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Transmission Channels and Noise Models for Wireless Sensor Networks and Blind Equalization

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Abstract

Wireless Sensor Network (WSN) is a self-organized distributed communication network, composed by a number of geographically separated, autonomous and low-cost sensor nodes with limited power and processing capability, which are cooperating with each other to connect and process data from the surrounding through wireless communication. To fulfill a common task, WSN cooperates through the wireless transmission medium. In recent years, WSN has attracted research interest because of its employment on land, underground,underwater and top of mountain,which are very wide. However, there are still obstacles to be more extensively employed. In this work, it is emphasized that blind equalization should be proactively utilized to develop WSNs furthermore. A method based on finding the easiest sensor location is derived and its performance is demonstrated in a comparative fashion.

Keywords

Wireless Sensor Network • Least Mean Square • Recursive Least Squares

Introduction

The estimation algorithms used in Wireless Sensor Networks (WSNs) can be classified into two categories: centralized and distributed. In the centralized estimation algorithms, the estimation of all sensors is carried out after receiving output data collected from all sensors. In this approach, each sensor must communicate with the fusion center to obtain the desired signal, but it reduces the most valuable communication resources of energy and bandwidth. On the other hand, in the distributed estimation algorithms, estimation of each sensor is updated by using the local observations and the information derived from the neighboring nodes. This approach reduces the latency and saves communication resources. Therefore, the distributed approach is more robust, protective of privacy, easier to extend and less complicated in computation. So far, there have been a number of distributed in-network processing algorithms, for example, adaptive approaches have been proposed in this research area, such as incremental Least Mean Square (LMS) [1], incremental affine projection algorithm [2], incremental Recursive Least Squares (RLS) [1], diffusion LMS [3], distributed LMS in consensus strategies [4] and so on. Most of the existing distributed estimation algorithms are training-based or non-blind. The training-based algorithms require the transmitted sequence as well as the desired signal as the training sequence at the receiver to estimate the unknown parameters. However, these algorithms have some drawbacks. The training signals are unavailable in most applications and may be unrealistic or impractical, reducing the data rate. Therefore, the system efficiency and the valuable channel capacity are reduced. In such cases, blind equalization is required, which does not require the transmitted sequence and only use the received sequence and some priori knowledge of the transmitted sequence statistics.

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Liu and Li in [5] developed a distributed diffusion Generalized Sato Algorithm (GSA) by extending the diffusion LMS [3], in which a distributed blind equalizer was designed for channel equalization and source signal estimation. Two types of this algorithm, named the Adapt-Then-Combine (ATC) diffusion GSA (ATC-GSA) and the Combine-Then-Adapt (CTA) GSA (CTA-GSA), were addressed. The performances of ATC-GSA and CTA-GSA are similar, but they are better than that of the Non-Cooporative (Nc) GSA (Nc-GSA). In the ATC-GSA and CTA-GSA, the information is exchanged with neighbors by sharing the complex tap coefficients of the blind equalizer. For a large network, however, the ATC-GSA and CTA-GSA require a large number of equalizers, which results in a long computation time to reach the desired estimation. In this work, a blind equalization method, which is more efficient and effective than the CTA-GSA, is derived and its performance is investigated.

Motivation

We consider a simple and static network model in which the sensor output is combined by applying the weights of the diffusion cooperation rule to the channel outputs. Using this model, we propose a method of identifying the optimal sensor location for blind equalization from noisy sensor outputs, which is recognized as the easiest sensor location. The transmitted signal is estimated blindly from the easiest path location using the generalized Sato equalizer.

The following four types of transmission channels and noise models are considered.

Case I: Common channels and common variance of noises.

Case II: Common channels and different variance of noises.

Case III: Different channels and common variance of noises.

Case IV: Different channels and different variance of noises.

In [5], only Case II was considered. In this work, the other three possible cases are additionally considered and the solution in each case is discussed and derived.

Proposed blind equalizer

A block diagram of the proposed blind equalizer is shown in Figure 1.

Here, a Single-Input Multi-Output (SIMO) channels model is considered. Common or different channels and common or different variance of noises are assumed as Cases I-IV.

To find the easiest sensor location for equalization, we use all sensor outputs. To accomplish this, the most straightforward approach may be the eigenvalue spread calculation of each correlation matrix of all sensor outputs. However, this becomes time-consuming as the equalizer length is increased. Therefore, instead of directly calculating the eigenvalue decomposition, we propose adaptive calculation of the normalized error, which is more efficient than the direct eigenvalue decomposition approach. Furthermore, the output of the prediction error filter used to calculate the normalized error is directly utilized as the input to the blind equalizer. This means the continuous implementation of the blind equalizer without collecting a large number of sensor output data. This feature is beneficial for wireless communication systems.

