Blind Signal Processing for Wireless Sensor Networks

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Abstract

In indoor sensor networks equalization algorithms based on the minimization of Euclidean distance (MED) for the distributions of constant modulus error (CME) have yielded superior performance in compensating for signal distortions induced from optical fiber links, wireless-links and for impulsive noise problems. One main drawback of MED-CME algorithms is a heavy computational burden hindering its implementation. In this paper, a recursive gradient estimation for weight updates of the MED-CME algorithm is proposed for reducing the operations $O(N^2)$ of the conventional MED-CME to $O(N)$ at each iteration time for N data-block size. From the simulation results of the proposed recursive method producing exactly the same results as the conventional method, the proposed estimation method can be considered to be a reliable candidate for implementation of efficient receivers in indoor sensor networks.

Keywords: Complexity, CME, Euclidean distance, Error distribution, Impulsive noise, Sensor networks

1. INTRODUCTION

Sensor networks are composed of spatially distributed sensors, actuators and communication links so that sensor networks with wireless links require dealing with wireless-related communication problems and signal processing in addition to operations of sensors and actuators.

Some harsh problems in sensor network communication environment are multipath propagation and severe fading [1]. Besides, impulsive noise from indoor electric devices with electromechanical switches affects the indoor wireless links [2].

For multipath fading compensation, training-aided equalization methods or blind methods may be used to mitigate multipath propagation and to improve both bandwidth and energy efficiency [3]. Training-aided equalization methods have to use a sufficiently long training sequence in each data packet since sensors usually work with low duty-cycle [4]. This implies that training-aided algorithms are not suitable for the reason of wasting bandwidth and power as well. Blind

equalizer algorithms in which training sequences are removed are useful to enhance power and bandwidth efficiency [5]. For blind equalization the constant modulus error (CME) is usually used to be minimized. The CME is defined as the difference between the output power and a constant modulus predefined according to the modulation schemes. Based on the mean squared error (MSE) criterion on the average power of CME, the well-known constant modulus algorithm (CMA) has been developed for blind equalization [5]. The MSE criterion of the CMA can mitigate the influence of Gaussian noise on the algorithm due to its averaging operation.

However, indoor wireless sensor networks are interfered with not only Gaussian noise but also impulsive noise from a various sources of impulse noise. Impulsive noise induces large instantaneous system errors that often make the CMA on the basis of MSE criterion fail [6]. Instead of the MSE criterion that utilizes error energy, the correntropy concept has been proposed to cope with impulsive noise problems [6]. The correntropy blind method known to be effective in correlative signaling systems has shown not as satisfying as expected in the modulation schemes employing independently distributed symbol points [7].

As an alternative to the correntropy cost function, the Euclidean distance (ED) between CME distribution and the Dirac-delta function has been proposed to cope with impulsive noise problem as well as channel distortions [7]. The blind

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algorithm based on ED has shown superior performance in compensation for multipath fading and impulsive noise, but it has a drawback of demanding heavy computations due to some double summation operations at each iteration time, and that problem indicates consuming more power in computation. For reliable and efficient signal demodulation and detection in sensor networks, computationally efficient techniques must be used [3].

In this paper, by way of recursively estimating the gradient of the weight update equation of the ED-CME, we develop an adaptive algorithm that has significantly reduced computational complexity while keeping the robustness of the ED-CME algorithm to those ill-conditions of channel environment the same.

2. METHODS

2.1 System Model and Blind Equalizer Algorithms

In wireless sensor networks, sensor signal is transmitted through the wireless channel and noise n_k is added to the channel output as depicted in baseband model in Fig. 1. The noise-added channel output is received at the equalizer. The multipath channel can be expressed as $H(z) = \sum h_i z^{-i}$ in z-transform and the equalizer input can be expressed as $x_k = \sum h_i d_{k-i} + n_k$ [3]. The equalizer structure is assumed as a tapped delay line (TDL) with L weights as in [9], then the equalizer output y_k at time k with the input vector $\mathbf{X}_k = [x_k, x_{k-1}, \dots, x_{k-L+1}]^T$ and weight vector $\mathbf{W}_k = [w_{0,k}, w_{1,k}, \dots, w_{L-1,k}]^T$ can be expressed as $y_k = \mathbf{W}_k^T \mathbf{X}_k$.

