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

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A fault-tolerant classification system in wireless sensor networks combining distributed detection with error-correcting codes has recently been proposed. Associated with a decision pattern, each sensor makes a local decision based on its detection result and a set of decision thresholds. The detection result must then be transmitted to a fusion center to make a final decision. The probability of misclassification when adopting this approach is high when the transmission channel is highly noisy. This work first describes an adaptive retransmission algorithm to reduce the misclassification probability. The fusion center calculates the reliability of each local decision received while making the final decision. If the final decision is not reliable, then the fusion center asks the sensor that has sent the received local decision with the lowest reliability to retransmit its decision. However, when some sensors have unrecognized faults, the fusion center tends to query the sensor with the same decision pattern as the faulty sensor to retransmit its decision. This tendency causes unbalanced network load. This work further presents a novel adaptive retransmission algorithm with balanced load to combat this problem. Each sensor carries all sets of decision thresholds. A sensor is randomly selected when the decision based on a set of thresholds must be retransmitted. The selected sensor then makes its new decision according to the threshold set and its detection result. The random selection means the load is balanced. Simulation results show that the misclassification probability can be effectively decreased through the retransmission with a balanced load.

Keywords: wireless sensor networks, retransmission, fault-tolerant, balanced load, distributed detection

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. The detection results are then transmitted 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 what phenomenon has occurred. The collection is realized using wireless communication tech-

Received September 15, 2006; accepted February 6, 2007.
Communicated by Ten H. Lai, Chung-Ta King and Jehn-Ruey Jiang.
* This work was supported by the National Science Council of Taiwan, R.O.C., under grants No. NSC 94-2213-E-305-002 and NSC 94-2213-E-305-001.

nology, and a wireless network is built for multiple accesses. To lower the transmission burden, the detection result is typically denoted by a local decision which is made by the sensor, and which requires fewer bits than the detection result. The local decision is transmitted rather than the detection result. Hence, each sensor must be able to collect, to process and communicate data.

The WSN sometimes must be able to function 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, is 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. Therefore, a fault-tolerant system must be developed to make the received local decisions error-resistant [6, 10].

Wang *et al.* [15] proposed Distributed Classification Fusion using Error-Correcting Codes (DCFECC) to solve this problem by combining the distributed detection theory [13] 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 code ($1 \times N$) corresponds to a phenomenon. Thus, M phenomena form an $M \times N$ code matrix. Each symbol with one bit is assigned to each sensor and a set of threshold can be computed to make a local decision. The local decision is made from the detection result, and is represented with the assigned symbol. DCFECC has a much lower probability of misclassification than the traditional distributed classification method when some sensors are faulty. DCFECC outperforms the method even when CSNR is not correctly estimated.

DCSD (distributed classification fusion using soft-decision decoding) [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 sensor. The soft-decision decoding, instead of hard-decision decoding, is utilized to increase decoding accuracy. First, the reliability of each received local decision is calculated at the fusion center. The fusion center then computes the distance between each codeword and the reliability of all received local decisions. Thus, M distances are obtained. The codeword with the minimum distance from the reliability of all received local decisions is identified. However, the misclassification probability remains high in the extreme case, *i.e.*, a very low SNR (including OSNRs and CSNRs) because of the large detection deviation and unreliable transmission channels. A two-dimensional coded classification scheme is presented to solve the low OSNR problem [8].

This work develops an adaptive retransmission algorithm to resolve the low CSNR problem [9]. If the difference between the minimum distance and the other $M - 1$ distances is not higher than a pre-set number, then the local decision must be retransmitted. The codeword with the minimum distance is compared with the codeword with the second closest distance to the received vector. The number of different symbols between these two codewords is represented as N_d. The fusion center requests the sensor, which is associated with one of 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, if some sensors are faulty when running the adaptive retransmission algorithm, then the sensor with the same decision pattern as the faulty sensor transmits its decision more often than the other. Since a sensor with a higher transmission load consumes more power, it stops working more quickly, shortening the life of the network. Therefore, a load-balanced algorithm was presented to resolve the unbalanced-load problem. Each sensor has all sets of thresholds (up to N threshold sets) instead of one set of thresholds. The fusion center randomly selects a sensor when retransmission is necessary. 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. Notably, the selected sensor may make a new detection if possible. The procedure is repeated until retransmission is not necessary. Since each sensor is chosen with the same probability, all sensors have the same transmission load.

