SPEECH ENHANCEMENT IN HANDS FREE COMMUNICATION

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Abstract:

The telecommunications sector is characterized by an increasing demand for user friendliness and interactivity. This shows the growing interest in hands-free communication systems. Hands-free communication ensures communication without any physical contact with either a microphone or a loudspeaker. Signal quality in current hands-free systems is unsatisfactory due to the acoustic echo. Echo cancellation plays a vital role in improving the quality and intelligibility of speech. Acoustic echo cancellation is important in acoustically coupled environments, where the signal generated by a loudspeaker is fed back into a microphone, thus disrupting the signal that the microphone originally intended to receive. To overcome this, many advanced signal processing techniques have been used. This paper focuses on the use of adaptive filtering techniques to reduce this unwanted echo, thus increasing speech quality. These techniques are known to have computationally efficient solutions. In Adaptive filters the weights of the filter are adjusted in order to reduce the error. This adaptation of weights can be achieved through several algorithms. In this paper the performance of Least Mean Square(LMS), Normalized LMS(NLMS), Variable Step size LMS(VSLMS), Variable Step size NLMS(VSNLMS) and Recursive Least Square(RLS) adaptive filters are compared and their results are discussed

Key-words: Hands-free Communication , Acoustic Echo, Adaptive Filters.

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1.Introduction:

Acoustic echo cancellation is a common occurrence in today's telecommunication systems. It occurs when an audio source and sink operate in full duplex mode; an example of this is a hands-free loudspeaker telephone. In this situation the received signal is output through the telephone loudspeaker (audio source); this audio signal is then reverberated through the physical environment and picked up by the systems microphone (audio sink). The effect is the return to the distant user of time delayed and attenuated images of their original speech signal.

The signal interference caused by acoustic echo is distracting to both users and causes a reduction in the quality of the communication. This paper concentrates on the use of two main adaptive filtering algorithm to reduce this unwanted echo, thus increasing communication quality.

Adaptive filters are a class of filters that iteratively alter their parameters in order to minimize a function of the difference between a desired target output and their output. This is then used to negate the echo in the return signal. The better the adaptive filter emulates this echo, the more successful the cancellation will be.

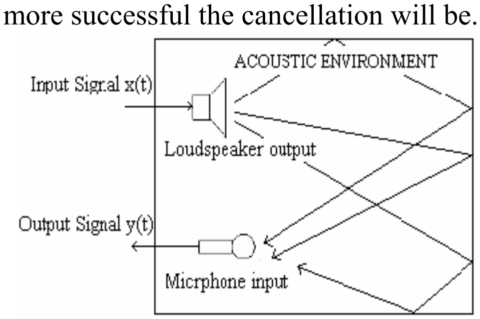


Figure 1.Origin of acoustic Echo.

2.Adaptive Filters:

2.1 Introduction

Figure 2 shows the block diagram of Acoustic Echo Canceller employing Adaptive Filter utilized in this paper.

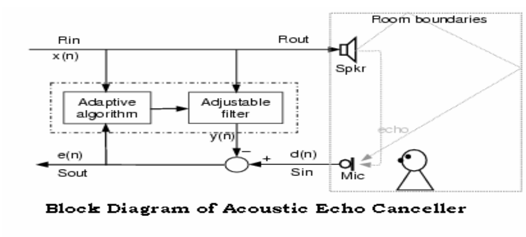


Figure 2. Acoustic Echo Canceller Setup

Here w represents the coefficients of the FIR filter tap weight vector, x(n) is the input vector samples, z -1 is a delay of one sample periods, y(n) is the adaptive filter output, d(n) is the desired echoed signal and e(n) is the estimation error at time n.

The aim of an adaptive filter is to calculate the difference between the desired signal and the adaptive filter output, e(n). This error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, known as the cost function. In the case of acoustic echo cancellation, the optimal output of the adaptive filter is equal in value to the unwanted echoed signal. When the adaptive filter output is equal to desired signal the error signal goes to zero. In this situation the echoed signal would be completely cancelled and the far user would not hear any of their original speech returned to them.