For constant modulus error $e_{CME,k}$ defined as in (1), the MSE criterion P_{MSE} in (2) has been widely used in blind equalization algorithms

$$e_{CME,k} = |y_k|^2 - R_2 \quad (1)$$

$$P_{MSE} = E[|e_{CME,k}|^2] \quad (2)$$

where $R_2 = E[|d_i|^4]/E[|d_i|^2]^2$ and $\{d_i\}$ is a set of symbol points predefined for modulation. Instead of taking (2), minimization of the instant power of CME $e_{CME,k}^2$ with respect to weight is employed as a cost function which is efficient for implementation in the well-known CMA algorithm. While the influence of the Gaussian noise can be mitigated owing to the expectation or mean operation $E[\cdot]$ in (2), impulsive noise may defeat the averaging operation since a single large impulse can dominate the mean operation. Therefore impulsive noise can

Fig. 1. Wireless transmission system model between a sensor node and its related network.

lead algorithms based on the MSE criterion to become unstable. This indicates that the instant error power e_{CME}^2 without being averaged may cause worse instability in the CMA.

As another cost function to be minimized, the Euclidean distance $ED[f_E(e_{CME}), \delta(e_{CME})]$ between the error PDF $f_E(e_{CME})$ and the Dirac-delta function $\delta(e_{CME})$ is defined as follows.

$$ED[f_E(e_{CME}), \delta(e_{CME})] = \int [f_E(e_{CME}) - \delta(e_{CME})]^2 de_{CME} \quad (3)$$

The minimization of $ED[f_E(e_{CME}), \delta(e_{CME})]$ forces CME samples to be concentrated on zero by matching the PDF of CME to the shape of Dirac-delta function located at zero. More importantly, the error PDF $f_E(e_{CME})$ is significantly less sensitive to strong impulses because it is constructed by the kernel density estimation method using Gaussian kernel and a block of N error samples as follows [8].

$$f_E(e_{CME}) = \frac{1}{N} \sum_{i=k-N+1}^k G_\sigma(e_{CME} - e_{CME,i}) \quad (4)$$

We can notice that a large argument of the Gaussian kernel, $e_{CME} - e_{CME,i}$ can be ignored since $G_\sigma(e_{CME} - e_{CME,i})$ is a decaying function. This implies that the ED of CME- PDFs (3) may be the better choice for adaptive blind algorithms than the MSE criterion (2) in impulsive noise environments.

The ED of CME-PDFs (ED-CME) in (3) can be arranged as the following three terms but the term $\int \delta^2(e_{CME}) de_{CME}$ is not related with system weights so that we can omit it in defining the cost function P_{ED} .

$$ED[f_E(e_{CME}), \delta(e_{CME})] = \int f_E^2(e_{CME}) de_{CME} - 2 \int f_E(e_{CME}) \delta(e_{CME}) de_{CME} + \int \delta^2(e_{CME}) de_{CME} \quad (5)$$

$$P_{ED} = \int f_E^2(e_{CME}) de_{CME} - 2 \int f_E(e_{CME}) \delta(e_{CME}) de_{CME} \quad (6)$$

Inserting (1) and (4) into (6) and rearranging it leads us to obtain the resulting cost function ED-CME as proposed in [9]

$$\begin{aligned}
 P_{ED} &= \frac{1}{N^2} \sum_{i=k-N+1}^k \sum_{j=k-N+1}^k G_{\sigma\sqrt{2}}(e_{CME,i} - e_{CME,j}) \\
 &\quad - 2 \frac{1}{N} \sum_{i=k-N+1}^k G_{\sigma}(e_{CME,i}) \\
 &= \frac{1}{N^2} \sum_{i=k-N+1}^k \sum_{j=k-N+1}^k G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2) \\
 &\quad - \frac{2}{N} \sum_{i=k-N+1}^k G_{\sigma}(-|y_i|^2 - R_2) \quad (7)
 \end{aligned}$$

where a block of output power samples $\{|y_k|^2, |y_{k-1}|^2, \dots, |y_{k-N+1}|^2\}$ is used instead of a block of error samples for the convenience of calculation.