The remainder of this paper is organized as follows. Section 2 briefly addresses the distributed detection problem in WSNs and the previous works on the problem. Section 3 then introduces the adaptive retransmission mechanism. The load-balanced retransmission mechanism is explained in section 4. Section 5 gives a performance evaluation of the proposed algorithms. Conclusions are finally drawn in section 6, along with recommendations for future research.

2. FAULT-TOLERANT DISTRIBUTED DETECTION AND THE PREVIOUS WORKS

Fig. 1 depicts a wireless sensor network for distributed detection with 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 SEnsor with Mobile Access (SENMA) [12, 16], Message Ferry [17] and Data Mule [11]. At the jth 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. If only L bits are allowed to send the local decision from the sensor to the fusion center for a particular phenomenon, then the L bits are applied to represent the decision.

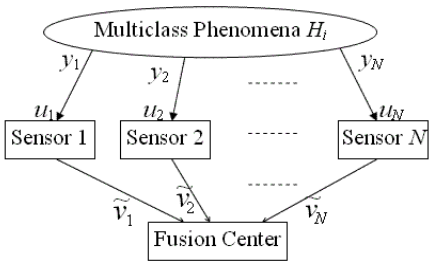

Fig. 1. Structure of a wireless sensor network for distributed detection using N sensors.

The DCFECC approach [15] set $L = 1$, and design an $M \times N$ code matrix **T** not only to correct transmission errors, but also to resist faulty sensors. The application of the

Table 1. The 4 × 10 optimal code matrix [7].

H_1	1	1	1	1	1	0	0	0	0	0
H_2	1	1	1	1	1	1	1	1	1	1
H_3	0	0	0	0	0	1	1	1	1	1
H_4	0	0	0	0	0	0	0	0	0	0

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 indicates a codeword $\mathbf{c}_i = (c_{i,1}, c_{i,2}, \ldots, c_{i,N})$ corresponding to hypothesis H_i, and $c_{i,j}$ denotes a 1-bit symbol corresponding to the decision of sensor j. The local decision at sensor j depends not only on the detection result, y_j, but also on the symbols, $(c_{1,j}, c_{2,j}, \ldots, c_{M,j})$, which represent the decision pattern of sensor j.

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

$$\tilde{v}_j = \alpha_j (-1)^{u_j} \sqrt{\frac{E_s}{L}} + n_j. \tag{1}$$

In the above equation, α_j denotes the attenuation factor. E_s is the total transmission energy per sensor, and n_j indicates 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

$$p(\tilde{\mathbf{v}} \mid \mathbf{c}_i) \geq p(\tilde{\mathbf{v}} \mid \mathbf{c}_k) \text{ for all } \mathbf{c}_k, \text{ where } k = 1, \ldots, M. \tag{2}$$

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

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

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

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

$$\Rightarrow \sum_{j=1}^{N} \ln \frac{\sum_{b_u=0}^{1} p(\tilde{v}_j \mid u_j = b_u) p(u_j = b_u \mid c_{i,j})}{\sum_{b_u=0}^{1} p(\tilde{v}_j \mid u_j = b_u) p(u_j = b_u \mid c_{k,j})} \geq 0. \tag{3}$$

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

$$\lambda_j = \ln \frac{\sum_{b_u=0}^{1} p(\tilde{v}_j \mid u_{l,j} = b_u) p(u_j = b_u \mid c_{i,j} = 0)}{\sum_{b_u=0}^{1} p(\tilde{v}_j \mid u_j = b_u) p(u_j = b_u \mid c_{k,j} = 1)}.$$

Eq. (3) is then equivalent to

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

$$\Leftrightarrow \sum_{j=1}^{N} [\lambda_j - (-1)^{c_{i,j}}]^2 \leq \sum_{j=1}^{N} [\lambda_j - (-1)^{c_{k,j}}]^2. \tag{4}$$

As demonstrated by Wang *et al.* of [14], DCSD outperforms DCFECC. However, the transmission channel between the sensor and the fusion center is highly noisy or deeply fading in a harsh environment. The oft-decision decoding does not improve the reliability of the received local decision at the fusion center. Consequently, the detection error probability is still high under a low CSNR.

