

Adaptive Retransmission with Balanced Load for Distributed Fault-Tolerant Detection in Wireless Sensor Networks*

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Abstract

An adaptive retransmission approach recently has been proposed to improve the misclassification probability of distributed detection with error-correcting codes in wireless sensor networks. A code matrix is designed and a codeword is assigned to each hypothesis. Each sensor is associated with a decision pattern and has a set of thresholds to make its local decision on its detection result. However, when some sensors have unrecognized faults, a fusion center tends to ask the sensor with the same decision pattern as the faulty sensor to retransmit its decision. This tendency causes unbalanced load of the network. This work proposes a novel adaptive retransmission algorithm with balanced load to combat this problem. Each sensor carries all sets of thresholds. When the decision based on a set of thresholds must be retransmitted, a sensor is randomly selected. The selected sensor then makes its new decision according to the threshold and its detection result. Because of the random selection, the load is balanced. Moreover, computer simulations show that the misclassification probability of the load-balanced algorithm is close to the previous approach.

1 Introduction

Wireless sensor networks (WSNs) comprise many tiny, low-cost, battery-powered sensors in a small area [1,3]. The sensors detect environmental variations and then transmit the detection results to other sensors or a base station [2,4]. The base station or a sensor, serving as a fusion center, collects all detection results and determines the phenomenon that has occurred. The collection is realized using wireless communication technology, and a wireless network is built for multiple accesses. To lower the transmission burden, the detection result is typically denoted by a local decision. The local decision is made by the sensor and requires fewer bits than the detection result. The local decision is transmitted rather than the detection result. Therefore, each sensor must be able to collect, process, and communicate data.

The WSN sometimes must be able to work under severe conditions, such as in a battlefield, fireplace, or polluted area. The transmission channel, as well as the environmental phenomenon observed by the sensor, are noisy. Furthermore, the observation signal to noise ratio (OSNR) and the channel signal to noise ratio (CSNR) may change quickly. The OSNRs and the CSNRs are thus impossible to estimate accurately. Some sensors may even have unrecognized faults. The traditional distributed classification method thus fails due to inaccurate estimates or faulty sensors. Thus, a fault-tolerant system must be created to make the received local decisions error-resistant [6,9].

Wang et al. [15] proposed Distributed Classification Fusion using Error-Correcting Codes (DCFECC) to solve this problem by combining the distributed detection theory [12] with the concept of error-correcting codes in communication systems [5]. One sample is detected in each of $N$ sensors for a given phenomenon. A codeword consisting of $N$ symbols is designed for each phenomenon. In other words, a one-dimensional $(1 \times N)$ code corresponds to a phenomenon. Thus, $M$ phenomena form an $M \times N$ code matrix and an $M \times 1$ decision pattern is associated with each sensor. Each symbol with one bit is assigned to each sensor. A set of threshold can be found for each sensor. A local decision using the threshold set is made from the detection result and is represented with the assigned symbol. DCFECC has a much lower probability of misclassification when some sensors are faulty than the traditional distributed classification method. DCFECC outperforms the method even when CSNR is not correctly estimated.

DCSD (distributed classification fusion using soft-decision decoding) [13,14] was later developed by improving DCFECC. DCSD adopts a symbol with $L$ bits, instead of one bit, to represent the detection result at each sen-
sensor. The soft-decision decoding, instead of hard-decision decoding, is utilized to increase decoding accuracy. First, the logarithm-likelihood ratio of each received local decision is calculated at the fusion center. The fusion center then compute the distance between each codeword and the logarithm-likelihood ratios of all received local decisions. Thus, $M$ distances are obtained. The phenomenon associated with the codeword, which has the minimum distance from the logarithm-likelihood ratios of all received local decisions, is identified. However, the misclassification probability remains high in the extreme case, i.e., very low SNRs (including OSNRs and CSNRs) because of large detection deviation and unreliable transmission channels.