As a new blind cost function using the kernel density estimation method based on the TDL structure, the correntropy distance (CD) between the source correntropy $V_S[m]$ and the system output correntropy $V_Y[m]$ has been introduced as in (8) [6].

$$P_{CD} = \sum_{m=1}^M (V_S[m] - V_Y[m])^2 \quad (8)$$

where the correntropy function $V_Y[m]$ is defined with a data vector $\{y_k, y_{k-1}, \dots, y_{k-L+1}\}$ and the number of lags M as

$$V_Y[m] = \frac{1}{N-m+1} \sum_{k=m}^N G_{\sigma}(\mathbf{Y}_k - \mathbf{Y}_{k-m}) \quad (9)$$

Through minimizing the cost function (8), the correntropy algorithm is obtained [6].

$$\begin{aligned}
 \mathbf{W}_{k+1} &= \mathbf{W}_k - \mu_{CD} \sum_{m=1}^M \sum_{k=m}^N \frac{1}{(N-m+1)\sigma^2} (V_S[m] \\
 &\quad - V_Y[m]) \cdot G_{\sigma}(y_i - y_{i-m}) \cdot (y_i - y_{i-m})(\mathbf{X}_i - \mathbf{X}_{i-m}) \quad (10)
 \end{aligned}$$

For the minimization of ED-CME (MED-CME) for deriving its algorithm on the TDL structure, a gradient descent method with the convergence parameter μ can be employed as

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu \frac{\partial P_{ED}}{\partial \mathbf{W}} \quad (11)$$

By differentiating (7) with respect to $\mathbf{W}$, the gradient $\frac{\partial P_{ED}}{\partial \mathbf{W}}$ in (11) is estimated as

$$\frac{\partial P_{ED}}{\partial \mathbf{W}} = A_k + B_k \quad (12)$$

where

$$\begin{aligned}
 A_k &= \frac{1}{\sigma^2 N^2} \sum_{i=k-N+1}^k \sum_{j=k-N+1}^k (|y_i|^2 - |y_j|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2) (y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) \quad (13)
 \end{aligned}$$

and

$$B_k = -\frac{4}{\sigma^2 N} \sum_{i=k-N+1}^k G_{\sigma}(|y_i|^2 - R_2) \cdot (R_2 - |y_i|^2) \cdot y_i \cdot \mathbf{X}_i^* \quad (14)$$

The equations (11)-(14) constitutes the MED-CME algorithm introduced in [9]. Based on the algorithm, some dc-noise resistant methods for sensing applications have been developed [9].

One of the drawbacks of the MED-CME algorithm may be the computational burden from the double summation operations in (13) at each iteration time. This burden prevents the efficient implementation of the MED-CME blind equalizer. In the following section, a new method of reducing the computational complexity significantly is proposed through the investigation of how the double summation is carried out.

2.2 Proposed Gradient Estimation for MED-CME

The conventional gradient estimation of (13) and (14) is considered as a block processing method of operating on a data block of $\{y_k, y_{k-1}, \dots, y_{k-N+1}\}$ at each iteration time. In this section we investigate how the next time gradient components A_{k+1} and B_{k+1} are related with the current gradient components A_k and B_k . And then a computation-reduced estimation method is proposed.

Let us define the state of the data block $\mathbf{Y}_k$ being not fully filled, that is, $1 \leq k \leq N$ as the initial state and the state of $\mathbf{Y}_k$ being full, that is, $k > N$ as the steady state. Then the gradient components A_k and B_k can be divided into two states as A_k and B_k in the initial state, A_k and B_k in the steady state, respectively.