3. ADAPTIVE RETRANSMISSION MECHANISM

According to the soft-decision decoding rule, the fusion center must first compute the logarithm-likelihood ratio of each received local decision, λ_j. The distance, Δ_i, between each codeword, $\mathbf{c}_i$, and the logarithm-likelihood ratios of all received local decisions, $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N)$, is then be calculated as follows:

$$\Delta_i = dist(\mathbf{c}_i, \Lambda) = \sum_{j=1}^{N} \delta_{i,j} = \sum_{j=1}^{N} [\lambda_j - (-1)^{c_{i,j}}]^2,$$

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

$$i_{\min} = \arg\min_i \Delta_i.$$

Restated, $\Delta_{i_{\min}}$ is the smallest value in $\mathcal{D} = \{\Delta_1, \Delta_2, \ldots, \Delta_M\}$.

Define $i_{\sec} = \arg \min_{i, i \neq i_{\min}} \Delta_i$.

That is, $\Delta_{i_{\sec}}$ is the second smallest value in $\mathcal{D}$. A larger difference Δ, between $\Delta_{i_{\min}}$ and $\Delta_{i_{\sec}}$, indicates a more reliable decoding result. Thus, transmission error probability is high when the difference is small, making retransmission of the local decision necessary.

If the fusion center has no information about the channel, then it may randomly select any sensor node to retransmit its local decision. However, since the fusion center has the codewords and the reliability of all received local decisions, $|\Lambda| = (|\lambda_1|, |\lambda_2|, \ldots, |\lambda_N|)$, it can use the information to perform the selection. Because the retransmission should help the fusion center to differentiate $\mathbf{c}_{i_{\min}}$ from $\mathbf{c}_{i_{\sec}}$, only the sensor, j', with different symbols corresponding to these two codewords should be chosen, *i.e.*, $c_{i_{\min},j'} \neq c_{i_{\sec},j'}$. For example, if $i_{\min} = 2$ and $i_{\sec} = 3$, the fusion center should choose a sensor for retransmission from sensor 1 to sensor 5 when applying the code matrix in Table 1. Moreover, since Δ should be as large as possible, the fusion center has to pick the sensor with the least reliability, that is, select sensor $j_{\min}$ such that

$$j_{\min} = \arg \min_{j'} |[\lambda_{j'} - (-1)^{c_{i_{\min},j'}}]^2 - [\lambda_{j'} - (-1)^{c_{i_{\sec},j'}}]^2| = \arg \min_{j'} |\lambda_{j'}|.$$

From the above observation, an adaptive retransmission mechanism is developed as follows:

Step 1: Calculate Λ.
Step 2: Compute Δ_i, $i = 1, 2, \ldots, M$.
Step 3: Derive $i_{\min}$, $i_{\sec}$ and $\Delta = \Delta_{i_{\sec}} - \Delta_{i_{\min}}$.
Step 4: If Δ is lower than a threshold T, then the fusion center asks sensor $j_{\min}$ to retransmit its local decision. Go to step 1. Otherwise, the fusion center decodes the received local decisions as $H_{i_{\min}}$.

The threshold T can be determined according to the required misclassification probability. A lower required misclassification probability indicates a larger threshold.

4. ADAPTIVE RETRANSMISSION WITH BALANCED LOAD

The adaptive algorithm significantly reduces the misclassification probability according to the simulation results presented in section 5. However, when some sensors are faulty, the sensor with the same decision pattern as the faulty sensor must retransmit its local decision more often than the other, causing unbalanced load of the network. Consequently, the network has a short life span. 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 σ^2 and means 0, 1, 2, and 3, respectively. Table 1 is used as the code matrix. The OSNR is defined as $-10 \times \log_{10} \sigma^2$ at every sensor. The attenuation factors α_j in Eq. (1) had identical and independent Rayleigh distributions with $E[\alpha_j^2] = 1$, and making CSNR equal to $10 \times \log_{10}(E_s/N_0)$. Table 2 lists all threshold sets found at OSNR = 20 dB. Sensors 1 to 5 have the same threshold set as do sensors 6

Table 2. Thresholds for sensors when OSNR = 20 dB.

