Blind Equalization Based on Normalized Error in Wireless Sensor Networks

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Abstract In this paper, we consider a single-input multiple-output (SIMO) channel-based static wireless sensor network and carry out blind equalization to estimate the transmitted signal blindly. Four cases of common or different channels and a common or different variance of noises are considered. For each case, the solution of blind equalization is derived. For the different-channel cases, we derive a new approach in which the best sensor output signal is found by adaptively implementing the normalized error used in speech processing. We estimate the transmitted signal from the corresponding sensor output by utilizing the generalized Sato equalizer. The mean square error (MSE) and symbol error rate (SER) are investigated on several communication channels. Computer simulations validate the solution for each case and show the effectiveness of the proposed method relative to the conventional methods.

Keywords: blind equalization, distributed network, normalized error, generalized Sato algorithm, wireless sensor network

1. Introduction

A wireless sensor network (WSN) is a self-organized distributed communication network composed of a number of geographically separated, autonomous and low-cost sensor nodes, which monitor regions through wireless communication [1]. In recent years, WSNs have attracted research interest because of their potential applications such as information gathering, precision agriculture, target detection, medical aid, environmental surveillance and military reconnaissance [2], [3].

The estimation algorithms used in 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 (FC) 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 for 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 [4]. 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) [5], an incremental affine projection algorithm [6], incremental Recursive Least Squares (RLS) [5], diffusion LMS [7], [8], [9], distributed LMS in consensus strategies [10] 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 [11]. 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 prior knowledge of the transmitted sequence statistics.

In [12], a distributed blind adaptive algorithm, named the distributed constant modulus algorithm (d-CMA), was proposed. This algorithm was based on the source signal, which has a constant envelope, and assumes that the communication topology is a simple Hamiltonian cyclic path. However, link and node failures are permeable through the Hamiltonian cyclic path. If a sensor fails in this method, then it is necessary to re-establish the path, which is very time-consuming. To mitigate this problem, the authors in [13] proposed a recursive distributed blind equalization algorithm. This method estimates the source signal in real time but requires high-dimensional data to be computed for transmission among neighbors, which also consumes a large amount of computational time.

In [14], the authors developed a distributed diffusion generalized Sato algorithm (GSA) [15] to reduce the computational complexity, 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) diffusion GSA (CTA-GSA), were addressed. In ATC-GSA, each sensor first adapts its estimate by exchanging information with its neighbors and then combining the information. In CTA-GSA, the operation is performed in the opposite order. The performances of ATC-GSA and CTA-GSA are similar. The information is exchanged with neighbors by sharing the complex tap coefficients of the blind equalizer. For a large network, however, this method requires a large number of equalizers, which results in a long computation time to reach the desired estimation. In addition, in [14] it was assumed that the transmission channel is common and the variance of individual noise addition is different for all sensors. However, in practical situations, this assumption may not be true because the transmitted signals suffer from multipath fading. When the transmission channels are different, CTA-GSA gives different performance at different sensor nodes. In this case, it is usually very difficult to obtain the best performance for CTA-GSA. For this reason, the CTA-GSA method requires the optimal sensor location to obtain the best performance. However, there has been no way to accomplish this task up to now.

In this paper, 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 proposed method gives better performance than conventional CTA-GSA [14].

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

This paper is organized as follows. In Sect. 2, the channel and WSN models are described. In Sects. 3 and 4, the common-channel cases (Cases I and II) and different-channel cases (Cases III and IV) are described, respectively. In Sect. 5, a blind equalizer to provide the solution in Cases III and IV is derived as the proposed method. The performance of the proposed method is shown in Sect. 6. Finally, Sect. 7 concludes this paper.

