow of signals shown in Figure 4.

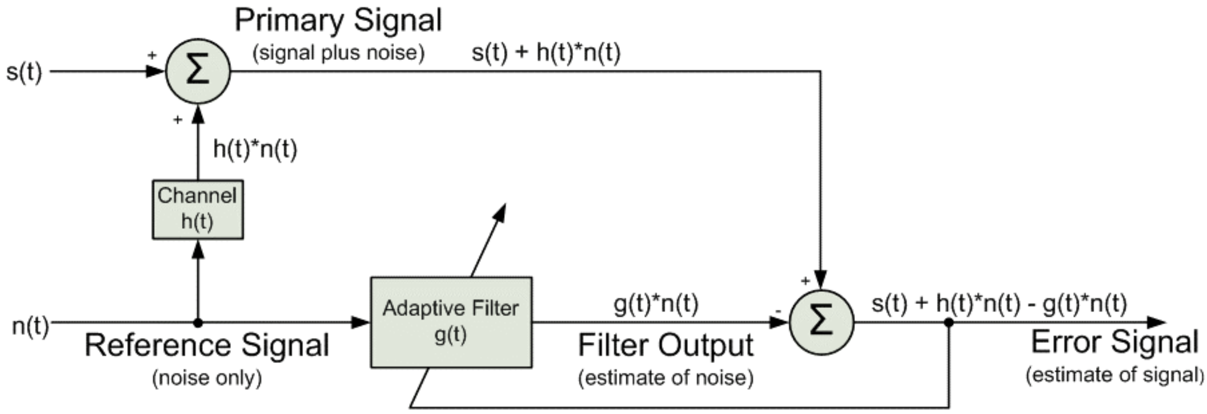

Figure 4 Signal flow in the interference cancellation topology

3. System Model Formulation

The system model shown in Figure 5 was created in the MATLAB programming environment to create model *primary* and *reference* signals. The function of each block was derived using properties of the underwater acoustic channel (Cook 1999), and the purpose of each block is summarised in the following table.

Block	Model Type	Aim of Model
Motor	Noise Model	Models the noise emitted by the boat motor. The output of this block will be a noise signal, $n(t)$.
Rx	Motion Model	Models the motion of the Rx due to boat motion and the non-stationary fixture. The output of this block will be a vector of distances representing the Rx positions, $x_s(t)$.
Channel	Delay Model Scaling Model AWGN Model	Models the transfer function of the propagation channel between the motor and Rx including delay, scaling, and AWGN effects. The input will be a vector of Rx distances, $x_s(t)$, and the noise signal, $n(t)$. The output will be the channel-modified noise signal, $h(t) * n(t)$.

Table 1 Model component description

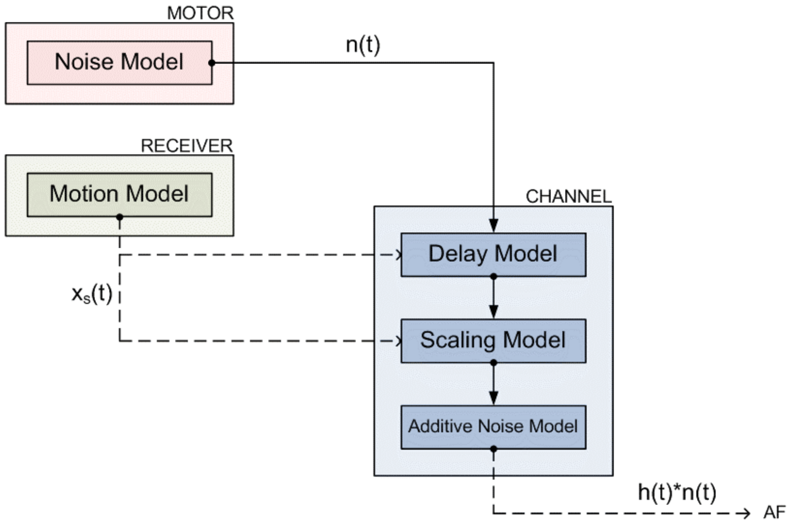

Figure 5 System model block diagram

The input to the system model represents the *reference signal*, and the output represents the noise component of the *primary* signal. The system model components have been intentionally separated for modularity, but can be summarised by the following expression:

$$\begin{aligned} \text{channel output} &= delay\{scale[n(t)]\} + AWGN \\ &= \frac{1}{x_s(t)} n\left(t - \frac{x_s(t)}{c}\right) + rand(t) \end{aligned} \tag{2}$$

