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Genetic algorithm assisted DS-UWB BPSK MMSE receiver

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ABSTRACT

Ultra Wide-band (UWB) in recent times draws much consideration as an indoor short range high-speed wireless communication technology for future networks. Direct sequence spread ultra-wide-band (DS-UWB) systems uses extremely short pulses and has the advantage of high path resolution and can get multi-path diversity. Mainly it is useful for indoor communication, which generates many multipaths. The effect of multipath components can be positively used, if rake structured receivers such as selective rake (S-rake) receiver is used. Unfortunately inter-symbol interference (ISI) will become a significant performance limitation when data rate is high. Adaptive algorithms such as Least-Mean-Square (LMS) based channel equalizer aim to minimize the Inter symbol Interference (ISI) present in the transmission channel. However the adaptive algorithms suffer from long training time and undesirable local minima during training mode.

A new adaptive channel equalizer using genetic algorithm (GA) is proposed here. This algorithm is suitably used to select the LMS convergence factor of the equalizer. The performance of the proposed channel equalizer is evaluated in terms of mean square error (MSE) and convergence rate and compared with analytical method.

1. Introduction

In modern digital communication systems, the transmission of high-speed data through a channel is limited by Inter symbol Interference (ISI) caused by distortion in the transmission channel. High-speed data transmission through channels with severe distortion can be achieved by designing an equalizer in the receiver that counteracts the channel distortion [1]. In practice, the channel is time varying and is unknown in the design stage due to variations in the transmission medium. Thus, we need an adaptive equalizer that provides precise compensation over the time-varying channel and attempts to recover the transmitted symbols [4].

The most frequently used structure of equalizer is a transversal adaptive filter. There are many adaptive filters which goes well with an adaptive filter such as least mean square (LMS) [2], recursive least squares (RLS), or QR-Decomposition-Based least squares lattice filter (QRD-LSL) [6]. The performances of the RLS and QRD-LSL algorithms are not dependent on the eigenvalue spread of covariance matrix, since the covariance matrix is inverted directly. On the other hand, slow convergence in the case of large eigenvalue spread of the sample covariance matrix is the main drawback of LMS algorith. However, these adaptive signal processing techniques pay large number of iterations to carry out channel equalization and thereby make their applications in real life exorbitant as they are computationally too affluent and are inappropriate for a fast dynamically changing channel as they require a latent time to collect the training data [3]. The convergence rate can be accelerated by use of the conjugate gradient (CG) method [6]. The goal of CG is to iteratively search for the optimum solution by choosing perpendicular paths for each new iteration. However, the above mentioned algorithms are based on the steepest descent algorithm.

Genetic algorithm is based upon the process of natural selection and does not require gradient statistics. As a consequence, a GA is able to find a global error minimum [6]. Moreover, the GA with small population size and high mutation rates can find a good solution fast.

2. Basic concepts

Fig. 1 represents the general block diagram of a typical DS-BPSK-UWB wireless communication system using adaptive MMSE receiver for received signal detection [7].

The adaptive MMSE receiver consists of a sampling filter and an adaptive filter. The sampling filter samples the total received

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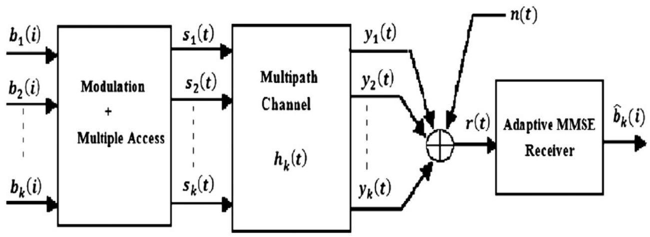

Fig. 1. Block diagram of DS-BPSK-UWB.

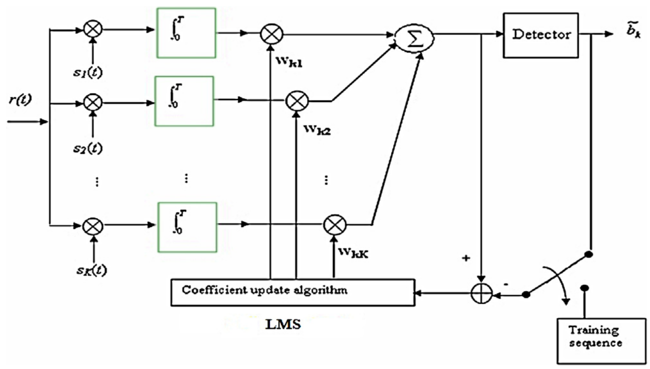

Fig. 2. General structure of adaptive MMSE receiver [6].