2. Channel and WSN Models

Let us assume a sensor network with a static topology in which N sensor nodes are spatially distributed over a square area. The maximum communication range is defined by the radius of this area. If the Euclidean distance between two nodes is less than or equal to this communication range, then they are connected. Otherwise, they are disconnected. In our assumption, the network topology is defined by an undirected graph. We show the WSN model in the middle part of Fig. 1. In the WSN model, a flow without an arrow indicates a bidirectional connection. The circular flow at each node means a connection with itself. Two nodes are said to be neighbors if they can share information with each other. Thus, the neighborhood of node $k$ is the set of neighbors of node $k$, including $k$ itself, which is denoted by $N_k$. Each sensor measures the distorted signal arriving from the output of a finite impulse response (FIR) channel [16]. On the basis of a single-input multiple-output (SIMO) channel model, as shown in Fig. 1, the channels are considered for common and different cases. In the diffusion strategy,
each node in the network has access to the estimates generated in its neighborhood, where each node is defined as \( l \in N_k \). All sensors are interested to share the common message from the sender, \( s(n) \), through the FIR channels with impulse response \( h_k(n) \).

With reference to Fig. 1, the channel output is \( x_k(n) \) at each sensor \( k \). The transmitted data signal \( s(n) \) and the FIR channel \( h_k(j) \) are combined to produce \( x_k(n) \) as

\[
x_k(n) = \sum_{j=0}^{J-1} h_k(j) s(n-j) + v_k(n)
\]

where \( v_k(n) \) is the additive white Gaussian noise at the \( k \)th sensor node, so that \( x_k(n) \) becomes a noisy channel output. In Eq. (1), it is assumed that \( h_k(j) \) has an impulse response of length \( J \). Then, the aggregate sensor output at the \( k \)th sensor, \( y_k(n) \), is obtained from the FIR channel output \( x_k(n) \) and the coefficients of the combination weight matrix of the \( k \)th-node neighbors, \( c_{lk} \), as

\[
y_k(n) = \sum_{l \in N_k} c_{lk} x_l(n)
\]

The coefficients \( c_{lk} \) are non-negative. The combination weight matrix, \( C \), whose elements are \( c_{lk} \), is a doubly stochastic symmetric matrix \([8], [9]\). For the combination weight matrix \( C \), two types, right stochastic and left stochastic, are considered. When the combination weight matrix is right stochastic, the sum of each of its rows adds up to one. On the other hand, when it is left stochastic, each of its columns adds up to one. The combination weight matrix represents the network topology. As a basic rule, the coefficients related to the neighbors of node \( k \) must add up to one, which is represented by

\[
\sum_{l \in N_k} c_{lk} = 1
\]

for \( k = 1, 2, ..., N \), where \( N \) is the number of nodes in the network.

Several rules are available to design this combination weight matrix \( C \). Some of them are the Metropolis rule \([8], [9], [13]\), the Laplacian rule \([9]\), the relative degree rule \([8]\), the nearest-neighbor rule \([9]\) and so on. The Metropolis rule has shown better performance than the other rules \([13], [17]\). Thus, in this paper we utilize the Metropolis rule. In this rule, the coefficients are defined as

\[
c_{lk} = \begin{cases} \frac{1}{\max(n_k, n_l)}, & \text{if } k \neq l \\ 1 - \sum_{l \in N_k} c_{lk}, & \text{if } k = l \\ 0, & \text{otherwise} \end{cases}
\]

where \( n_k \) and \( n_l \) are the degrees of nodes \( k \) and \( l \), respectively, which indicate the sizes of their neighborhoods.

The coefficients \( c_{lk} \) satisfy \( C1 = 1, C^T C = 1 \), where \( 1 \) denotes a vector with all entries equal to one. In this paper, we will consider a static topology, and for this reason the combination weight matrix \( C \) is kept constant during the adaptation.

### 3. Common-Channel Cases

In this paper, on the basis of the channel and WSN models in Fig. 1, we attempt to find the solution for blind equalization to estimate the transmitted data signal \( s(n) \) from all of the sensor outputs, \( y_k(n), k = 1, 2, ..., N \). We first consider, Cases I and II mentioned in Sect. 1.