Then the gradient components in the initial state A_k and B_k are written as

$$\begin{aligned}
 A_k^I &= \frac{1}{\sigma^2 k^2} \sum_{i=1}^k \sum_{j=1}^k (|y_i|^2 - |y_j|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2) (y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) \quad (15)
 \end{aligned}$$

$$B_k^I = -\frac{4}{\sigma^2 k} \sum_{i=1}^k G_{\sigma}(|y_i|^2 - R_2) \cdot (R_2 - |y_i|^2) \cdot y_i \cdot \mathbf{X}_i^* \quad (16)$$

Then A_{k+1}^I and B_{k+1}^I at time $k+1$ become

$$\begin{aligned}
 A_{k+1}^I &= \frac{1}{\sigma^2 (k+1)^2} \sum_{i=1}^{k+1} \sum_{j=1}^{k+1} (|y_i|^2 - |y_j|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2) (y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) \quad (17)
 \end{aligned}$$

$$B_{k+1}^I = -\frac{4}{\sigma^2 (k+1)} \sum_{i=1}^{k+1} G_{\sigma}(|y_i|^2 - R_2) \cdot (R_2 - |y_i|^2) \cdot y_i \cdot \mathbf{X}_i^* \quad (18)$$

We can notice that the gradients A'_{k+1} and B'_{k+1} at time $k+1$ can be divided into the terms related with y_{k+1} and the remaining.

Firstly we rewrite A'_{k+1} as

$$\begin{aligned}
 A'_{k+1} &= \frac{1}{\sigma^2(k+1)^2} \sum_{i=1}^k \left(\sum_{j=1}^{k+1} (|y_i|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) \Big) \\
 &\quad + \frac{1}{\sigma^2(k+1)^2} \left(\sum_{j=1}^{k+1} (|y_{k+1}|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_{k+1} \mathbf{X}_{k+1}^*) \Big) \\
 &= \frac{1}{\sigma^2(k+1)^2} \sum_{i=1}^k \left(\sum_{j=1}^k (|y_i|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) + (|y_i|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_i \mathbf{X}_i^*) \Big) \\
 &\quad + \frac{1}{\sigma^2(k+1)^2} \left(\sum_{j=1}^k (|y_{k+1}|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_{k+1} \mathbf{X}_{k+1}^*) \\
 &\quad + (|y_{k+1}|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_{k+1} \mathbf{X}_{k+1}^*) \Big) \\
 &= \frac{k^2}{(k+1)^2 \sigma^2 k^2} \sum_{i=1}^k \sum_{j=1}^k (|y_i|^2 - |y_j|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) \\
 &\quad + \frac{1}{\sigma^2(k+1)^2} \sum_{i=1}^k (|y_i|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_i \mathbf{X}_i^*) \\
 &\quad + \frac{1}{\sigma^2(k+1)^2} \sum_{j=1}^k (|y_{k+1}|^2 - |y_j|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_{k+1} \mathbf{X}_{k+1}^*) \\
 &= \frac{k^2}{(k+1)^2} A'_k + \frac{1}{\sigma^2(k+1)^2} \sum_{i=1}^k (|y_i|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_i \mathbf{X}_i^*) \\
 &\quad + \frac{1}{\sigma^2(k+1)^2} \sum_{j=1}^k (|y_{k+1}|^2 - |y_j|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_{k+1} \mathbf{X}_{k+1}^*) \\
 &= \frac{k^2}{(k+1)^2} A'_k + \frac{2}{\sigma^2(k+1)^2} \sum_{i=1}^k (|y_i|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_i \mathbf{X}_i^*) \quad (19)
 \end{aligned}$$