4. Implementation

The implementation consists of a small toolbox of algorithms implemented in MATLAB. Focus was placed on the RLS and LMS families of adaptive filter algorithms due to the popularity, simplicity, and other desirable functional properties of these algorithm branches. The implemented algorithms determine the method for updating the filter's tap weight vector, $\mathbf{w}$, which describes the tapped delay line of the adaptive filter.

4.1. The LMS Algorithms

LMS type algorithms belong to the *stochastic gradient* algorithm family (Zaknich 2005; Haykin 2002). The operation principle of the LMS algorithms is to minimise the error function by using an approximate solution to the *method of steepest descent* for solving the Wiener-Hopf equations, which describe the optimal weight vector for the filter. The method of steepest descent uses an update function described by the following equation:

$$\mathbf{w}[k+1] = \mathbf{w}[k] - \eta \nabla_{E\{e^2[k]\}} \tag{3}$$

Where η is a small positive gain factor controlling stability and rate of convergence, and $\nabla_{E\{e^2[k]\}}$ is the gradient of the mean square error function.

The LMS approximation assumes that the true value for the gradient, $\nabla_{E\{e^2[k]\}}$, can be approximated by the square of a single error sample, $e^2[k]$. This results in the following LMS update equation:

$$\mathbf{w}[k+1] = \mathbf{w}[k] - \mu e[k]\mathbf{x}[k] \tag{4}$$

Where: $\mu = 2\eta$ is the step size

$e[k]$ is the error signal, desired output - actual output; $e[k] = d[k] - y[k]$

$y[k] = \mathbf{w}^T \mathbf{x}[k]$ is the actual output

$\mathbf{x}[k] = [x_k, x_{k-1}, ..., x_{k-(p-1)}]^T$ is the tap vector at instance k

The step size parameter, μ , effects both stability and convergence rate, and choosing its value requires a compromise between the two conflicting requirements. This has lead to the implementation of *variable step size* (VSS LMS) algorithms, which allow the step size to vary with time using various methods (Zhang et al 2008; Zhang et al 2007; Zhang et al 2006; Shengkui et al 2007). The following update equation describes the general VSS LMS case, which is an extension of equation (4) with time varying step size, $\mu[k]$:

$$\mathbf{w}[k+1] = \mathbf{w}[k] - \mu[k]e[k]\mathbf{x}[k] \tag{5}$$

4.2. The RLS Algorithm

The RLS algorithm belongs to the *least squares estimation* (LSE) family, and can be seen as a special case of the Kalman filter (Zaknich 2005). The RLS algorithm is described by the following set of update equations:

$$\begin{aligned}
\mathbf{k}(n) &= \frac{\lambda^{-1}\mathbf{P}(n-1)\mathbf{x}^*[n]}{1+\lambda^{-1}\mathbf{x}^T[n]\mathbf{P}(n-1)\mathbf{x}^*[n]} \\
\alpha(n) &= d[n] - \mathbf{w}[n-1]\mathbf{x}^*[n] \\
\mathbf{w}[n] &= \mathbf{w}[n-1] + \alpha(n)\mathbf{k}[n] \\
\mathbf{P}(n) &= \lambda^{-1}\left\{\mathbf{P}(n-1) - \mathbf{k}(n)\mathbf{x}^T[n]\mathbf{P}(n-1)\right\}
\end{aligned} \tag{6}$$

4.3. Comparisons

The main algorithmic difference between the LMS and RLS types of algorithms is that the RLS algorithm uses all the information available (all inputs applied to the filter), where as the LMS algorithm uses only information available instantaneously.