In Case I, all channels \( h_k(n), k = 1, 2, ..., N \), are assumed to be common for all sensor nodes. In this case, the output \( x_k(n) \) collected at each sensor \( k \) is described as

\[
x_k(n) = \sum_{j=0}^{J-1} h(j) s(n-j) + v_k(n)
\]

where

\[
h(n) = h_1(n) = h_2(n) = ... = h_N(n)
\]

that is, \( h(n) \) is a common channel impulse response. Then, the output at the \( k \)th sensor, \( y_k(n) \), is expressed as

\[
y_k(n) = \sum_{l,k=1}^{N} c_{lk} x_l(n)
\]

\[
= c_{1k} x_1(n) + c_{2k} x_2(n) + ... + c_{Nk} x_N(n)
\]

\[
= (c_{1k} x_1(n) + c_{2k} x_2(n) + ... + c_{Nk} x_N(n)) (h(n) \ast s(n)) +
\]

\[
= h(n) \ast s(n) + \eta_k(n)
\]

where

\[
c_{1k} + c_{2k} + ... + c_{Nk} = 1
\]

is used and the noise addition is represented as

\[
c_{1k} v_1(n) + c_{2k} v_2(n) + ... + c_{Nk} v_N(n) = \eta_k(n)
\]

\( \eta_k(n) \) is correlated with only \( v_k(n) \). The noise variance is assumed to be common,

\[
\sigma^2 = \sigma_1^2 = \sigma_2^2 = ... = \sigma_N^2
\]

In this case, we do not need to implement the CTA-GSA method for blind equalization. The performance
of the CTA-GSA method becomes equivalent to that of the single GSA method at any sensor output. This is because all sensor outputs are represented by (7) and the variance of $\eta_k(n)$ is common. This is validated in Sect. 6.

In Case II, Eq. (6) is satisfied but Eq. (10) is not satisfied. In Eq. (7), $\eta_k(n)$ does not have a constant variance. This means that at each sensor, the level of additive noise is different. In this case, a lower level for noise is better for the equalizer to improve the performance. Since the signal transmission part, $h(n) \ast s(n)$, is common and this part gives a unified power, it is possible to find the best sensor output by calculating the power of each $y_k(n)$. When the power of $y_k(n)$ is smallest, the noise level included in $y_k(n)$ is smallest, which means that $y_k(n)$ gives the highest signal-to-noise ratio (SNR) for the equalizer input. In this case, the best performance of the equalizer is obtained, which is also validated in Sect. 6.

4. Different-Channel Cases

In this section, Cases III and IV mentioned in Sect. 1 are considered. Our target, blind equalization, is the same as before.

We first consider different channels $h_k(n)$ with a common noise variance of $\eta_k(n)$ at sensor node $k$, where $y_k(n)$ is given by

$$y_k(n) = h_k(n) \ast s(n) + \eta_k(n)$$ (11)

This case corresponds to Case III. In this case, the CTA-GSA method cannot provide the same performance at each sensor output, although this feature of the CTA-GSA method was not revealed in [14]. This feature is visualized in Sect. 6 when different channels are assumed. From this feature of the CTA-GSA method, in real situations, the optimal sensor location is required to obtain the optimal performance. To overcome this defect of the CTA-GSA method, in this paper, we derive a novel technique to find the optimal sensor location, which is used for source signal estimation, and we propose a single use of the GSA method at the corresponding sensor output.

The optimal sensor location can be found by measuring the eigenvalue spread of the correlation matrix of the sensor output. In the equalization problem, it is known that a smaller eigenvalue spread of the input correlation matrix for the equalizer provides better performance [18]. However, a direct calculation of
the eigenvalues from the correlation matrix is time-consuming. From this viewpoint, in the next section, we derive a more efficient form of calculation relying on the principle of the normalized error [19], which is used in speech processing. The original form of calculation the normalized error is batch processing. However, in this paper, an adaptive form of calculation the normalized error is derived.

In Case IV, different channels $h_k(n)$ and different noise variances $\eta_n$ are considered. In this case, the different noise levels affect the eigenvalue spread calculation. Commonly, a small eigenvalue spread of the input correlation matrix is desired for the equalizer. However, the additive noise tends to decrease the eigenvalue spread of the input correlation matrix. Since the increase in the noise level reduces the performance of the equalizer, there may be a trade-off between the eigenvalue spread and the additive noise level. In general, we cannot accurately estimate the noise power only from the sensor output. Therefore, in this paper, we assume that different variances of noise are added in each channel, but we also assume that the degree of difference is small. In this case, the method applicable to Case III is used. Hence, as a method for Cases III and IV, we commonly propose a single use of the GSA method at the optimal sensor location as described in the next section.