Sensors	Thresholds
1, 2, 3, 4, 5	2.5
6, 7, 8, 9, 10	1.5, 3.5

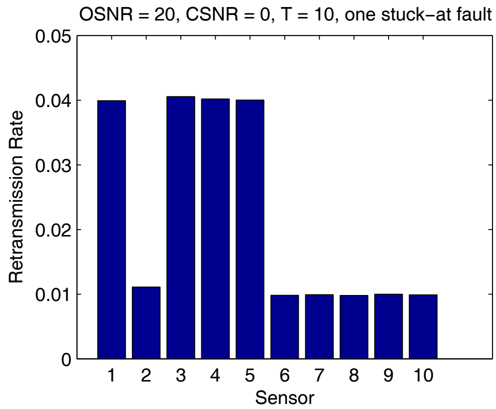

Fig. 2. Retransmission rate for each sensor at OSNR = 20 dB, CSNR = 0 dB, and T = 10 when sensor 2 has a stuck-at fault.

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. 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) when H_3 (H_4) occurs and λ_2 is around or lower than − 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 by using the adaptive algorithm. Since $|\lambda_2|$ is large, one of sensors 1, 3, 4, and 5 may be chosen with a higher probability than sensor 2. Therefore, the sensor with the same decision pattern as the faulty sensor is asked to retransmit its decision with a higher probability than the other sensors. Fig. 2 presents the average number of retransmissions per detection (*i.e.*, retransmission rate) for each sensor at OSNR = 20 dB, CSNR = 0 dB, and T = 10. Sensors 1, 3, 4, and 5 have much larger retransmission rate than sensors 6 to 10. Because of this unbalanced transmission load, sensors 1, 3, 4 and 5 consume much more power and have a shorter life time than sensors 6 to 10. The network cannot work properly if half of the sensors in the network do not function.

An algorithm was further proposed to resolve the unbalanced problem. Each sensor carries all sets of thresholds. The fusion center can choose any sensor in the network when retransmission is necessary. If a sensor is selected, then 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 $|\lambda'_{j'}| > |\lambda_{j'}|$, then the fusion center replaces $\lambda_{j'}$ with $\lambda'_{j'}$ to decide whether the retransmission is need. Otherwise, the fusion center repeats the retransmission process. The load-balanced algorithm can be summarized as follows:

Step 1: Calculate Λ.
Step 2: Compute Δ_k, $k = 1, 2, \ldots, M$.
Step 3: Determine i, i', and $\Delta = \Delta_i - \Delta_{i'}$.
Step 4: If Δ is greater than a threshold T, then decode the received local decisions as H_i. The algorithm stops; otherwise, go to step 5.
Step 5: Randomly chooses a sensor to make a new local decision on its detection result using the same threshold set as sensor j'. The chosen sensor then sends its new decision to the fusion center.
Step 6: If $|\lambda'_{j'}| > |\lambda_{j'}|$, then the fusion center replaces $\lambda_{j'}$ with $\lambda'_{j'}$. Go to step 2. Otherwise, go to step 5.

5. 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 4, a fusion center and $N = 10$ sensors were deployed to detect and classify four hypotheses H_1, H_2, H_3, and H_4. These hypotheses were also assumed to have Gaussian-distributed probability density functions with the same standard deviation σ^2 and means 0, 1, 2, and 3, respectively. The attenuation factors α_j had identical and independent Rayleigh distributions with $E[\alpha_j^2] = 1$. The code matrix in Table 1 was utilized.