This part examines adaptive filters and various algorithms utilized. The various methods used in this paper can be divided into two groups based on their cost functions. The first class are known as Mean Square Error (MSE) adaptive filters, they aim to minimize a cost function equal to the expectation of the square of the difference between the desired signal d(n), and the actual output of the adaptive filter y(n)

$$\xi(n) = E[e^2(n)] = E[(d(n) - y(n))^2] \quad \text{(eq.2.1)}$$

The second class are known as Recursive Least Squares (RLS) adaptive filters and they aim to minimize a cost function equal to the weighted sum of the squares of the difference between the desired and the actual output of the adaptive filter for different time instances. The cost function is recursive in the sense that unlike the MSE cost function, weighted previous values of the estimation error are also considered. The cost function is shown below in equation 2.2, the parameter λ is in the range of 0<λ<1. It is known as the forgetting factor as for λ<1 it causes the previous values to have an increasingly negligible effect on updating of the filter tap weights. The value of 1/(1- λ) is a measure of the memory of the algorithm, this paper will primarily deal with infinite memory ,i.e. λ =1. The cost function for RLS algorithm, ζ(n), is stated in equation.

$$\zeta(n) = \sum_{k=1}^{n} \rho_n(k) e_n^{\,2} \quad \text{(eq. 2.2)}$$

$$\rho_n(k) = \lambda^{n-k}$$

Where k=1, 2, 3…n., k=1 corresponds to the time at which the RLS algorithm commences. Later we
will see that in practice not all previous values are considered; rather only the previous N(corresponding to the filter order) error signals are considered.

2.2 Mean Square Error (Mse) Adaptive Filters

2.2.1 Least Mean Square (Lms) Algorithm

The LMS algorithm is a type of adaptive filter known as stochastic gradient-based algorithms as it utilizes the gradient vector of the filter tap weights to converge on the optimal wiener solution. It is well known and widely used due to its computational simplicity. With each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula

$$w(n+1) = w(n) + 2\mu e(n) x(n) \quad \text{(eq.2.3)}$$

Here **x**(n) is the input vector of time delayed input values, **x**(n) = [x(n) x(n-1) x(n-2) …. x(n-N+1)] ^{T} . The vector **w**(n) = [w_0(n) w_1(n) w_2(n) …. w_{N-1}(n)] ^{T} represents the coefficients of the adaptive FIR filter tap weight vector at time n. The parameter μ is known as the step size parameter and is a small positive constant. This step size parameter controls the influence of the updating factor. Selection of a suitable value for μ is imperative to the performance of the LMS algorithm, if the value is too small the time the adaptive filter takes to converge on the optimal solution will be too long; if μ is too large the adaptive filter becomes unstable and its output diverges.

Implementation of the LMS algorithm.

Each iteration of the LMS algorithm requires 3 distinct steps in this order:

1. The output of the FIR filter, y(n) is calculated using equation 2.4.

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = w^T(n)x(n) \quad \text{(eq.2.4)}$$

2. The value of the error estimation is calculated using equation 2.5.

$$e(n)=d(n)-y(n) \quad \text{(eq.2.5)}$$

3. The tap weights of the FIR vector are updated in preparation for the next iteration, by equation 2.6.

$$w(n+1) = w(n) + 2\mu e(n)x(n) \quad \text{(eq.2.6)}$$

2.2.2 Normalised Least Mean Square (Nlms) Algorithm

One of the primary disadvantages of the LMS algorithm is having a fixed step size parameter for every iteration. This requires an understanding of the statistics of the input signal prior to commencing the adaptive filtering operation. In practice this is rarely achievable.

The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by selecting a different step size value, μ (n), for each iteration of the algorithm. This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector **x**(n). This sum of the expected energies of the input samples is also equivalent to the dot product of the input vector with itself, and the trace of input vectors auto-correlation matrix, **R**

$$\begin{aligned} tr[R] &= \sum_{i=0}^{N-1} E\left[x^2(n-i)\right] \\ &= E\left[\sum_{i=0}^{N-1} x^2(n-i)\right] \end{aligned} \quad \text{(eq. 2.7)}$$

Implementation of the NLMS algorithm.