Pai et al. [8] have developed an adaptive retransmission algorithm to improve misclassification probability at low CSNRs. They first define the **absolute** logarithm-likelihood ratio as the **reliability**. If the difference between the minimum distance and the other $M - 1$ distances is not higher than a pre-set number, retransmission of the local decision is necessary. The codeword with the minimum distance is compared with the codeword with the second closest distance to the received vector. Denote the number of different symbols between these two codewords as $N_d$. The fusion center asks the sensor, which is associated with one of the $N_d$ symbols and has the lowest reliability, to retransmit its decision. The procedure is repeated until the difference between the minimum distance and the other $M - 1$ distances is over the pre-set number. The misclassification probability can be effectively reduced through the retransmission mechanism. However, when some sensors are faulty, the sensors with the same decision pattern as the faulty sensor transmit their decisions more often than others. Since the sensors with higher transmission load consume more power, they are dead more quickly and then the network has a shorter life time.

In this work, we develop a load-balanced algorithm to resolve the shorter network life time problem. Each sensor has all sets of thresholds (up to $N$ threshold sets) instead of one set of threshold. When the retransmission is necessary, the fusion center randomly selects a sensor. The selected sensor makes a new local decision based on its detection result and the same threshold set as the sensor with the lowest reliability. The new decision is then transmitted to the fusion center. Notice that the selected sensor may make a new detection if possible. The procedure is repeated until the retransmission is not necessary. Since each sensor is selected with the same probability, all sensors have the same transmission load.

The remainder of this work is organized as follows. Section 2 briefly addresses the distributed detection problem in WSNs and the previous works on the problem. Section 3 introduces the load-balanced retransmission mechanism. Section 4 gives a performance evaluation of the proposed algorithm. Concluding remarks and suggestions for future work are given in Section 5.

## 2 Distributed Detection And The Previous Works

Figure 1 depicts a wireless sensor network for distributed detection using $N$ sensors deployed for collecting environment variation data and a fusion center for making a final decision of detections. This network architecture is similar to the so-called SEnor with Mobile Access (SENMA) [11, 16], Message Ferry [17], and Data Mule [10]. At the $j$th sensor, one observation $y_j$ is undertaken for one of phenomena $H_i$, where $i = 1, 2, \ldots, M$. The observation is normally a real number represented by many bits. Transmitting the real number to the fusion center would consume too much power, so a local decision, $u_j$, is made instead. For a phenomenon, if only $L$ bits are allowed to send the local decision from the sensor to the fusion center, then the $L$ bits are used to represent the decision.

In the DCFECC approach [15], $L = 1$, and an $M \times N$ code matrix $T$ is designed not only to correct transmission errors but also to resist faulty sensors. The application of the code matrix is derived from error-correcting codes. Table 1 shows an example of $T$, which is the optimal code matrix found in [7]. Row $i$ of the matrix is a codeword $c_i = (c_{i,1}, c_{i,2}, \ldots, c_{i,N})$ corresponding to hypothesis $H_i$, and $c_{i,j}$ is a 1-bit symbol corresponding to the decision of sensor $j$. The local decision at sensor $j$ does not only depend on the detection result, $y_j$, but also the symbols, $c_{i,j}$, $i = 1, 2, \ldots, M$. In addition, Sensor $j$ is associated with a decision pattern, $(c_{1,j}, c_{2,j}, \ldots, c_{M,j})$. Some of the sensors may have the same decision pattern. For example, Sensors 1, 2, 3, 4, and 5 in Table 1 have the same decision pattern.
Let $v_j$ be the received local decision at the fusion center, where $v_j \in \{0, 1\}$. A cost function is then defined as

$$C_{v,c} = \begin{cases} 1 - \frac{1}{q}, & c_i \text{ is one of } q \text{ solutions of } \arg \min_{c_k} \delta(v, c_k) : \\ 1, & \text{else.} \end{cases}$$

Notably, $\delta(v, c_k)$ denotes the Hamming distance between a received vector $v = (v_1, v_2, \ldots, v_N)$, and a codeword, $c_k$. Hence, the Bayes risk function [12] represents the probability of misclassification,

$$P_e = \sum_{i,v} \int p(v, y, H_i) C_{v,c} d\mathbf{y},$$

where $y = (y_1, y_2, \ldots, y_N)$. Wang et al. adopted a person-by-person optimization (PBPO) to determine all of the local decision rules such that $P_e$ is minimized. The decision region at sensor $j$ can be represented by a set of thresholds such that a local decision rule associated with this threshold set can be performed to determine $u_j$ when $y_j$ is observed. Notably, the size of the threshold set is related to the decision pattern.

