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Blind Channel Equalization using Constant Modulus Criterion

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Abstract - We are in such a world wherein every communication services such as mobile phones, modems require high data rate and good quality. It is the duty of the designer of such devices to make use of innovative and robust equalization algorithms in order to reduce noice in the communication channel. In the past decade, many equalization algorithms are being developed by the researchers to optimize the performance. Blind Channel equalization is one such type, which makes use of only transmitted signal statistics making this type of algorithm better than other conventional Equalization algorithms. In this paper, I have brie y outlined the properties and working principle of Blind Channel Equalization. The reader is expected to have good knowledge of di erent equalization techniques and di erent channels used in communication models.

Keywords - Blind equalizers, Adaptive algorithms, LMS algorithm, Wireless communication

I. Introduction

Conventional equalizers like Decision feedback require training sequence for adaptation, where the adaptive equalizers like Blind channel equalizer do not require such type of sequences making more attrctive for number of applications. Blind equalization is a digital signal processing technique in which the transmitted signal is inferred from received signal while making use only of the transmitted signal statistics. Because of such behavior we call it blind equalizer. It is basically a blind deconvolution applied in the digital communication system models. In this technique, main emphasis is given on estimation of equalization lter and it is the inverse of channel impulse response, rather than the estimation of the channel impulse response itself. This is due to blind deconvolution common mode of usage in digital communications systems, as a means to extract the continuously transmitted signal from the received signal, with the channel impulse response being of secondary intrinsic importance. The estimated equalizer is then convolved with the received signal to yield an estimation of the transmitted signal.

Multipath interference is one of the common problems that the present communication channels are facing. Due to ISI (Inter Symbol Interference) and ICI (Inter Carrier Interference) in the multipath in a communication channel, there will be a signi cant noise and there might be a huge loss of data in the channel making reception of the transmitted data very di cult. Basically in blind equalization algorithm we use constant modulus criterion (CMA) to calculate tap coe ecients. Even though CMA is slow converging, we use this criterion because of the feature that it does not require training sequences to retrieve back the transmitted data at the receiver.

II. Background

The rst known blind equalization algorithm was introduced by Sato . Sato's blind equalization algorithm error function was later generalized by Benveniste et al. Godard also described a class of cost functions that generalizes Sato's. The constant modulus algorithm (CMA), which is a special case of Godard's algorithm, was developed separately by Treichler et al. based on property restoral concept. Bellini et al. followed a di erent approach and developed \Bussgang Techniques." Based on some assumptions about the equalizer and the channel parameters, a maximum likelihood estimator of the reference signal was derived. This estimator depends on the type of modulation used and the signal-to-noise ratio (SNR). It was shown that the algorithms due to Sato and Godard can be viewed as special cases of the Bussgang technique.

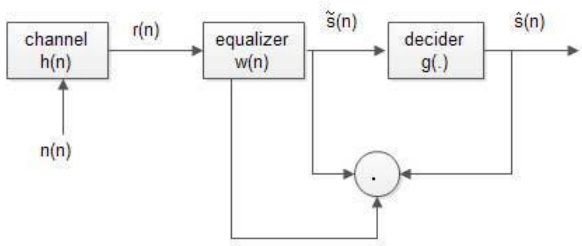

Fig.1 Blind Channel Equalization model

s(n) is the channel input sequence, h(n)is the channel input sequence, n(n)is noise, w(n) are equalizer tap sequence,s(n) is ~ ^ coe cients, s(n) is equalizer output judgment sequence.

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The above algorithms use nonconvex cost functions which possess local minima to which the blind equalizer might converge. Some of these equilibria may be undesirable, i.e., at those equilibria the equalizer will not be able to remove ISI. This was demonstrated by Ding et al. for the Godard algorithm and for the Sato algorithm . In the ill convergence of the Benveniste et al. algorithm was also shown, thus proving that none of the previous algorithms was globally convergent. For these algorithms equalizer initialization becomes an important issue. One would initialize the equalizer away from the neighborhood of the local minima.