Secondly, we can apply this approach to B'_{k+1} at time $k+1$ as

$$\begin{aligned}
 B'_{k+1} &= \frac{k}{(k+1)} \frac{-4}{\sigma^2 k} \left(\sum_{i=1}^k G_{\sigma}(|y_i|^2 - R_2) \cdot (R_2 - |y_i|^2) \cdot y_i \cdot \mathbf{X}_i^* \right) \\
 &\quad - \frac{4}{\sigma^2(k+1)} G_{\sigma}(|y_{k+1}|^2 - R_2) \cdot (R_2 - |y_{k+1}|^2) \cdot y_{k+1} \cdot \mathbf{X}_{k+1}^* \\
 &= \frac{k}{(k+1)} B'_k - \frac{4}{\sigma^2(k+1)} G_{\sigma}(|y_{k+1}|^2 - R_2) \\
 &\quad \cdot (R_2 - |y_{k+1}|^2) \cdot y_{k+1} \cdot \mathbf{X}_{k+1}^* \quad (20)
 \end{aligned}$$

The iterative equations (19) and (20) indicate that the initial state gradient components A'_{k+1} and B'_{k+1} at the next iteration can be obtained recursively from the current A'_k and B'_k .

Similarly, the steady state gradient components A^S_k and B^S_k are investigated if they can be separated into the terms related with y_{k+1} and the ones related with y_{k-N+1} .

From (13),

$$\begin{aligned}
 A^S_{k+1} &= \frac{1}{\sigma^2 N^2} \sum_{i=k-N+2}^{k+1} \sum_{j=k-N+2}^{k+1} (|y_i|^2 - |y_j|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) \\
 &= \frac{1}{\sigma^2 N^2} \sum_{i=k-N+2}^{k+1} \left(\sum_{j=k-N+1}^k (|y_i|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) + (|y_i|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_i \mathbf{X}_i^*) + (|y_i|^2 - |y_{k-N+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k-N+1}|^2)(y_{k-N+1} \mathbf{X}_{k-N+1}^* - y_i \mathbf{X}_i^*) \Big) \\
 &= \frac{1}{\sigma^2 N^2} \sum_{i=k-N+1}^k \left(\sum_{j=k-N+1}^k (|y_i|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_i \mathbf{X}_i^*) + (|y_i|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_i \mathbf{X}_i^*) + (|y_i|^2 - |y_{k-N+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k-N+1}|^2)(y_{k-N+1} \mathbf{X}_{k-N+1}^* - y_i \mathbf{X}_i^*) \Big) \\
 &\quad + \frac{1}{\sigma^2 N^2} \left(\sum_{j=k-N+1}^k (|y_{k+1}|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_{k+1} \mathbf{X}_{k+1}^*) + (|y_{k+1}|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_{k+1} \mathbf{X}_{k+1}^*) \\
 &\quad - (|y_{k+1}|^2 - |y_{k-N+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k+1}|^2 - |y_{k-N+1}|^2)(y_{k-N+1} \mathbf{X}_{k-N+1}^* - y_{k+1} \mathbf{X}_{k+1}^*) \Big) \\
 &\quad - \frac{1}{\sigma^2 N^2} \left(\sum_{j=k-N+1}^k (|y_{k-N+1}|^2 - |y_j|^2) \right. \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k-N+1}|^2 - |y_j|^2)(y_j \mathbf{X}_j^* - y_{k-N+1} \mathbf{X}_{k-N+1}^*) \\
 &\quad + (|y_{k-N+1}|^2 - |y_{k+1}|^2) \\
 &\quad \cdot G_{\sigma\sqrt{2}}(|y_{k-N+1}|^2 - |y_{k+1}|^2)(y_{k+1} \mathbf{X}_{k+1}^* - y_{k-N+1} \mathbf{X}_{k-N+1}^*) \\
 &\quad - (|y_{k-N+1}|^2 - |y_{k-N+1}|^2)
 \end{aligned}$$

Fig. 2. Impulsive noise for the simulation.