5. Proposed Method

In this section, a blind equalizer applicable to Cases III and IV is derived, the whole block diagram of which is also shown in Fig. 1. At the equalizer part, the transmitted signal $s(n)$ is estimated as $\hat{s}(n)$ where $\hat{()}$ denotes an estimate utilizing the noisy sensor output signal $y_k(n)$. The decision center finds and chooses the easiest sensor location for the following blind equalizer.

5.1 Finding easiest sensor location

To find the easiest sensor location for equalization, we use all sensor outputs $y_k(n), k = 1, 2, ..., N$. To accomplish this, the most straightforward approach may be the eigenvalue spread calculation of each correlation matrix of $y_k(n), k = 1, 2, ..., N$, as mentioned in Sect. 4. Here, let us assume that the correlation matrix of the $k$ th sensor output $y_k(n)$ is represented by $R_k$. By calculating the minimum and maximum eigenvalues of $R_k$, $\lambda_{k,\text{min}}$ and $\lambda_{k,\text{max}}$, respectively, we can define the condition number of $R_k$ as

$$\text{Cond}(R_k) = \frac{\lambda_{k,\text{max}}}{\lambda_{k,\text{min}}}$$  \hspace{1cm} (12)

When $\text{Cond}(R_k)$ is very large, it is known that matrix $R_k$ is ill-conditioned. In this case, the task of equalization becomes very severe. Therefore, by finding the case with the smallest $\text{Cond}(R_k)$ among all sensor outputs, we can identify the easiest sensor output $y_k(n)$ for equalization. However, to do this, we have to collect a large number of each $y_k(n)$ and calculate the eigenvalue decomposition of each $R_k$, which becomes time-consuming as the equalizer length is increased. Therefore, in this section, 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.

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 (random signal) [19]. At the $k$ th sensor output, $y_k(n)$, the normalized error, $\psi_k(n)$, is calculated as

$$\psi_k(n) = \frac{P_k(n)}{\nu_k(n)}$$  \hspace{1cm} (13)

where $P_k(n)$ is the prediction error power at the $k$ th sensor and $\nu_k(n)$ is the variance of the sensor output $y_k(n)$ at the $k$ th sensor. In Fig. 2, a block diagram to implement Eq. (13) is shown, where the prediction error filter is denoted as a prefilter. When the power spec-

![Fig. 2 Block diagram for the normalized error calculation](image)
trum 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).

In this section, we propose adaptive implementation of the normalized error in Eq. (13). The prediction error for time \( n \) at the \( k \) th sensor, \( e_k(n) \), is defined as

\[
e_k(n) = y_k(n) - \hat{y}_k(n)
\]

where

\[
\hat{y}_k(n) = y_k^T(n)\hat{w}_k(n)
\]

In Eq. (15), \( y_k(n) \) is the input vector given by \( y_k(n) = [y_k(n-1), y_k(n-2), ..., y_k(n-m)]^T \), where \( T \) denotes transpose, and \( \hat{w}_k(n) \) is the tap coefficient vector of the adaptive prediction error filter, which is \( \hat{w}_k(n) = [\hat{w}_{k1}(n), \hat{w}_{k2}(n), ..., \hat{w}_{km}(n)]^T \), where \( m \) is the filter length. The tap coefficient vector is updated by the least mean square (LMS) algorithm [20] defined as

\[
\hat{w}_k(n + 1) = \hat{w}_k(n) + \alpha_k e_k(n)y_k^*(n)
\]

where \( \alpha_k \) is the step size of the filter and \( * \) denotes complex conjugate.

Given \( P_k(1), P_k(2), ..., P_k(n) \), the numerator in Eq. (13) is defined as

\[
P_k(n) = \frac{1}{n} \sum_{i=1}^{n} e_k^2(i)
\]

(17)

The denominator in Eq. (13), \( \nu_k(n) \), is the variance of \( y_k(n) \), which is defined in the same way as in Eq. (17),

\[
\nu_k(n) = \frac{1}{n} \sum_{i=1}^{n} y_k^2(i)
\]

(18)

Therefore, to reduce the computational complexity in Eqs.(17) and (18), we can perform a sample-by-sample calculation as follows:

\[
P_k(n) = \frac{1}{n} e_k^2(n) + \frac{n-1}{n} P_k(n-1)
\]

(19)

\[
\nu_k(n) = \frac{1}{n} y_k^2(n) + \frac{n-1}{n} \nu_k(n-1)
\]

(20)

According to Eqs. (19) and (20), we can calculate the normalized error Eq. (13) by combining Eqs. (14)-(16).