With respect to performance, it is known that the LMS algorithm is slower to converge than the RLS algorithm, but performs better in time-varying environments where the tracking mode of the filter is required (Zaknich 2005).

5. Experimental Setup

5.1. Trial Data

The trial data was acquired with the L-3 Nautronix HAIL (Hydro Acoustic Information Link) system. A common HAIL System configuration was used, comprising of communication between two "vessels", represented by two HAIL units; one on a jetty and the other on a small boat. The transmitter unit was set up on the jetty, and this produced the *information signal*. The receiver unit was set up on the boat, where the *primary* and *reference* signals were recorded using the setup shown in the following figure.

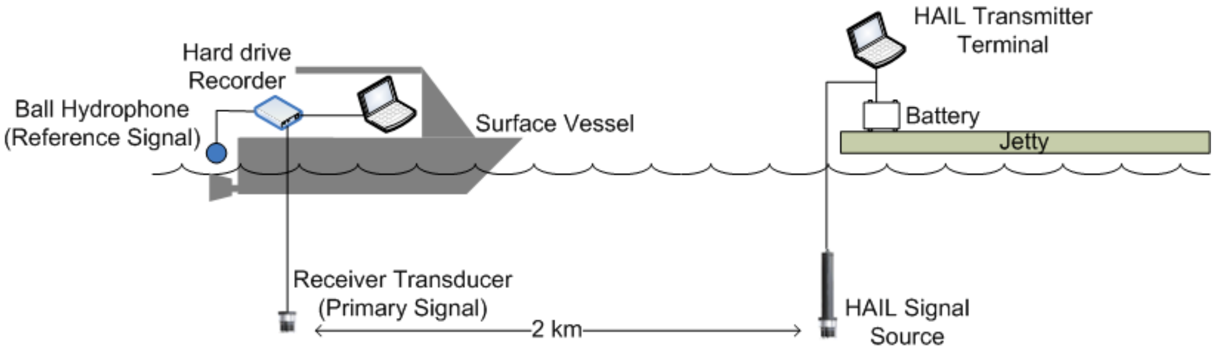

Figure 6 Trial setup for real data acquisition

The ball hydrophone captured a pure boat noise signal representing the *reference signal*. The transducer captured the modified boat noise and the incoming information signal, which together represent the *primary signal*. The trial data was processed using the RLS ($forgetting = 1$), LMS ($leakage = 1, \mu = 0.7$), and VSS LMS ($\mu_{max} = 0.7, \mu_{min} = 0.01$, $\alpha = 0.999999$, $\gamma = 0.001$) algorithms.

5.2. Model Data

The model environment was used to create realistic signals by using a similar setup to the trial. The following table shows the values of parameters used to generate the signals.

Property	Model	Details
Signal Properties	48 kHz sampling rate, 16 bit, 5 seconds length	Same signal properties as the trial data.
Reference Signal	Brown Noise and Boat Noise	The Brown noise was generated in Adobe Audition, The boat noise was recorded on trial.
Information Signal	HAIL signal recording	5 seconds of data was extracted from a trial recording with no boat noise (26 dB SNR). The HAIL text message contained in the recording: **D0E0F101112131415161718191A1B1C1D1E**
Primary Signal	Signal and noise	The information signal + channel modified noise signal.
Transducer Motion Model	$2 + 0.1\sin(2\pi 0.25)$	The motion model describes the swing of the transducer (in meters) due to the slow sway of the boat in the waves.
Inband SNR	-15 dB	-15 dB at the input corresponds to around 12 dB at the output (the worst case trial value) due to the coding gain provided by the HAIL system.
Algorithm Parameters	Filter length: 150 LMS step size: Brown noise: 0.01 Boat noise: 0.5	The step size parameters were experimentally found to give best results.