III. CMA Approach

To minimize the dispersion of output of the equalizer, we use CMA which is a stochastic gradient algorithm where it adapts lter coe ecients at time 'n' in order to minimize error $"^2$.

$$"^2 = E[jj\ y(n)\ j^2 \quad A\ j^2]$$

where A is the desired modulus and

$$y(n) = \sum_{k=0}^{L\ 1} !_n(k)x(n \quad k) = W_n^t X_n$$

here x(n) is is the signal to be equalized and y(n) is the complex equalizer output , $!_n(k)$ are the adaptive lter taps and//

$$X_n = [x(n)x(n \quad 1):::x(n\ \ N + 1)]^T$$

$$W_n = [!_n(0)!_n(1):::!_n(N \quad 1)]^T$$

The initial weight vector coe ecients are set to zero. A stochastic gradient update of the lter coe ecients is given by:

$$!_{n+1}(k) = !_n(k) \quad 4\ ((j\ y(n)\ j^2) \quad A^2)y(n)x\ (n \quad k)$$
$$= !_n(k) \quad Kx\ (n\ \ k)$$

where

$$K = 4(j\ y(n\ j^2 \quad A^2)y(n)$$
$$W_{n+1} = W_n \quad 4\ ((j\ y(n)\ j^2) \quad A^2)y(n)X_n$$
$$= W_n \quad KX_n$$

The step factor is typically a constant selected through experimentation.

Of this family of algorithms, only the 1-1, 1-2, 2-1 and 2-2 forms are of much interest. As with the 2-2 CMA algorithm is described above, the stochastic gradient updates take the general form

$$W_{n+1} = W_n \quad K_{p;q}X_n$$

Where

$$K_{1;1} = sign(j\ y_n\ j \quad A) \frac{y_n}{j\ y_n\ j}$$

$$K_{1;2} = 2(j\ y_n\ j \quad A) \frac{y_n}{j\ y_n\ j}$$

$$K_{2;1} = 2sign(j\ y_n\ j^2 \quad A^2)y_n$$

IV. LMS Algorithm

The LMS Algorithm is a developed form of steepest descent adaptive lter, in the family of stochastic gradient algorithms, which has a weight vector update equation given by:

$$!_{n+1} = !_n + \ e(n)x\ (n)$$

The above equation is known as the LMS algorithm. The simplicity of thefact that the update for the k^{th} coe ecient requires only one multiplication and one addition. The updated equation for the k^{th} coe ecient is given by

$$!_{n+1}(k) = !_n(k) + \ e(n)x\ (n \quad k)$$

The step size determines the algorithm convergence rate. Too small step size will make the algorithm take a lot of iterations while too large step-size will not convergence the weight taps. Step size may be calculated by rule of thumb as it is shown in the below equation

$$= \frac{1}{5(2N + 1)P_R}$$

Where N is the equalizer length, P_R is the received power that can be estimated at the receiver.

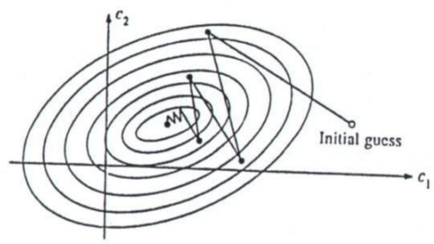

Fig. 2 LMS convergence graph

LMS algorithm convergence graph is illustrated in Figure.2. The initial weight vector coe cients are set to zero. The weights are updated each iteration by equation. This is basically going in the opposite of the gradient vector, until get the MMSE (Minimum Mean Square Error) is reached, meaning the MSE is 0 or a very close value to it. (In practice error of 0 cannot be reached since noise is a random process and the error could only be decreased to a value below the desired minimum).

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V. Result analysis

To understand the nature of LMS algorithm and Blind channel equalization, let us consider two Gaussian communication channels with the following z-transforms

$$H_1 = \frac{1}{1 \quad 0{:}9Z^{1}}$$

$$H_2 = \frac{1}{1 + 0{:}9Z^{1}}$$

and while simulating we are using QPSK modulatiion with zero mean and white gaussian noise with 10^{6} variance. If a signal passes through Channel H1, the output for length-2 lters has less dispersed eigenvalues, but it has more dispersed eigenvalues while using channel H2. In other words, channel 1 is complex than channel 2 making it di cult to handle channel 1. In this experiment implementation of an equalizer of length 2 for CMA and length 8 for LMS is carried out. The step size taken for LMS is 0.007 and 0.001 for CMA. Now after simulation, we get the results for LMS algorithm and CMA (1,1) as shown in the gure 3 and 4 respectively. These implementations are done in Channel 1. Similarly for channel 2, we have implemented LMS and CMA (1,1) and shown in the gure 5 and 6 respectively.

