An Adaptive filter as Noise Cancellation by using LMS /Newton Algorithm

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Abstract— **Today many adaptive filter structures are proposed for noise cancellation and error detection. The adaptive filter essentially minimizes the mean-squared error between a primary input, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated in the primary input. An adaptive recurrent filter structure is design for acquiring the impulse response of the normal QRS decomposition. The primary input of the filter is the signal to be analyzed, while the reference input is an impulse train coincident with the QRS complexes. This method is applied to several noise detection problems. In this paper using the technique of LMS (least mean square) and by using the Newtown recursion method we made the filter which have minimize 30% of mis adjustment and increase in adaptation. The result has been simulated and presented in Matlab simulink version 7.10.**

Keywords- ***Adaptive filter,LMS/ Newton algorithms, Recursion algorithms, FIR, QRS Decomposition*** **Ease of Use**

I. INTRODUCTION

The development of digital very large scale integration (VLSI) technology allowed the widespread use of adaptive signal processing techniques in a large number of applications. An adaptive filter is defined as a self-designing system that relies for its operation on a recursive algorithm, which makes it possible for the filter to perform satisfactorily in an environment where knowledge of the relevant statistics is not available . Adaptive filter is filters are attractive in many applications as they exhibit a number of desirable properties such as stability and modal performance surface. Adaptive filters are mainly two types (i) linear and (ii) non linear,

Linear adaptive filters compute an estimate of a desired response by using a linear combination of the available set of observables applied to the input of the filter. None linear adaptive filter categories in two types supervised and unsupervised adaptive filter. Supervised adaptive filters require the availability of a training sequence that provides different realizations of a desired response for a specified input signal vector. The desired response is compared against the actual response of the filter due to the input signal vector. and the resulting error signal is used to adjust the free parameters of the filter. The process of parameter adjustments is continued in a step-by-step fashion until a steady-state condition is established and second Unsupervised adaptive filters, performs adjustments of its free parameters without the need for a desired response. For the filter to perform its function, its design includes a set of rules that enable it to compute an input-output mapping with specific desirable properties. In the signal-processing literature, unsupervised adaptive filtering is often referred to as blind de convolution or blind adaptation. Application of adaptive filter VLSI implementation ECE ,Minimum error recursion method ,digital camera ,camcorders, medical monitoring equipment, cell phones and communication devices[3].

II. ADAPTIVE FILTER STRUCTURE

The particular adaptive filter realizations can be extract by a variable filter with an estimate of desired signal. The structure has following assets.

(a) The input signal is the sum of a desired signal which is compound of input data and weighted signal identify X_{lk} and W_{lk} respectively.

(b) The variable filter has a Finite Impulse Response structure .For such structure the impulse response is equal to the Filter Coefficients .

(c) The error signal or cost function is the Difference between the desired and the estimated signal.
(d) The variable filter or processor estimates the desired signal by convolving the input signal with the impulse response.
(e) The function of adaptive algorithm generates the correction factor for the Filter coefficients which is based on the input and error signal [3].

III. ADAPTIVE FILTER STRUCTURE

The SER algorithm is manipulated by using Newton’s method for that purpose we using the LMS/Newton’s algorithms. Figure 2 shows the block diagram of LMS/Newton algorithm. The least mean square (LMS) algorithm was developed by windrow and Hoff in 1960 for use in training neural networks the algorithm is a member of stochastic gradiant algorithm[. The LMS algorithm

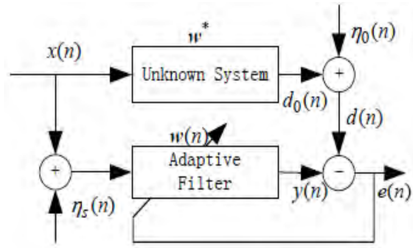

Figure 1. Block Diagram LMS/Newton algorithm)

is a linear adaptive filtering process which consist of two basic process filtering process and adaptive process In basic LMS process the output of adaptive filter which represented y(n) and computing by vector input signal x(n) and generating an estimation error e(n) by comparing the output signal y(n) with desired response d(n).To derive the LMS/ Newton algorithm, the form of Newton's algorithm which is given below