Table 2 Model enviroment setup and properties

6. Results

6.1. Model Data

Model data was created using both Brown noise and boat noise as the interfering signal, and was processed using the LMS and RLS algorithms. The original model data and the processed data were passed through the HAIL Receiver Software. The following plots show the SNR's of each of the signals.

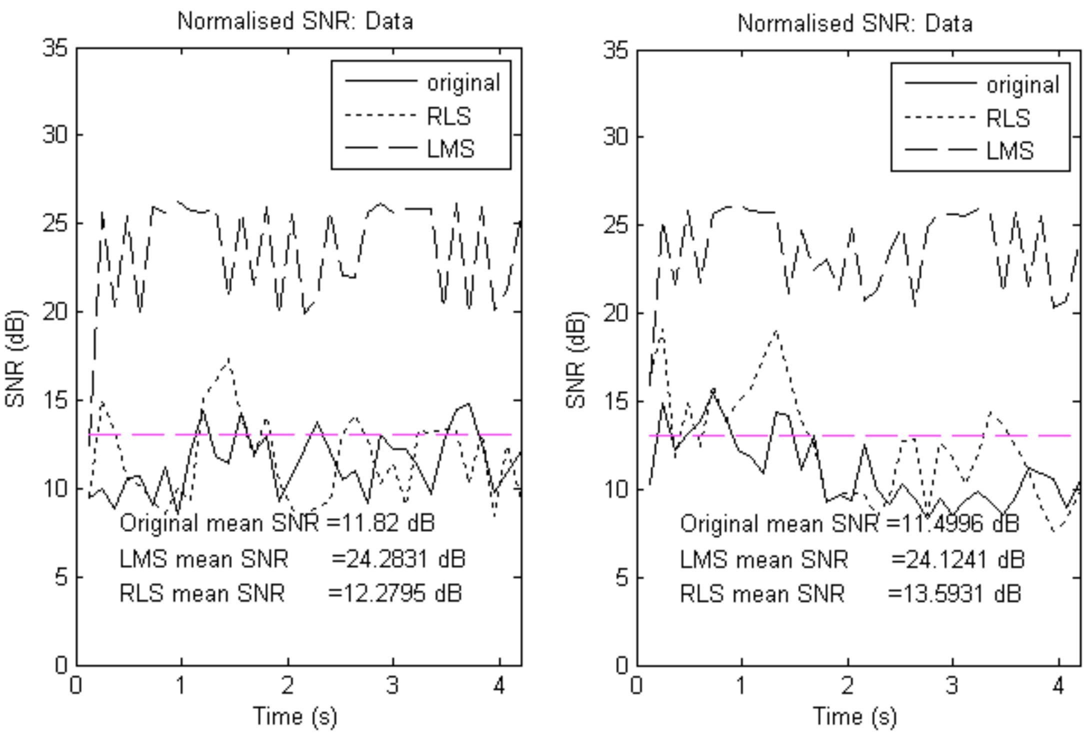

Figure 7 SNR's for (a) Brown noise interference, (b) boat noise interference

The following table shows the messages decoded by the HAIL Receiver for each signal, and the improvement in SNR provided by the RLS and LMS algorithms.

Measure	Brown Noise	Boat Noise
Original	C_"""Y-SY_"121314_%X1"_1718191A\B1C1_X_1ED	"D0E0F10111213_0_151:"""83"1?"^""_=D1E
LMS	**"D0E0F1011**121314**1516**1718191A**1**B1C1**D**1E	"D0E0F10111213**1415161718191A1B1C1**D1E
RLS	C**D**_""Y"Z"[_**1**11213_Y"S]"""_1718191A**1**B_X"""_	"D0E0F10111213_0"#(V"_**17**_"_**81**_"_**1A1B**_0"GL7_E
LMS SNR Improvement	12 dB	12 dB
RLS SNR Improvement	0.7 dB	2 dB

Table 3 Model data results

The symbols shown in italics have been decoded incorrectly by the HAIL Receiver, and the symbols shown in bold have been corrected by the algorithms. These results show that Brown noise is a good approximation to boat noise due to the similar results. When real boat noise is used as the interfering signal, the LMS algorithm gives a huge improvement, and manages to recover the whole message. The RLS algorithm has trouble tracking the changes in the channel, and cannot lock on fast enough. This is congruent with the initial hypothesis that the LMS algorithm has superior tracking behaviour, and so is more appropriate for time varying channels.