DCSD approach utilizes multiple bits and soft decoding, respectively, to improve the reliability of the local and final decisions [13, 14]. Set $u = (u_1, u_2, \ldots, u_N)$. The local decision $u_j$ is transmitted for the final decision to the fusion center. The received data at the fusion center are $\bar{v} = (\bar{v}_1, \bar{v}_2, \ldots, \bar{v}_N)$, where

$$\bar{v}_j = \alpha_j (-1)^{u_j} \sqrt{E_s} \mathcal{N}(0) + n_j.$$  

(1)

Notice that $\alpha_j$ is the attenuation factor, $E_s$ is the total transmission energy per sensor, and $n_j$ is the additive white Gaussian noise (AWGN) with the two-sided power spectral density $N_0/2$. The maximum a posteriori (MAP) criterion on code matrix is employed for data fusion. If all hypotheses are equally likely to occur, as implied by

$$p(H_i) = p(H_k); \; i, k \in \{1, 2, \ldots, M\},$$

then the MAP decoding rule is equivalent to the maximum-likelihood (ML) decoding rule. Thus, the received data are decoded as hypothesis $i$ if

$$p(\bar{v}|c_i) \geq p(\bar{v}|c_k) \text{ for all } c_k, \text{ where } k = 1, \ldots, M. \quad (2)$$

For simplicity, let $L = 1$. The soft decoding rule can be derived as follows. If the $j$th local decision, $u_j$, is only dependent on the $j$th observation, $y_j$, and the $j$th received local decision, $v_j$, is only dependent on the $j$th local decision, $u_j$, (2) can be rewritten as

$$\prod_{j=1}^{N} p(\bar{v}_j|c_{i,j}) \geq \prod_{j=1}^{N} p(\bar{v}_j|c_{k,j}).$$

Since $\bar{v}_j$ does not depend on $c_{i,j}$ given $u_j$, the above equation can be expanded to

$$\prod_{j=1}^{N} \sum_{b_u=0}^{1} p(\bar{v}_j|u_j = b_u) p(u_j = b_u|c_{i,j}) \geq \prod_{j=1}^{N} \sum_{b_u=0}^{1} p(\bar{v}_j|u_j = b_u) p(u_j = b_u|c_{k,j}),$$

$$\Rightarrow \sum_{b_u=0}^{1} \frac{1}{\prod_{j=1}^{N} p(\bar{v}_j|u_j = b_u) p(u_j = b_u|c_{i,j})} \geq 0. \quad (3)$$

Because $c_{i,j}$ and $c_{k,j}$ are binary, the bit logarithm-likelihood ratio of the received data at the fusion center can be defined as

$$\lambda_j = \ln \frac{\sum_{b_u=0}^{1} p(\bar{v}_j|u_j = b_u) p(u_j = b_u|c_{i,j})}{\sum_{b_u=0}^{1} p(\bar{v}_j|u_j = b_u) p(u_j = b_u|c_{k,j})}. \quad (4)$$

Equation (3) is then equivalent to

$$\sum_{j=1}^{N} (-1)^{c_{i,j}} \lambda_j - (-1)^{c_{k,j}} \lambda_j \geq 0.$$

$$\Rightarrow \sum_{j=1}^{N} \lambda_j - (-1)^{c_{k,j}} \lambda_j \geq \sum_{j=1}^{N} \lambda_j - (-1)^{c_{k,j}} \lambda_j \geq 0. \quad (4)$$

Define the logarithm-likelihood ratios of all received local decisions, $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N)$, and the distance between $\Lambda$ and codeword $k$,

$$\Delta_k = \text{dist} (c_k, \Lambda) = \sum_{j=1}^{N} \delta_{k,j},$$

where $\delta_{k,j} = [\lambda_j - (-1)^{c_{k,j}}]^2$. The fusion center decodes the received data as hypothesis $i$ if

$$i = \arg \min_k \Delta_k. \quad (5)$$
Table 2. Thresholds for Sensors when OSNR=20 dB