$$W_{K+1} = W_K - \mu R^{-1}\nabla \qquad (1a)$$

Equation (1) shows, under ideal condition the optimum weighted vector W_k and single step that is starting from .The ideal conditions are:μ=½ is a constant that governs stability and rate of Convergence.2. Exact knowledge of the gradient vector , at each iteration.3. Exact knowledge of the (unchanging) signal inverse correlation matrix, R^{-1}.If the first of these condition is removed and μ is made to be between 0 and 0.5the algorithm requires a larger number of steps, but still proceeds along a straight path to W *,. The latter is similar to except that μ has been reduced from 0.5 to 0.05, thus requiring more than just one step to reach the optimum weights. The specific error surface used is the same as that used in with N =16 and Ø =0.01.Next remove the second condition above and assume that we must use a noisy gradient ∇_k , in place of ∇ . Then we have

$$W_{K+1} = W_K - \mu R^{-1}\nabla k \qquad (1b)$$

The algorithm is now ideal only because of the third condition, that is, only because an exact knowledge of $R^{-1}$is still assumed. Without relaxing the third condition, we can now convert into an "LMS" type of algorithm by using the same sort of gradient estimate used, by using ε as an estimate for ζ this gradient estimate is given by

$$\nabla_k = -2\varepsilon_k X_k \qquad (2)$$

Where X_k is of course the input signal vector at the K_{th} iteration., we have

$W_{k+1} = W_K + 2\mu R^{-1}\varepsilon_k X_k$ (3)

Above equation (3) result same as the LMS algorithm in except for the presence of R^{-1} in the weight increment term. We can increase the similarity between the two algorithms by nothing that when **R** is diagonal with eigenvalues, Thus given μ the same range of values as in by using λ_{av} as scaling factor to obtain

$$W_{k+1} = W_K + 2\mu\lambda_{av} R^{-1}\varepsilon_k X_k \qquad (4)$$

The "LMS/Newton" algorithm is defined as the units of λ_{av} and $\varepsilon_k X_k$ which are units of power, the units of R^{-1} and μ are units of reciprocal of power and W is of course dimensionless, so that is correct dimensionally. Notice also that the range of μ has now been scaled by λ_{av}, and, from condition 1 above, we now have For convergence: 1/ λ_{av} > μ > 0,For one-step convergence μ= 1/ 2 λ_{av} under noiseless conditions. The LMS/Newton algorithm is ideal in the sense that an exact knowledge of R^{-1} is assumed. We have already discussed how such knowledge is usually not available in adaptive situations, that is, X is usually non stationary and R is considered to change slowly with time, in an unknown way. The LMS/Newton algorithm is also ideal because, under noiseless conditions on a parabolic error surface, the weight track is a direct path to W*.

$$R^{-1} = \begin{bmatrix} r_1 & r_2 \\ r_2 & r_1 \end{bmatrix}^{-1} \quad (5)$$

$$= \frac{1}{r_1^2 - r_2^2} \begin{bmatrix} r_1 & -r_2 \\ -r_2 & r_1 \end{bmatrix} \quad (6)$$

Equation (5) and (6) elements r1 and r2 with N=16 and Ø = 0.01. Also for the LMS/Newton algorithm, we need λ_{av} by

$$\lambda_1, \lambda_2 = r_1 \pm r_2 \quad (7)$$

$$\lambda_{av} = r_1 = 0.51 \quad (8)$$

IV. THE SEQUENTIAL REGRESSION ALGORITHM

Comparing the LMS and LMS/Newton algorithm, we see that it is the knowledge of R^{-1} that allows W to take the direct path, rather than the path of steepest descent, to W *. To develop an algorithm more like the LMS/Newton, we might therefore think in terms of estimating R^{-1}at each step, and thus approaching the ideal. The sequential regression (SER) algorithm [1, 2] embodies precisely this sort of improvement. It computes an estimate of R^{-1} that generally improves with each iteration, and thus approaches. To develop the SER algorithm, let us look first at how we might estimate **R**, which is simpler problem than that of estimating R^{-1}.Using the notation, we have the elements of R given by the input correlation function, where n is the distance from the main diagonal:

$$\emptyset_{xx}[n] = E[X_k X_{k+n}] \quad (9)$$

Thus we can write

$$R = E[X_k X_{k+n}] \quad (10)$$

Instead of letting the expectation go over all values of k, suppose now that we have a finite number of observations of the signal X, say X_0 through X_k. Under stationary conditions, our best unbiased estimate of R would then be

$$R_k = \frac{1}{k+1} \sum_{l=0}^{k} X_l X_l^T \quad (11)$$

In adaptive situations where X is non stationary, we can see that would not be a good estimate of R. Because of its infinite memory, this estimate would become insensitive to changes in :R for large values of k. To provide the effect of a short-term memory in the estimate of **R**, consider the following function;

$$Q_k = \sum_{l=0}^{k} \alpha^{k-1} X_l X_l^T \quad (12)$$

Comparing the equation(11) and (12) we have measure the scaling factor which is R times of the stationary vector X, thus the value of α

$$0 < \boldsymbol{\alpha} < 1 \quad (13)$$

From equation (13) the total value of this scaling factor over k iterations is

$$\sum_{l=0}^{k} \alpha^{k-l} = \frac{1-\alpha^{k+1}}{1-\alpha} \quad (14)$$

and thus our modified estimate of **R** at the K^{th} iteration (which would be exact, for example, if X_k were constant for k > 0).is

$$R_k = \frac{1-\alpha}{1-\alpha^{k+1}} Q_k \quad (15)$$

in the equations (12),(13),(14) and (15) it is being observed that the limit of scaling factor where X_k is stationary for all time, **α** approaches 1 and if we take the limit as **α** approaches 1, we get agreement Having the estimate R_K and ready to begin the derivation of the SER algorithm. we begin with the formula for the optimum weight vector given first(ref 4.3).

$$\hat{\nabla} = 2R.W - 2.P \quad (16)$$

$$R_k . W_k = P_k \quad (17)$$

In the equation (16) and (17) the K^{th} estimates that have the relation P and R estimates respectively. then from the definition of P we obtain

$$P_k = \frac{1-\alpha}{1-\alpha^{k+1}} \sum_{l=0}^{k} \alpha^{k-l} d_l X_l \quad (18)$$

After cancel the scaling factor and obtain

$$Q_k W_k = \sum_{l=0}^{k} \alpha^{k-l} d_l X_l \quad (19)$$

The SER algorithm is now developed as follows beginning with that W_{k+1} (rather than W_K) is to be computed from terms of R_K and P_k Then we,

$$Q_k W_{k+1} = \sum_{l=0}^{k-1} \alpha^{(k-1)-l} d_l X_l + d_k X_k \quad (20)$$

$$= \alpha Q_{k-1} W_k + d_k X_k \quad (21)$$

$$= (Q_k - X_k X_k^T) W_k + d_k X_k \quad (22)$$

Referred to K^{th} iteration we get

$$Q_k = \alpha Q_{k-1} + X_k X_k^T \quad (23)$$

Next we substitute the desired signal,

$$Q_k W_{k+1} = (Q_k - X_k X_k^T) W_k + (Q_k + X_k X_k^T W_k) X_k \quad (24)$$

$$= Q_K W_k + e_k X_k \quad (25)$$

We now multiply on the left by Q_k^{-1} and finally obtain

$$W_{k+1} = W_k + Q_k^{-1} e_k X_k \quad (26)$$

Since Q_k^{-1} is scaled approximation to R we have here the form of the LMS/Newton algorithm. Now we consider to state here

$$Q_k^{-1} = \frac{1-\alpha}{1-\alpha^{k+1}} R_k^{-1} \quad (27)$$

And under the steady-state case where k is large enough to neglect α^{k+1} in, we make an approximation as follows

$$W_{k+1} = W_k + \frac{2\mu\lambda_{av}}{1-\alpha} Q_k^{-1} e_k X_k \quad (28)$$