Each iteration of the NLMS algorithm requires these steps in the following order

1. The output of the adaptive filter is calculated.

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = w^T(n)x(n) \quad \text{(eq.2.8)}$$

2. An error signal is calculated as the difference between the desired signal and the filter output.

$$e(n) = d(n) - y(n) \quad \text{(eq.2.9)}$$

3. The step size value for the input vector is calculated.

$$\mu(n) = \frac{1}{x^T(n)x(n)} \quad \text{(eq.2.10)}$$

4. The filter tap weights are updated in preparation for the next iteration.

$$w(n+1) = w(n) + \mu(n)e(n)x(n) \quad \text{(eq.2.11)}$$

As the step size parameter is chosen based on the current input values, the NLMS algorithm shows far greater stability with unknown signals.

2.2.3 Variable Step Size Lms Algorithm

Both the LMS and the NLMS algorithms have a fixed step size value for every tap weight in each iteration. In the Variable Step Size Least Mean Square (VSLMS) algorithm the step size for each iteration is expressed as a vector, μ (n). Each element of the vector μ (n) is a different step size value corresponding to an element of the filter tap weight vector, **w**(n).

Implementation of the VSLMS algorithm.

The VSLMS algorithm is executed by following these steps for each iteration.

1. The output of the adaptive filter is calculated.

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = w^T(n)x(n) \quad \text{(eq.2.12)}$$

2. The error signal is calculated as the difference between the desired output and filter output.

$$e(n) = d(n) - y(n) \quad \text{(eq.2.13)}$$

3. The gradient, step size and filter tap weight vectors are updated using the following equations in preparation for the next iteration.

For i = 0, 1,…., N-1

$g_i(n) = e(n)\, x(n-i)$

$g(n) = e(n)\, x(n)$
$\mu_i(n) = \mu_i(n-1) + \rho g_i(n) g_i(n-1)$
If $\mu_i(n) > \mu_{max}(n)$, $\mu_i(n) = \mu_{max}$
If $\mu_i(n) < \mu_{min}(n)$, $\mu_i(n) = \mu$
$W_i(n+1) = w_i(n) + 2\mu_i(n) g_i(n)$ (eq.2.14)

2.2.4 Variable Step Size Normalised Lms Algorithm.

In VSNLMS algorithm the step size calculation of NLMS is incorporated, in order to increase stability for the filter without prior knowledge of the input signal statistics. In this algorithm the upper bound available to each element of the step size vector, $\mu(n)$, is calculated for each iteration.

Implementation of the VSNLMS algorithm.

VSNLMS is essentially an extension of the implementation of the VSLMS algorithm with the added calculation of a maximum step size parameter for each iteration.

1. The output of the adaptive filter is calculated.

$$y(n) = \sum_{i=0}^{N-1} w(n) x(n-i) = w^T(n) x(n) \quad \text{(eq.2.15)}$$

2. The error signal is calculated as the difference between the desired output and the filter output.

$$e(n) = d(n) - y(n) \quad \text{(eq.2.16)}$$

3. The gradient, step size and filter tap weight vectors are updated using the following equations in preparation for the next iteration.

For $i = 0, 1, \ldots, N-1$
$g_i(n) = e(n)\, x(n-i)$
$g(n) = e(n)\, x(n)$
$\mu_i(n) = \mu_i(n-1) + \rho g_i(n) g_i(n-1)$
$\mu_{max}(n) = 1 / 2X^T(n)X(n)$
If $\mu_i(n) > \mu_{max}(n)$, $\mu_i(n) = \mu_{max}(n)$
If $\mu_i(n) < \mu_{min}(n)$, $\mu_i(n) = \mu_{min}(n)$
$W_i(n+1) = w_i(n) + 2\mu_i(n) g_i(n)$ (eq.2.17)

ρ is an optional constant the same as is the VSLMS algorithm.