6.2. Trial Data

The trial data was processed in the same matter as the model data. The absolute SNRs and SNR improvements are shown in the following figure.

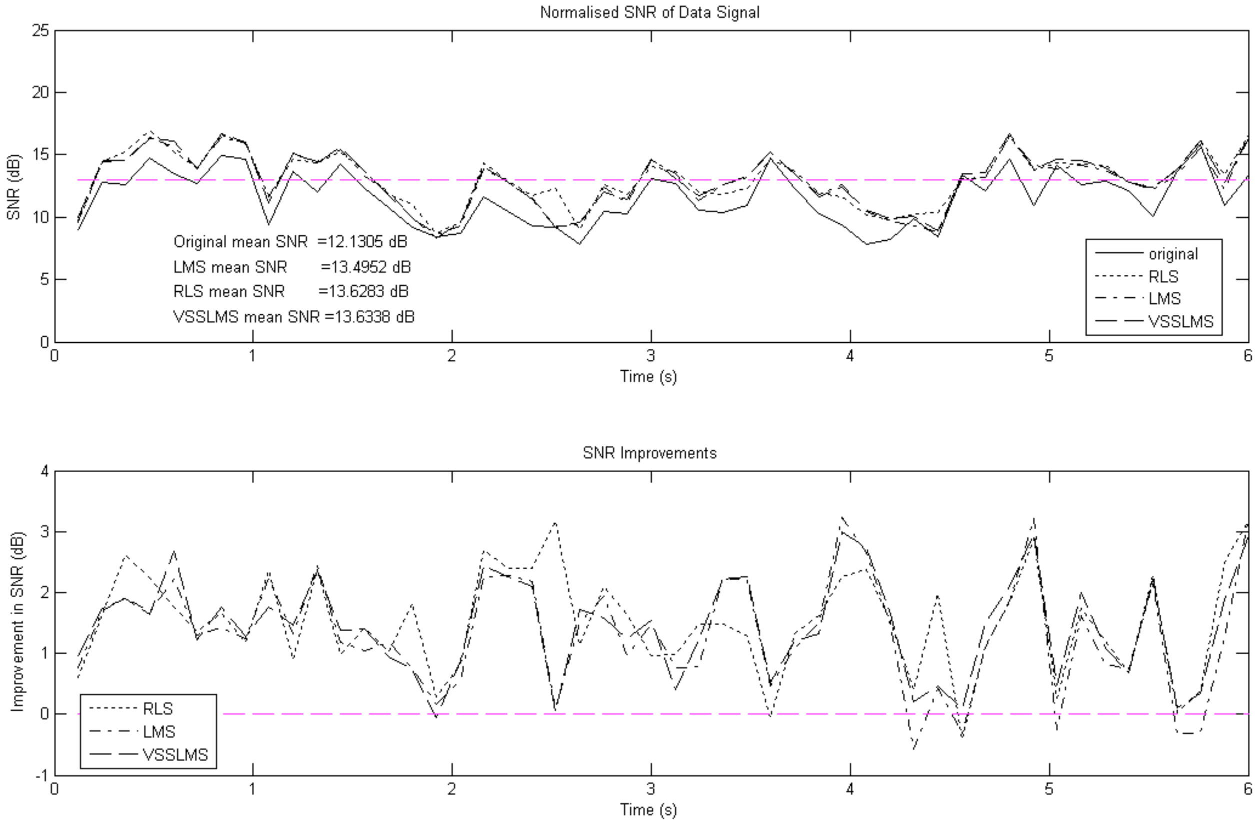

Figure 8 (a) Absolute SNRs, (b) SNR improvements

The following table shows the messages decoded by the HAIL Receiver for each signal, and the improvement in SNR provided by the RLS and LMS algorithms.