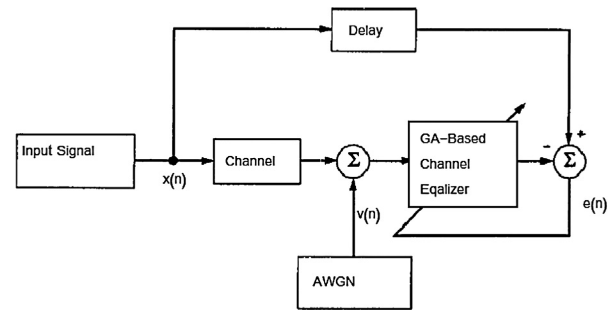

Fig. 3. General structure of adaptive MMSE receiver .

signal at least as fast as the Nyquist rate and its output is taken as the adaptive filter's input [8]. The adaptive filter is a finite-impulse response (FIR) filter that essentially acts as a linear corrector with MMSE criterion that minimizes the mean square error (MSE) with different adaptive algorithms.

During each bit decision period, a bit decision b_k is made at the output of the adaptive filter and is then fed back to the adaptive filter to compute MSE [3]. In order to capture enough multipath energy, the observation window of the adaptive filter is typically longer than one bit interval and therefore, windows overlap in time. The whole adaptation works in two stages: training and decision directed stages. In the training stage, a training sequence is transmitted to adapt the channel. In the decision directed stage, hard decisions are made for information bits and at the same time the tap coefficients are updated with MMSE criterion. Fig. 2 depicts the general structure of a typical adaptive MMSE receiver for a total of K asynchronous users. An LMS adaptive algorithm is used to update the receiver weighting coefficients.

3. Adaptive algorithm

The length M weighting vector $W_k(n)$ contains the coefficients of the transversal filter. The a posteriori error $e_k(n)$ between the transmitted bit $b_k(n)$ and the filter output is given by:

$$e_k(n) = b_k(n) - w_k^T(n)r(n) \tag{1}$$

In order to minimize the mean-square error, a weighting vector must be found that minimizes the cost function

$$J(n) = E\left[(e_k(n))^2\right]^2 = E\left[\left(b_k(n) - w_k^T(n)r(n)\right)\right]^2 \tag{2}$$

From (2), we can see that the cost function, $J(n)$, is quadratic in $W_k(n)$ and no local minima exist.

The most commonly used non-blind adaptive algorithms to minimize the cost function, $W_k(n)$, is the Least Mean Square (LMS).

4. Least mean square(LMS) algorithm

The LMS algorithm is by far the most widely used adaptive algorithm for several reasons. The main features that attracted the use of the LMS algorithm are low computational complexity, proof of convergence in stationary environment, unbiased convergence in the mean to the Wiener solution, and stable behavior when implemented with finite-precision arithmetic. The LMS update of the filter coefficients that minimize the cost function.

$$w_k(n+1) = w_k(n) + 2\mu e_k(n)r(n) \tag{3}$$

where the convergence factor μ should be chosen in a range to guarantee convergence

5. GA-based channel equalization

The LMS based channel equalizers aim to minimize the ISI present in the linear dispersive communication channel. These are gradient based learning algorithms and therefore there is possibility that during training mode of the channel equalizer, its weights do not reach to their optimum values due to the mean square error (MSE) being trapped to local minimum. A new adaptive channel equalizer using GA optimization technique is proposed here which is essentially a derivative free optimization tool. This algorithm is used to update the weights of the equalizer by selecting optimum value of μ as explained in the following steps:

Fig. 3 System model of GA based adaptive Channel Equalizer Simulate the signals as illustrated in Fig. 2, the Input signal block provides the test signal $x(n)$ used for probing the channel, whereas AWGN block serves as the source of additive white noise $v(n)$ that corrupts the channel output. The GA based adaptive equalizer has the task of correcting for the distortion produced by the channel in the presence of the additive white noise. Input Signal block, after suitable delay, also supplies the desired response $d(n)$ applied to the GA based equalizer in the form of a training sequence. This system is simulated as follows (Fig. 4):

6. Simulation parameters for GA

Initial population size = 20.
No of iterations = 50.
Probability of crossover = 1.
Probability of mutation = 0.01.
No of inputs = number of bits
Decimal encoding.
Stopping criterion:
If error is less than 10^{-4}.
If number of generation exceeds 50.

- Simulate some useful signal to be transmitted by using random bipolar (−1,1) sequence.
- Each of the input data samples is passed through the channel and then contaminated with the additive noise of known variance (where its variance is determined by the desired signal-to-noise ratio). The resultant signal is passed through the equalizer. In