5.2 Decision center

In Fig. 1, the decision center of the proposed method holds all normalized error values for all sensor nodes, \( \psi_k(n) \), \( k = 1, 2, ..., N \), as well as all the sensor output signals, \( y_k(n) \), \( k = 1, 2, ..., N \). Observing \( \psi_k(n) \) for all sensor outputs, we can find the easiest sensor location, for which the value of \( \psi_k(n) \) is nearest to one, among all sensor locations, in real time. Hence, we utilize only the easiest sensor output \( y_k(n) \) for equalization.

5.3 Blind equalization

In the blind equalizer part in Fig. 1, the GSA is used for equalization. The GSA minimizes the following cost function:

\[
J_k(n) = E[|\gamma csgn(z_k(n)) - z_k(n)|^2]
\]

(21)

where \( E \) indicates the statistical expectation and \( \gamma \) is a positive constant used to set the gain of the equalizer. \( \gamma \) depends only on the transmitted data signal \( s(n) \) and is defined as

\[
\gamma = \frac{E[|s_r(n)|^2]}{E[|s_i(n)|^2]} = \frac{E[|s_r(n)|^2]}{E[|s_i(n)|]}
\]

(22)

where \( s_r(n) \) and \( s_i(n) \) are the real and imaginary parts of the transmitted signal \( s(n) \), respectively. In Eq. (21), \( csgn \) is the complex sign function for the complex data symbol defined as,

\[
csgn(z_k(n)) = sgn(z_{kr}(n)) + jsgn(z_{ki}(n))
\]

(23)

where \( z_{kr}(n) \) and \( z_{ki}(n) \) are the real and imaginary parts of the blind equalizer output signal, \( z_k(n) \), respectively. \( z_k(n) \) is the equalizer output for the \( k \) th sensor and is given by

\[
z_k(n) = y_k^T(n)q_k(n)
\]

(24)
where \( q_k(n) = [g_{k1}(n), g_{k2}(n), \ldots, g_{kM}(n)]^T \) is the vector of the tap coefficients, \( y_k(n) = [y_k(n-1), y_k(n-2), \ldots, y_k(n-M+1)]^T \) is the equalizer input vector at sensor \( k \), and \( M \) is the length of the equalizer. The estimated error sequence and updated tap coefficients of the blind equalizer are given by

\[
\zeta_k(n) = \gamma c \text{sgn}(z_k(n)) - z_k(n) \quad (25)
\]

\[
q_k(n+1) = q_k(n) + \mu_k \zeta_k(n) y_k^*(n) \quad (26)
\]

respectively, where \( \mu_k \) is the step size parameter of the GSA. There are two ways of implementing the GSA. One way is to start the GSA after finding the easiest path at the \( n \)-th iteration to evaluate Eq. (13). The other way is to connect the blind equalizer to the prediction error filter at the \( n \)-th iteration used to evaluate Eq. (13). In the latter case, the prediction error filter is used as the prefilter for the input \( y_k(n) \). After the \( n \)-th iteration, when the coefficients of the prefilter are fixed and used, the performance of the blind equalizer is promising as shown in [18].

6. Simulation Results

In this section, we demonstrate the performance of the proposed method by carrying out simulation experiments. We use non-minimum phase channels in a static WSN that consists of five sensor nodes \((N = 5)\). Each node is randomly distributed over a square region of \([0, 1.2] \, \text{m} \times [0, 1.2] \, \text{m} \) and has a maximum communication range of 3 m. If the Euclidean distance between two sensor nodes is equal to or within this range, then they are connected to each other and said to be neighbors and able to exchange information. Otherwise, there is no connection between the nodes. We use the network topology shown in Fig. 3, and the resulting combination weight matrix is presented in Table 1.