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,2,3,4,5</td>
<td>2.5</td>
</tr>
<tr>
<td>6,7,8,9,10</td>
<td>1.5, 3.5</td>
</tr>
</tbody>
</table>

Although DCSD outperforms DCFECC [14], the misclassification probability is still high when the wireless transmission channel is highly noisy in a harsh environment. An adaptive retransmission mechanism [8] has been proposed to combat the poor transmission channel. Let

\[ i' = \arg \min_{k, k \neq i} \Delta_k. \quad (6) \]

According to the coding theory, most decoding errors occur when \( \Delta_i \) is close to \( \Delta_i' \). That is, when the received data are located around the decision boundary between two codewords, the fusion center may make a wrong decision with higher probability. Thus, when the difference between \( \Delta_i \) and \( \Delta_i' \) is lower than a pre-set number \( T \), the retransmission process starts. Define \( |\lambda_j| \) as the reliability of the received local decision \( j \). The fusion center chooses the sensor, which has different symbols in codewords \( i \) and \( i' \) and has transmitted the local decision with the lowest reliability, to retransmit its local decision. Restated, the fusion center selects sensor \( j' \) to retransmit, where

\[ j' = \arg \min_{j, \lambda_i \neq \lambda_j} |\lambda_j|. \quad (7) \]

The fusion center compares the reliability of the new received local decision with the reliability of the old one. The one with the higher reliability is kept for making a final decision. The retransmission process stops until \( \Delta_i' - \Delta_i > T \).

3 Adaptive Retransmission with Balanced Load

The adaptive algorithm significantly reduces the misclassification probability. However, when some sensors are faulty, sensors with the same decision pattern as the faulty sensor have to retransmit their local decision more often than others, causing unbalanced load of the network. As a result, the network has a shorter life time. For example, four hypotheses \( H_1, H_2, H_3, \) and \( H_4 \), are detected and classified with \( N = 10 \) sensors and a fusion center. These hypotheses are assumed to have Gaussian-distributed probability density functions (pdfs) with the same standard deviation \( \sigma^2 \) and means 0, 1, 2, and 3, respectively. The code given in Table 1 is used as the code matrix. At each sensor, OSNR is defined as \(-10 \times \log_{10} \sigma^2\). The attenuation factors \( \alpha_j \) in (1) had identical and independent Rayleigh distributions with \( E[\alpha_j^2] = 1 \) and then CSNR is \( 10 \times \log_{10}(E_x/N_0) \). Table 2 shows all threshold sets found at OSNR = 20 dB. Sensors 1 to 5 have the same threshold set. So do sensors 6 to 10. For instance, if the detection result of sensor 1 is less than 2.5, then sensor 1 makes a local decision of 1. Otherwise, it makes a local decision of 0. If the detection result of sensor 6 is between 1.5 and 3.5, then sensor 6 makes a local decision of 1. Otherwise, it makes a local decision of 0.

When sensor 2 with stuck-at faults always sends out 1, the Hamming distance of two codeword pairs, \((H_3, H_2)\) and \((H_4, H_1)\), becomes 4. When \( H_3 \) (\( H_4 \)) occurs and \( \lambda_2 \) is close to or lower than \(-1 \), the received data at the fusion center tend to be located around the decision boundary between \( H_3 \) (\( H_4 \)) and \( H_2 \) (\( H_1 \)). One of the sensors with different symbols in \( H_3 \) (\( H_4 \)) and \( H_2 \) (\( H_1 \)), i.e., sensors 1 to 5, must retransmit its local decision while performing the adaptive algorithm given in [8]. Since \( |\lambda_2| \) is large, one of sensors 1, 3, 4, and 5 could be chosen with higher probability than sensor 2. Therefore, the sensor with the same decision pattern as the faulty sensor is asked to retransmit its decision with higher probability than the other sensors. Figure 2 describes the average number of retransmissions for each sensor at OSNR = 20 dB, CSNR = 0 dB, and \( T = 10 \) when sensor 2 has a stuck-at fault.
Figure 3. The average number of retransmissions for each sensor at OSNR = 20 dB, CSNR = 0 dB, and $T = 10$ when sensor 2 has a stuck-at fault and the load-balanced algorithm is performed.