$$\begin{aligned}
 & \cdot G_{\sigma\sqrt{2}}(|y_{k-N+1}|^2 - |y_{k-N+1}|^2)(y_{k-N+1}\mathbf{X}_{k-N+1}^* - y_{k-N+1}\mathbf{X}_{k-N+1}^*) \\
 & = A_k^S + \frac{2}{\sigma^2 N^2} \sum_{i=k-N+1}^k (|y_i|^2 - |y_{k+1}|^2) \\
 & \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k+1}|^2)(y_{k+1}\mathbf{X}_{k+1}^* - y_i\mathbf{X}_i^*) \\
 & - \frac{2}{\sigma^2 N^2} \sum_{i=k-N+1}^k (|y_i|^2 - |y_{k-N+1}|^2) \\
 & \cdot G_{\sigma\sqrt{2}}(|y_i|^2 - |y_{k-N+1}|^2)(y_{k-N+1}\mathbf{X}_{k-N+1}^* - y_i\mathbf{X}_i^*) \quad (21)
 \end{aligned}$$

We can observe in (21) that the next gradient component A_{k+1}^I can be obtained recursively from the current gradient component A_k^S and other terms related with y_{k+1} and y_{k-N+1} . Similarly, based on B_k^S in (14), B_{k+1}^S is analyzed to see if it can be estimated recursively.

$$\begin{aligned}
 B_{k+1}^S & = -\frac{4}{\sigma^2 N} \sum_{i=k-N+2}^{k+1} G_{\sigma}(|y_i|^2 - R_2) \cdot (R_2 - |y_i|^2) \cdot y_i \cdot \mathbf{X}_i^* \\
 & = -\frac{4}{\sigma^2 N} \sum_{i=k-N+1}^k G_{\sigma}(|y_i|^2 - R_2) \cdot (R_2 - |y_i|^2) \cdot y_i \cdot \mathbf{X}_i^* \\
 & - \frac{4}{\sigma^2 N} G_{\sigma}(|y_{k+1}|^2 - R_2) \cdot (R_2 - |y_{k+1}|^2) \cdot y_{k+1} \cdot \mathbf{X}_{k+1}^* \\
 & + \frac{4}{\sigma^2 N} G_{\sigma}(|y_{k-N+1}|^2 - R_2) \cdot (R_2 - |y_{k-N+1}|^2) \cdot y_{k-N+1} \cdot \mathbf{X}_{k-N+1}^* \\
 & = B_k^S - \frac{4}{\sigma^2 N} G_{\sigma}(|y_{k+1}|^2 - R_2) \cdot (R_2 - |y_{k+1}|^2) \cdot y_{k+1} \cdot \mathbf{X}_{k+1}^* \\
 & + \frac{4}{\sigma^2 N} G_{\sigma}(|y_{k-N+1}|^2 - R_2) \cdot (R_2 - |y_{k-N+1}|^2) \cdot y_{k-N+1} \cdot \mathbf{X}_{k-N+1}^* \quad (22)
 \end{aligned}$$

In summary, the weight update in (11) can be carried out with the gradient $\frac{\partial P}{\partial \mathbf{W}} = A_k + B_k$ in which each component A_k and B_k can be obtained recursively by (21) and (22), respectively in steady state $k > N$. The initial state gradient components are estimated by (19) and (20). Compared to the conventional block-processed gradient estimation depicted in (21) and (24) that has

Fig. 3. MSE convergence curves.

$O(N^2)$, the proposed recursive gradient estimation method has a significantly reduced computational complexity of $O(N)$.

In the following section, it will be proved that the proposed gradient estimation method which has a greatly reduced calculation complexity yields the same estimation results as the block-processed gradient estimation method.