The non-minimum phase channels used are as follows:

\[
h_1 = [0.2500 \, 1.0 \, 0.2500] \]

\[
h_2 = [0.3087 \, 1.0 \, 0.3087] \]

\[
h_3 = [1.0 \, 2.2 \, 0.4] \]

\[
h_4 = [0.3482 \, 0.8704 \, 0.3482] \]

\[
h_5 = [0.2602 \, 0.9298 \, 0.2602] \]

The transmitted signal \( s(n) \) is generated from a four-Quadrature Amplitude Modulation (4-QAM) constellation. To compare the performances of the proposed method, the CTA-GSA [14] and Nc-GSA (non-cooperative GSA) [21] methods are also implemented. In the Nc-GSA case, the combination weight matrix is a unit matrix (i.e., only the diagonal elements are 1).

The initialization condition of the weight vector for the blind equalizer is commonly set up such that the center tap equals one and the other taps equal zero [22]. As the measures of the performance, we use the mean square error (MSE) and symbol error rate (SER) at the output of the equalizer.

The MSE performance of the CTA-GSA method for Case I is reduced to that for a single use of the GSA as shown in Sect. 3. This is validated here. Channel \( h_3 \) is used for \( h(n) \) in (6) and the other parameter settings are an equalizer length of \( M = 10 \) and a step size of \( \mu_k = 0.001 \). An additive noise is generated and the resulting SNR of the channel output is 30 dB. Commonly, the same step size is used for the CTA-GSA method and the single GSA. Figure 4 shows the MSE performance for both equalizers over 100 individual trials. In Fig. 4, we can observe that the convergence curves almost overlap.

For the validation of Case II, channel \( h_3 \) is commonly used with a different additive noise at each sensor node. The additive noise \( \nu_k(n) \) is generated such that the SNR of each channel output is randomly distributed within \([15, 30] \, \text{dB} \) e.g., SNR = \([15, 22, 25, 21, 26] \). In this situation, the power calculation of each sensor output \( y_k(n) \) is sufficient to find the best sensor location for equalization. Table 2 shows the power calculation results. From Table 2, we can see that Sensor 5 has the smallest power among the sensors. When Sensor 5 is used as the best path for equalization, the highest performance of the GSA is obtained as shown in Fig. 5. In Fig. 5, the parameter settings are an equalizer length of \( M = 6 \) and an equalizer step size of \( \mu_k = 0.005 \). One hundred individual trials are av-

Table 1 Combination weight matrix

| Sensor number | Power |
|---------------|-------|
| Sensor 1      | 12.42 |
| Sensor 2      | 12.44 |
| Sensor 3      | 12.34 |
| Sensor 4      | 12.48 |
| Sensor 5      | 12.22 |

Table 2 Signal power

| Sensor number | Power |
|---------------|-------|
| Sensor 1      | 12.42 |
| Sensor 2      | 12.44 |
| Sensor 3      | 12.34 |
| Sensor 4      | 12.48 |
| Sensor 5      | 12.22 |
When different channels are utilized to transmit the source signal \( s(n) \), the conventional CTA-GSA method gives different performances at the different sensors. Figure 6 shows the MSE performance of the CTA-GSA method for Case IV over 100 individual trials in which channel output is SNR = 30 dB, the equalizer length is \( M = 8 \) and the equalizer step size is \( \mu_k = 0.01 \). From Fig. 6, it can be seen that the CTA-GSA method gives different performances depending on the sensor location. In real situations, we have no information about the suitability of the sensor selection for the CTA-GSA method. In this case, random sensor selection will lead to deteriorating the best performance of the CTA-GSA method.

Figure 7 shows an example of adaptive implementation for the normalized error in Eq. (13) for a single trial. The parameters are a prefilter length of \( m = 6 \), and a prefilter step size of \( \alpha_k = 0.0012 \). Here, 4000 data samples are used to find the solution. Figure 7 indicates that the normalized error of Sensor 2 becomes closer to 1 than that of the other sensor nodes. In addition to this result, Table 3 presents the corresponding condition numbers for all of the sensor nodes, which indicates that Sensor 2 has the smallest condition number. Table 3 validates the result in Fig. 7. Therefore, from Fig. 7, we can select the output of Sensor 2 as the easiest path or best path for equalization.