We propose an algorithm to resolve the unbalanced problem. Assume that each sensor carries all sets of thresholds. When the retransmission is necessary, the fusion center can choose any sensor in the network. If a sensor is selected, it employs the same threshold set as sensor $j'$ to make a new local decision on its detection result. The new local decision is then transmitted to the fusion center. The fusion center compares the reliability of the new local decision, $|\lambda_j'|$, with the reliability of the old one, $|\lambda_j|$. If $|\lambda_j'| > |\lambda_j|$, the fusion center replaces $\lambda_j$ with $\lambda_j'$ to decide whether the retransmission is necessary or not. Otherwise, the fusion center repeats the retransmission process. The load-balanced algorithm can be summarized as follows:

**Step 1:** Calculate $\Delta$.

**Step 2:** Compute $\Delta_k$, $k = 1, 2, \ldots, M$.

**Step 3:** Find $i, i'$ according to (5) and (6), respectively. Calculate $\Delta = \Delta_i - \Delta_{i'}$.

**Step 4:** If $\Delta$ is larger than a threshold $T$, the fusion center decodes the received local decisions as $H_i$. The algorithm stops. Otherwise, go to Step 5.

**Step 5:** The fusion center randomly chooses a sensor to make a new local decision on its detection result using the same threshold set as sensor $j'$ found by (7). The chosen sensor then transmits its new decision to the fusion center.

**Step 6:** If $|\lambda_j'| > |\lambda_j|$, the fusion center replaces $\lambda_j$ with $\lambda_j'$. Go to Step 2. Otherwise, go to Step 5.

4 Performance evaluation

The proposed scheme was evaluated using several simulations, each comprising $10^6$ Monte Carlo tests. Similar to the distributed classification example in Section 3, a fusion center and $N = 10$ sensors were deployed to detect and classify four hypotheses $H_1, H_2, H_3,$ and $H_4$. We also assumed that these hypotheses have Gaussian-distributed probability density functions with the same standard deviation $\sigma^2$ and means $0, 1, 2,$ and $3$, respectively. The attenuation factors $\alpha_j$ had identical and independent Rayleigh distributions with $E[\alpha_j^2] = 1$. The code matrix in Table 1 was used.

We would like to demonstrate that each sensor has the same transmission load by using the load-balanced algorithm when some faulty sensor appear in the WSN. Figure 3 shows simulation results at OSNR = 20 dB, CSNR = 0 dB, and $T = 10$ when sensor 2 has a stuck-at fault. Figure 4 shows simulation results at OSNR = 20 dB, CSNR = 0 dB, and $T = 10$ when sensor 2 has a random fault and the load-balanced algorithm is performed.
Figure 5. Comparison of the load-balanced and load-unbalanced algorithms in $P_f$ at OSNR = 20 dB when sensor 2 has a stuck-at fault.

Figure 6. Comparison of the load-balanced and load-unbalanced algorithms in $P_f$ at OSNR = 20 dB when sensor 2 has a random fault.

5 Conclusions and future work

This work presents an adaptive retransmission algorithm with balanced load to combat the load-unbalanced problem of the adaptive retransmission approach in wireless sensor networks with faulty sensors. In this algorithm, the fusion center randomly selects the sensor. The selected sensor then make a new local decision on its detection result using the same threshold set as the sensor which had sent out the local decision with the lowest reliability. Compared with the previous adaptive mechanism, this load-balanced algorithm can make all sensors have the same transmission load with little performance loss.

In the future, we will analyze the performance of the load-balanced algorithm. That is, when the difference $\Delta$ goes to infinity, the tendency of the misclassification probability, $P_f$, will be investigated. Moreover, the relationship among $\Delta$, $T$, and $P_f$ should be studied in details. Finally, when $\Delta \ll T$, one sensor per selection/retransmission may not be efficient. When the retransmission is necessary, we will find out the optimal number of sensors per selection/retransmission.

References