The first set of simulations demonstrates that Δ is inversely proportional to the misclassification probability, P_f. That is, a larger Δ leads to a lower P_f. The CSNR was set to be 0 dB. Fig. 3 displays simulation results at OSNR = 10 dB. The misclassification probability, P_f, was around 0.35 when the difference, Δ, ranges from 0 to 5. Simulation

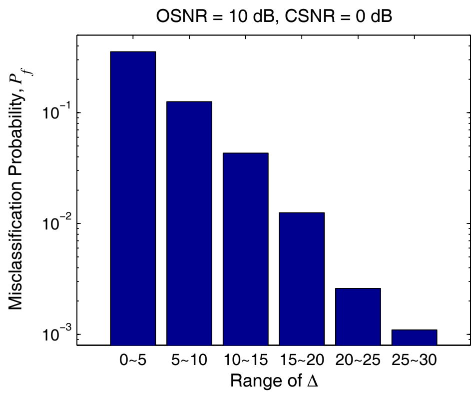

Fig. 3. Δ vs. P_f when CSNR = 0 dB and OSNR = 10 dB.

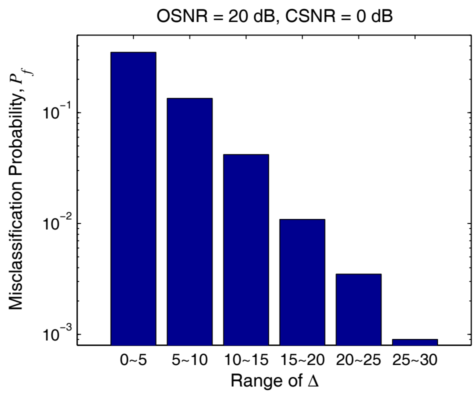

Fig. 4. Δ vs. P_f when CSNR = 0 dB and OSNR = 20 dB.

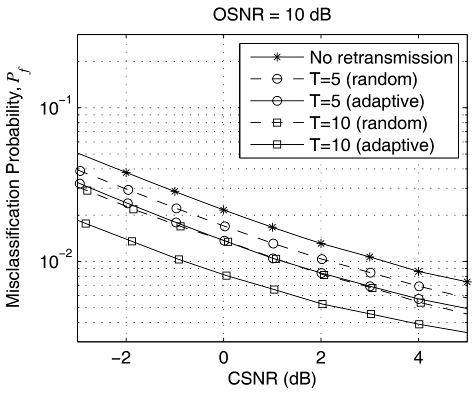

Fig. 5. Performance comparison of the adaptive and random mechanisms in P_f when OSNR = 10 dB.

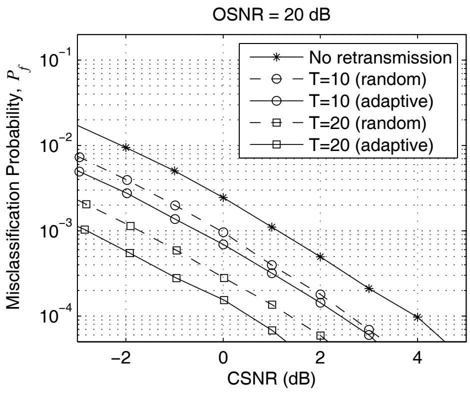

Fig. 6. Performance comparison of the adaptive and random mechanisms in P_f when OSNR = 20 dB.

results reveal that P_f falls as Δ increases. Finally, P_f was around 0.001 when Δ ranged from 25 to 30. Fig. 4 shows similar results at OSNR = 20 dB.

The second set of simulations was performed to verify the superiority of the proposed mechanism. The adaptive retransmission mechanism was compared with a random retransmission mechanism. In the random retransmission mechanism, the fusion node randomly chooses a sensor to retransmit its local decision when $\Delta < T$. The OSNRs were set to be 10 dB and 20 dB, and the CSNRs were varied from − 3 dB to 5 dB. The results for the mechanism without retransmission are also presented. Figs. 5 and 6 indicate that the adaptive mechanism had a lower misclassification probability than the random mechanism and the mechanism without retransmission while T = 5, 10 and T = 10, 20, respectively. The transmission power was normalized with respect to the retransmission times. For example, by Fig. 5, the coding gains on CSNR of the proposed mechanism over the mechanism without retransmission were about 2 dB and 4 dB, for OSNR = 10 dB and $P_f = 10^{-2}$, when T = 5 and T = 10, respectively. The coding gains on CSNR of the proposed mechanism over the random mechanism were around 1 dB and 2 dB, for OSNR = 10 dB and $P_f = 10^{-2}$, when T = 5 and T = 10, respectively. Fig. 6 shows the simulation results for OSNR = 20 dB and also demonstrates the superiority of the proposed mechanism. Because a few local decision errors arose when OSNR =10 dB and the retransmission mechanism cannot correct the local decision errors, the misclassification probability converges toward a non-zero constant even at a high CNSR. By contrast, the misclassification probability can be reduced close to zero when OSNR = 20 dB because the local decisions were almost correct. Meanwhile, the adaptive mechanism had a fewer retransmissions on average per detection than the random mechanism as presented in Figs. 7 and 8. For instance, the retransmission rate of the proposed mechanism was half of that of the random mechanism for T = 5 and 10 when OSNR = 10 dB, according to Fig. 7.