The proposed method utilizes the easiest sensor output (that of Sensor 2) for equalization and acquires the best performance, which is shown in Fig. 8 in the case of a channel output of SNR=30 dB. The parameter settings are an equalizer length of \( M = 8 \) and an equalizer step size of \( \mu_k = 0.005 \). 100 individual trials are averaged. From Fig. 8, it is observed that steady-state MSE performance of the proposed method is sig-

| Sensor number | Cond(\( R_k \)) |
|---------------|-----------------|
| Sensor 1      | 19.1            |
| Sensor 2      | 14.4            |
| Sensor 3      | 15.2            |
| Sensor 4      | 34.4            |
| Sensor 5      | 15.6            |
significantly improved relative to those of the Nc-GSA and CTA-GSA methods when the random selection of the sensor output for the CTA-GSA method chooses Sensor 2, while the same step size is commonly used for all equalizers.

Figure 9 illustrates the SER performance for the Nc-GSA, CTA-GSA and proposed methods after the convergence of each equalizer. To evaluate the SER performance, 100000 data samples were used. From Fig. 9, it can be seen that the proposed method provides better SER performance than the conventional methods. The proposed method attains almost 1.8 and 4 dB improvement relative to the CTA-GSA method and Nc-GSA method, respectively, at an SER level of $10^{-4}$.

The computational complexity required to implement the proposed method is much lower than that of the Nc-GSA and CTA-GSA methods. The numbers of complex multiplications and complex additions for each update of the coefficients for the Nc-GSA, CTA-GSA and proposed methods are shown in Table 4. The computational complexity of the Nc-GSA method is $N^2 M + N(M + 1)$ complex multiplications and $N(M + 1)$ complex additions per iteration. The CTA-GSA method requires $N^4 M + N^2 M + N(M + 1)$ complex multiplications and $2N^2 M + N(M - 1)$ complex additions per iteration. On the other hand, the proposed method requires $N^2 + 2(M + 1)$ complex multiplications and $N^2 - (N - M) + 1$ complex additions per iteration. In addition, in the proposed method, the adaptive normalized error calculation is used, which requires $LN(2m + 3)$ complex multiplications and $LN(m + 2)$ complex additions where $L$ is the number of samples required for the calculation, which equals to the number of iterations.

As an example, let us consider the case of $N = 5$ (number of sensor nodes), $M = 8$ (equalization filter length), $m = 6$ (prefilter length) and $L=4000$ (number of iterations). This results in the Nc-GSA requiring 245 complex multiplications and 45 complex additions per iteration and the CTA-GSA requiring 5245 complex multiplications and 435 complex additions per iteration. The computational complexity of the proposed method is significantly lower, requiring 120 complex multiplications and 30 complex additions per iteration.

Table 4  Computational complexity

| Methods   | Complex Multiplication | Complex Addition |
|-----------|------------------------|------------------|
| Nc-GSA    | $N^2 M + N(M + 1)$     | $N(M + 1)$       |
| CTA-GSA   | $N^4 M + N^2 M + N(M + 1)$ | $2N^2 M + N(M - 1)$ |
| Proposed  | $N^2 + 2(M + 1)$       | $N^2 - (N - M) + 1$ |
iteration. On the other hand, the proposed method requires only 43 complex multiplications and 29 complex additions per iteration. A single calculation of the normalized error on all the data samples \((L=4000)\) requires \(75L\) complex multiplications and \(40L\) complex additions. From these results, we see that the complexity of the CTA-GSA is considerably greater than that of the Nc-GSA and proposed methods. The proposed method has a much lower complexity relative than the conventional methods.

7. Conclusion

In this paper, a simple and static distributed in-network processing model has been considered, and a blind equalizer based on the GSA has been proposed to estimate the transmitted sequence in which the channel information is unknown. Each solution has been derived for four cases of channels and noises. For the different-channel cases, a novel technique has been proposed to estimate the best sensor location for equalization by calculating the normalized error adaptively. Experimental results have validated the solution for each case. For the different-channel cases, the experiments have shown that the proposed method achieves better MSE and SER performances than the conventional Nc-GSA and CTA-GSA methods. In addition, the computational complexity of the proposed method is significantly lower.

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