3. RESULTS AND DISCUSSION

In this section, it will be investigated whether the proposed gradient estimation of MED-CME algorithm yields the same results as the block-processed gradient estimation. We use the same blind signal processing environment as in [9] except that impulsive noise is used instead of Gaussian and DC noise. The symbol points d_i to be transmitted are $\{d_1 = -3, d_2 = -1, d_3 = 1, d_4 = 3\}$. Then the constant modulus R_2 becomes 8.2. The randomly generated symbol points are transmitted through the multipath channel $H(z) = 0.26 + 0.93z^{-1} + 0.26z^{-2}$. Then impulsive noise is added to the channel output. The impulsive noise is generated according to the work [13] with variance 50 and incident rate 0.02 as depicted in Fig. 1. The variance of the background white noise is 0.001. This channel-distorted and noise-added signal is used as an input to the blind equalizer with $L = 11$. The data-block size for the MED-CME algorithm is $N = 20$, the kernel size is $\sigma = 6$, and the convergence parameter $\mu = 0.02$ is used. The kernel density estimation in (4) requires a large data-block size N (sample size) in order to guarantee a desired level of estimation accuracy. But this brings a computational cost for implementation [10].

The parameter values are $N = 20$, $\sigma = 6$ and $\mu = 0.02$ which produce the lowest steady state MSE in this simulation. The

Fig. 4. Gradient estimation results of the conventional block-processing method and the proposed recursive method.

Fig. 6. Trace of the first weight for the conventional method and the proposed one.

Fig. 5. Gradient comparison in the initial part of iteration.

Fig. 7. Initial-part trace of the first weight for the conventional method and the proposed one.

computational complexity with respect to the data-block size N will be compared and discussed in this section.

The initial values of A'_k and B'_k are equally set to be zero. For MSE performance comparison, we tested the well known CMA, the correntropy and the proposed MED-CME algorithm. The correntropy algorithm is known to have immunity to impulsive noise. The convergence parameters for the correntropy algorithm and CMA are 0.01 and 0.000001, respectively. The number of lags for the correntropy is 20 and its data-block size is 30. And the kernel size for the correntropy is 2.8. All these parameter values were also chosen in the case that each algorithm produced the lowest steady state MSE.

In the Fig. 3 we observe that the correntropy and the proposed MED-CME algorithm converge but the CMA fails to do even

with the very small convergence parameter 0.000001 due to its vulnerability to impulsive noise. Compared to the correntropy algorithm, the MSE curve for MED-CME has a significantly lower steady state MSE reaching around -27 dB and showing above 8 dB of error performance difference.

Fig. 4 shows the trace of gradient estimation results for the first tap weight (the other tap weights are omitted in this paper just for the page-limit). The dotted line is the result of the conventional block-processing method by (13) and (14), and the solid line is for the proposed estimation. We didn't find any differences so that the results for the initial part of iteration (1-50) are depicted in Fig. 5 for the comparison in more detail. This shows that the initial part ($1 \leq k < 20$) of the trace of gradient estimation by (19) and (20) runs differently but gradually comes close to that of the block processing method. In the steady state, that is, a full block data

$\{y_k, y_{k-1}, \dots, y_{k-N+1}\}$ is utilized for the gradient estimation, the two traces are united as one showing that the proposed gradient estimation in the steady state ($k \geq 20$) by (21) and (22) yields the same result as the block processing method does. Similar results are observed in Fig. 6 and 7 that show the trace of weight values being updated as in (11). Except for the Initial-part trace ($1 \leq k < 20$), the updated weight values are exactly the same for the two methods.

These results indicate that the proposed recursive algorithm produces the same performance with a significantly reduced computational complexity as the conventional algorithm which may be inappropriate for implementation due to its heavy computational burden.

4. CONCLUSIONS

The received signal through optical fiber or wireless links in indoor sensor networks is distorted due to dispersion, multipath fading and impulsive noise from indoor electric devices. In order to recover the transmitted sensor information in those environments, equalization algorithms based on the MED-CME criterion have been known to yield superior MSE performance.

One of the drawbacks of MED-CME algorithms is a heavy computational burden due to some double summation operations carried out at each iteration time. In this paper, a recursive method of gradient estimation for weight updates of the MED-CME algorithm is proposed. This approach reduces the double summation operations in the algorithm to some single summation operations. In the simulation results, the proposed gradient estimation method produces exactly the same results in the steady state as the conventional block processing method. This result leads us to the conclusion that the proposed method having a significantly reduced computational complexity can implement

efficient and reliable receivers in indoor sensor networks.

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