Note that under nonstationary conditions, λ_{av} is changing quantity that may have to be adjusted during the adaptive process, Note also that omitting the factor ($1-\alpha^{k+1}$) from the last term is equivalent to using a larger value of at first. If initial conditions are important, one could include the factor and SER to obtain

$$W_{k+1} = W_k + \frac{2\mu\lambda_{av}}{1-\alpha} [1-\alpha^{k+1}] Q_k^{-1} e_k X_k \quad (29)$$

V. SIMULATION RESULT

The LMS/NEWTON Methodologies having a criterion for optimum performance of the filter. It has one way to remove the noise by using the potential loss of adaptive filter .The system simulation is used to see the real effect and implementation before its development. In the example we runs the adaptation process for 1000 iteration which demonstrate quardrature phase shift keying (QPSK) adaptive equalization using a 32 co-efficient bit FIR filter as shown in Fig[2,3]. In this the existing system takes N=16 Number of delay samples that can be used to verify analytical solutions. In this technique we then take the numerator co-efficient of channel, Denominator co-efficient of channel and Number of iteration respectively for decision is made for simulation. The QRD process with coefficients [1 0.7 1 -0.7 0 0.05] and signal step size and projection order is 4 is used in . It is essential to consider first what mathematical techniques might be applied to derive an analytical solution such as QRD or SVD methodology. Now we take a baseband signal which comprising a random Noise signal .This Baseband with Noise signal is received at the Filter input. Now we recover the received signal by desired signal or delayed QPSK signal by using the step and Projection order, The parameters in our experiment are mu=0.1 , Po= 4, offset= 0.05, B=exp(j*pi/4)*[-0.7 1]A= [1 -0.7];Ntr= 1000;This step, projection offset technique is probably done by adaptive filter and filter simulation methodologies as shown in Fig [4,5] .The existing system design can be used to verify analytical solution ,methodologies and requirement can be determined by simulation different capabilities for the system.

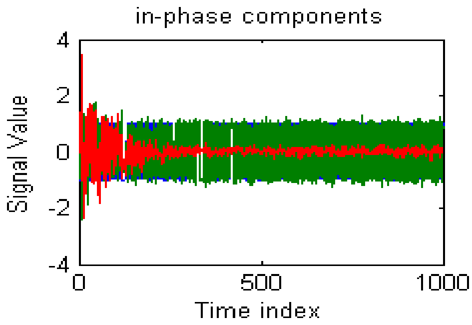

Figure 2In-phase components

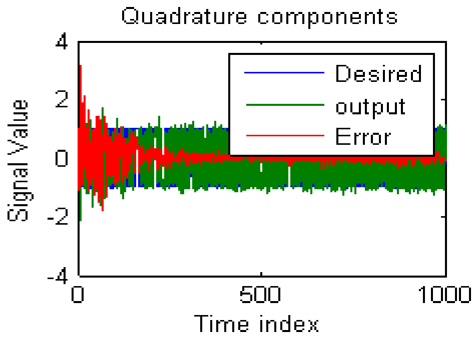

Figure 3Quadrature component

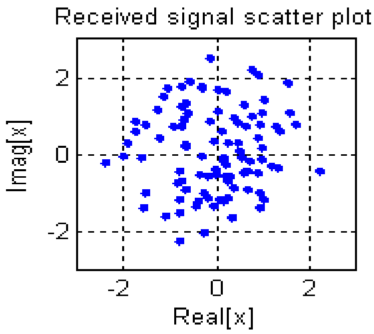

Figure 4 scatter plot of receive signal

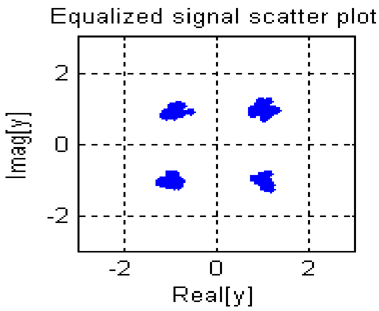

Figure 5scater plot of equalized signal

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