In Figure 1, the decision center of the proposed method holds all normalized error values for all sensor nodes as well as all the sensor output signals. Observing all normalized error values of all sensor outputs, we can find the easiest sensor location, for which the value of the normalized error is nearest to one, among all sensor locations, in real time. Hence, we utilize only the easiest sensor output for equalization. In the blind equalizer part in Figure 1, the GSA is used for equalization.

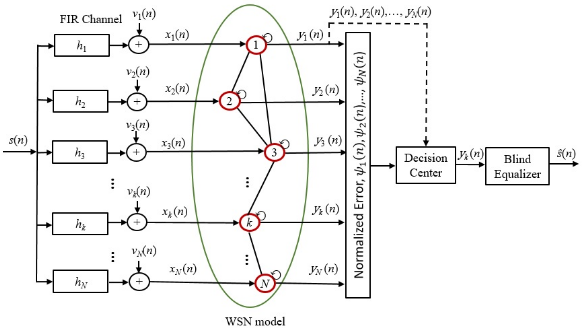

Figure 1. System model.

Originally, the normalized error was defined as the ratio of the power of the minimum prediction error to the power of the input speech signal [6]. In Figure 2, a block diagram to implement it is shown, where the prediction error filter is denoted as a prefilter. When the power spectrum spread of the sensor output signal is small (this case corresponds to a small condition number case), the normalized error is closer to one. On the other hand, the normalized error becomes close to zero if the power spectrum of the signal is largely spread (this case corresponds to a large condition number case). We propose adaptive implementation of the normalized error.

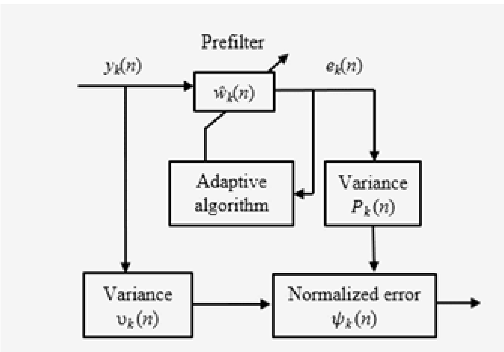

Figure 2. Block diagram for the normalized error calculation.

Simulations

By carrying out simulation experiments, we demonstrate the performance of the proposed method. We use non-minimum phase channels in a static WSN that consists of five sensor nodes. The transmitted signal is generated from a four Quadrature Amplitude Modulation (QAM) constellation. To compare the performance of the proposed method, the CTA-GSA and Nc-GSA are also implemented. Figure 3 shows an example of Symbol Error Rate (SER) performance after the convergence of each equalizer. It is observed in Figure 3 that the proposed method provides an improvement relative to the CTA-GSA and Nc-GSA.

The result in Figure 3 corresponds to that in Case IV where different channels and different variance of noises are assumed. Results in Case I, Case II and Case III are found in [7].

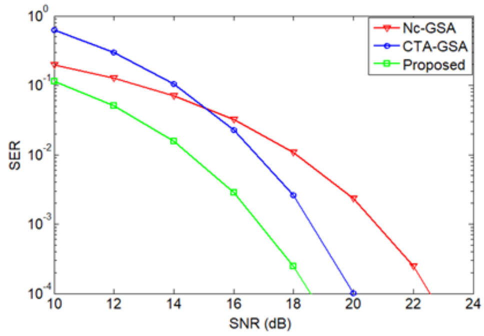

Figure 3. SER performance for Nc-GSA, CTA-GSA and proposed methods.

Conclusion

In the centralized estimation algorithms, the estimation of all sensors is carried out after receiving output data collected from all sensors. In this approach, each sensor must communicate with the fusion center to obtain the desired signal, but it reduces the most valuable communication resources of energy and bandwidth. On the other hand, in the distributed estimation algorithms, estimation of each sensor is updated by using the local observations and the information derived from the neighboring nodes. However, there are still obstacles to be more extensively employed. In this work, it has been emphasized that blind equalization should be proactively utilized to develop WSNs furthermore. A method based on finding the easiest sensor location has been derived and its performance has been demonstrated in a comparative fashion.

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