2.3 Recursive Least Squares (Rls) Adaptive Filter.

The other class of adaptive filtering techniques studied in this paper is known as Recursive Least Squares (RLS) algorithms. These algorithms attempt to minimize the cost function in equation 2.18. Where k=1 is the time at which the RLS algorithm commences and λ is a small positive constant very close to, but smaller than 1. With values of $\lambda<1$ more importance is given to the most recent error estimates and thus the more recent input samples, this results in a scheme that places more emphasis on recent samples of observed data and tends to forget the past.

$$\zeta(n) = \sum_{k=1}^{n} \lambda^{n-k} e_n^2(k) \quad \text{(eq.2.18)}$$

RLS algorithms are known for excellent performance when working in time varying environments…these advantages come with the cost of an increased computational complexity and some stability problems.

Implementation of the RLS algorithm.

To implement the RLS algorithm, the following steps are executed in the following order.

1. The filter output is calculated using the filter tap weights from the previous iteration and the current input vector.

$$\overline{y}_{n-1}(n) = \overline{w}^T(n-1) x(n) \quad \text{(eq.2.19)}$$

2. The intermediate gain vector is calculated using equation 2.20.

$$u(n) = \psi_{\lambda}^{-1}(n-1) x(n)$$
$$k(n) = \frac{1}{\lambda + x^T(n) u(n)} u(n) \quad \text{(eq.2.20)}$$

3. The estimation error value is calculated using equation 2.21.

$$\overline{e}_{n-1}(n) = d(n) - \overline{y}_{n-1}(n) \quad \text{(eq.2.21)}$$

4. The filter tap weight vector is updated using equation 2.21 and the gain vector calculated in equation 2.20.

$$w(n) = \overline{w}^T(n-1) + k(n) \overline{e}_{n-1}(n) \quad \text{(eq.2.22)}$$

5. The inverse matrix is calculated using equation 2.23.

$$\psi_{\lambda}^{-1}(n) = \lambda^{-1}\left(\psi_{\lambda}^{-1}(n-1) - k(n)\left[x^T(n)\psi_{\lambda}^{-1}(n-1)\right]\right) \quad \text{(eq.2.23)}$$

3. Results:

A summary of the performance of the adaptive algorithms is expressed in the given table.

Algorithm	Average attenuation	Multiplication operation
LMS	-17.39dB	2N+1
NLMS	-19.36dB	3N+1
VSLMS	-9.71dB	4N+1
VSNLMS	-9.82dB	5N+1
RLS	-56.4dB	$4N^2$

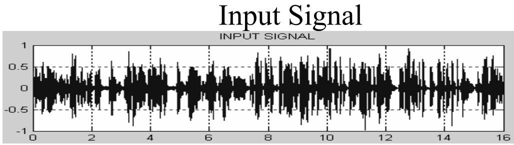
Table 1. Summary of adaptive filter algorithm performances.

4. Conclusion:

It can be seen that when considering the attenuation values and the number of multiplications for each algorithm, the NLMS algorithm is the obvious choice for the real time acoustic echo cancellation. At present the work is further extended in Frequency Domain Adaptive Filters to improve the efficiency in real time applications.

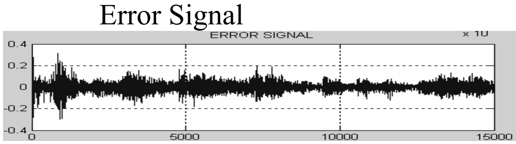
5. Matlab Simulation Results Of Adaptive Filtering Algorithms:

Input Signal

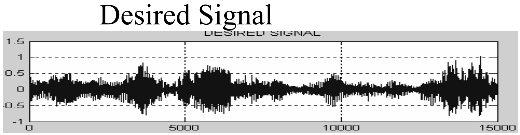


Lms Algorithm:

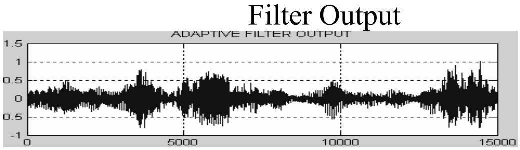
Error Signal



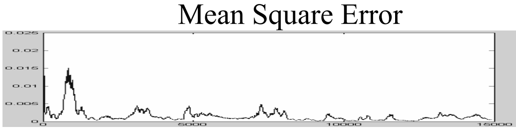
Desired Signal



Filter Output

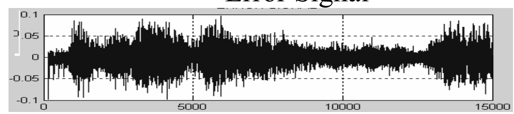


Mean Square Error

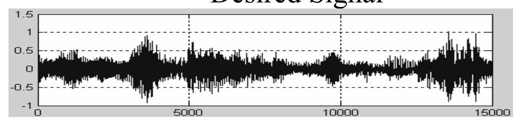


Nlms Algorithm:

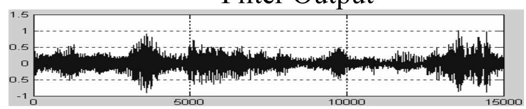
Error Signal



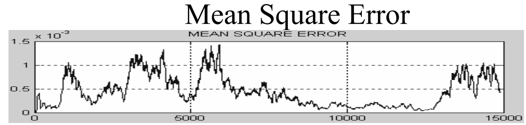
Desired Signal



Filter Output

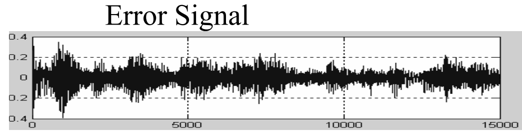


Mean Square Error

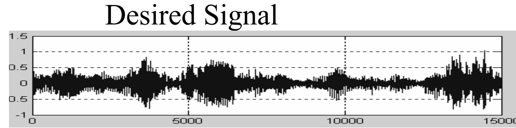


Vslms Algorithm:

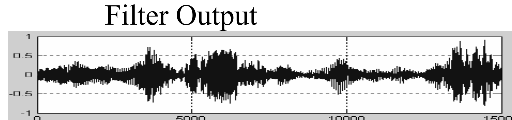
Error Signal



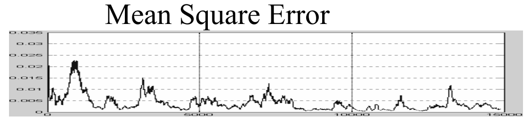
Desired Signal



Filter Output

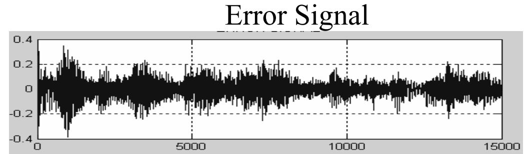


Mean Square Error

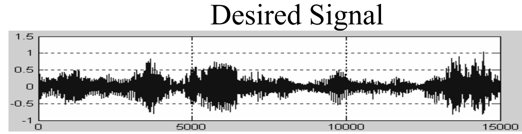


Vsnlms Algorithm:

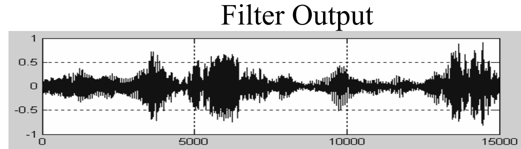
Error Signal



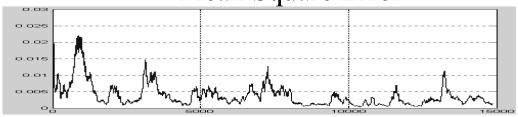
Desired Signal



Filter Output

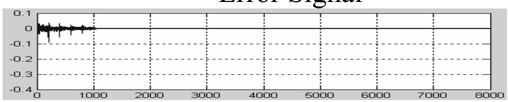


Mean Square Error

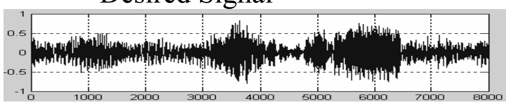


Rls Algorithm:

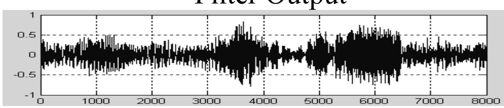
Error Signal



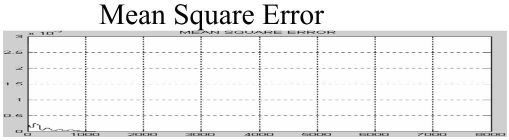
Desired Signal



Filter Output



Mean Square Error



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