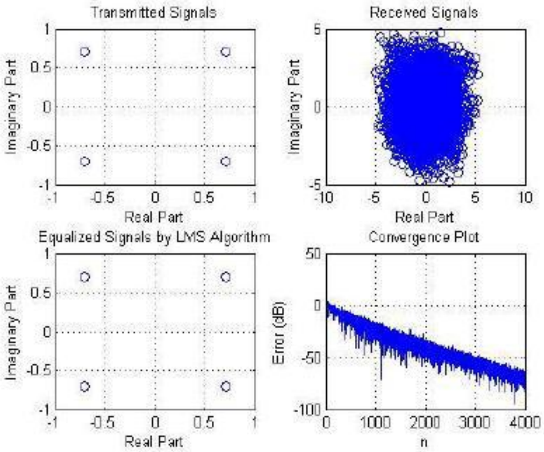

Fig.3 Signal equalization based on LMS algorithm for channel 1.

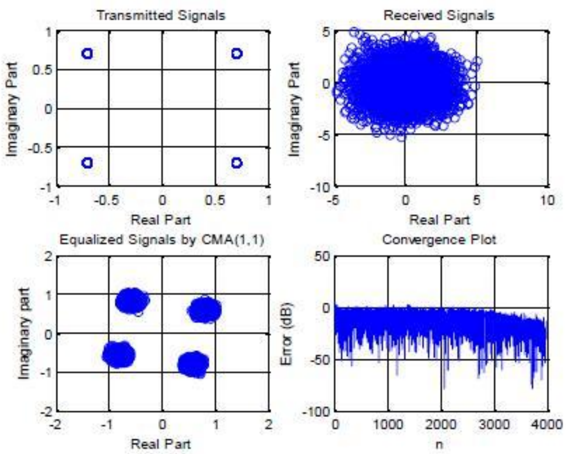

Fig.4 Signal equalization based on CMA(1,1) for channel 1.

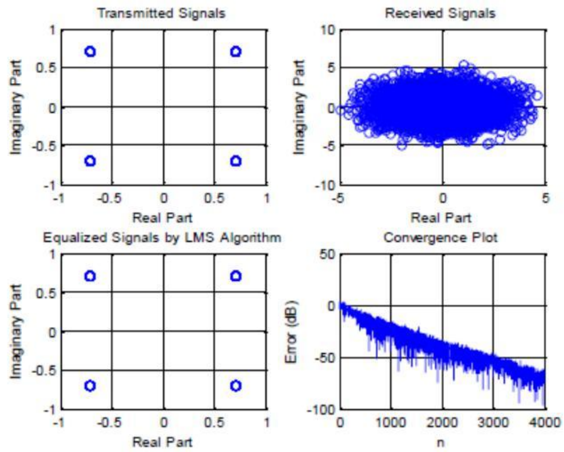

Fig.5 Signal equalization based on LMS algorithm for channel 2.

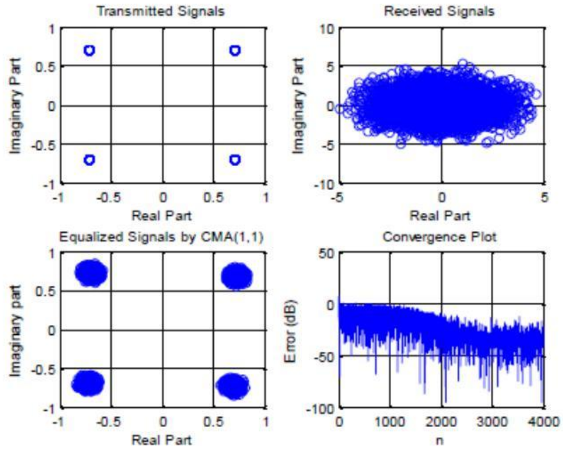

Fig.6 Signal equalization based on CMA(1,1) for channel 2.

IV. Conclusions

By the end of this paper we can come to a conclusion that CMA algorithm for Blind channel equaliztion is used only when there are no training sequences available and we do not have the knowledge about the incoming sequence of data. From the results we got from the MATLAB, it is clear that LMS algorithm is faster in performance when compared to CMA(1,1), CMA(1,2),CMA(2,1),CMA(2,2).But when we take convergence rate as the parameter, CMA systems have greater convergence rate and have upper hand over LMS systems. Since for a system, it is important that the coe ecients of the lter approach optimum value at faster rate, CMA algorithm with Blind Channel Equalization is preferred over LMS algorithm based systems. When we use chirp sequence in the system, the equalizer coe cients were obtained in closed form via the minimization of a constrained least-squares problem. Moreover, the method can be con gured to deliver the equalization solutions corresponding to di erent delays in a simple manner.

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