Data	Message	Average SNR Improvement	Max SNR Improvement
Original	"020304050607*H"R"01"V!*C0D0E0F101*"""$="*415161718191A	-	-
RLS	"020304050607**08***8R***0A0B***C*C0D0E0F101**1121***["*415161718191A	1.5 dB	3.2 dB
LMS	"02030405060708*NR***0A0***J"*C0D0E0F101**1121***["*415161718191A	1.4 dB	3.2 dB
VSS LMS	"02030405060708*IR***0A0***J"*C0D0E0F101**1121=***"*415161718191A	1.5 dB	3.0 dB

Table 4 Trial data results

The LMS and RLS algorithms provide similar numerical improvement. Since LMS is a much more efficient algorithm, it is preferred to the slower RLS algorithm. While the average SNR looks modest, the improvement in SNR (Figure 8b) is very promising. The effect of the increase is demonstrated by the number of symbols that have been corrected in the processed data (shown in bold).

7. Conclusions

An adaptive filtering approach has been used to demonstrate the potential of noise reduction on the HAIL Receiver performance. It has been shown through a realistic model setup that significant SNR improvements can be achieved through adaptive filtering. This hypothesis was demonstrated by the results of processing trial data.

The results show that a real world SNR improvement of up to 3 dB can be achieved using the RLS and LMS algorithms, with crude primary and reference signal recordings. The model setup showed that theoretical SNR improvements of around 12 dB can be expected when the primary and reference signals are well correlated, which can be achieved practically by selecting appropriate positions for the sensors, and using quality equipment.

Future work will focus on determining ideal parameter choices, and experimenting with sensitivity to change. Ultimately, the purpose of the research performed in this project is to extend the theory to a real time implementation. Future research beyond the scope of this project will involve acquiring more trial data to investigate the ideal placement of the sensors for recording highly correlated primary and reference signals.

8. References

Cook 1999, *A Swept-Carrier Technique for Underwater Acoustic Communications*, Ph.D. dissertation, Dept. of Electrical and Electronic Engineering, University of Western Australia, Nedlands, W.A.

Elliott, Nelson 1993, "Active Noise Control", *Signal Processing Magazine, IEEE*, vol. 10, no. 4, pp. 12-35.

Haykin (ed.) 2000, *Unsupervised Adaptive Filtering, Vol 1: Blind Source Separation*, John Wiley & Sons, Canada.

Haykin 2002 , *Adaptive Filter Theory* 4th ed., Prentice-Hall, New Jersey.

Shengkui, Zhihong, Suiyang 2007, "A Fast Variable Step-Size LMS Algorithm with System Identification", *Industrial Electronics and Applications, 2007. ICIEA 2007. 2nd IEEE Conference on,* pp. 2341-2345.

Veen, Buckley 1988, "Beamforming: A Versatile Approach to Spatial Filtering", *IEEE ASSP Magazine*, pp. 4-14.

Zaknich 2005, *Principles of Adaptive Filters and Self-learning Systems*, Springer, Germany.

Zhang, Li, Chambers 2006, "New Gradient Based Variable Step-Size LMS Algorithm", *The 8th International Conference On Signal Processing,* vol. 1, pp. 16-20.

Zhang, Li, Chambers, Wang, Kendrick, Cox 2007, "A New Variable Step-Size LMS Algorithm with Robustness to Nonstationary Noise", *Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on*, vol. 3, pp. iii 1349 - iii 1352.

Zhang, Li, Chambers, Hao 2008, "New Gradient-Based Variable Step Size LMS Algorithms," *EURASIP Journal on Advances in Signal Processing*, Article ID 529480.