Finally, this work demonstrates that each sensor had the same transmission load using the load-balanced algorithm when the faulty sensor appeared in the WSN. Fig. 9 shows the simulation results for OSNR = 20 dB, CSNR = 0 dB and T = 10 when sensor 2 has a stuck-at fault. Each sensor has the same retransmission rate. When a sensor in the

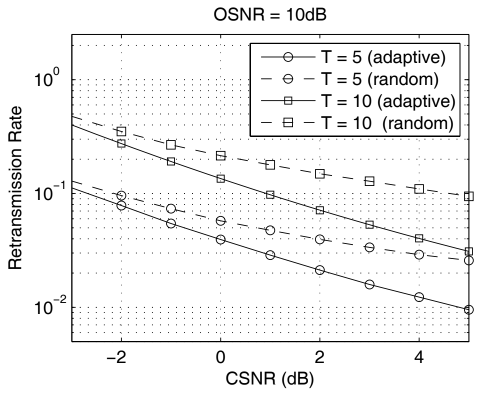

Fig. 7. Performance comparison of the adaptive and random mechanisms in the retransmission rate when OSNR = 10 dB.

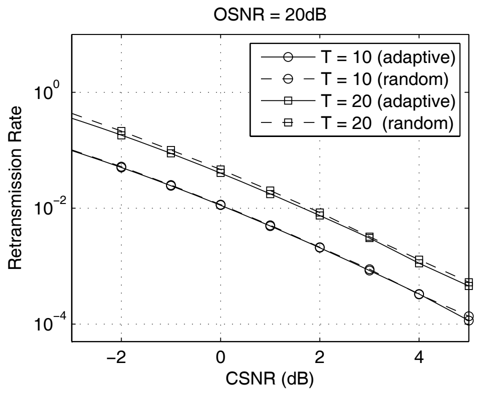

Fig. 8. Performance comparison of the adaptive and random mechanisms in the average number of retransmissions per detection when OSNR = 20 dB.

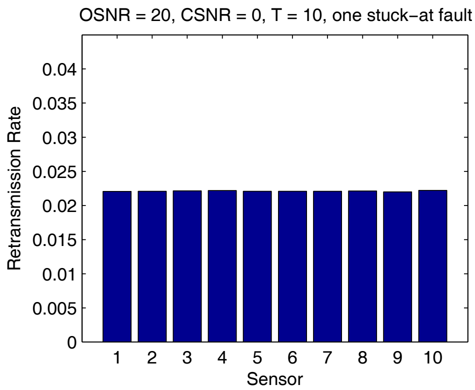

Fig. 9. Retransmission rate for each sensor at OSNR = 20 dB, CSNR = 0 dB and $T = 10$ when sensor 2 has a stuck-at fault using the load-balanced algorithm.

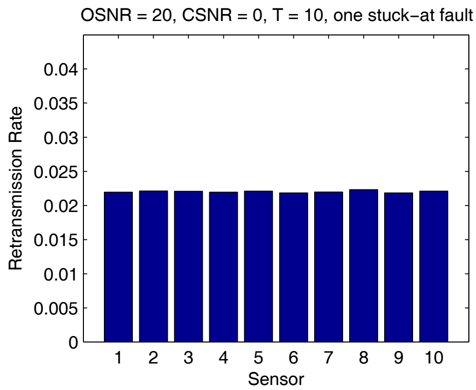

Fig. 10. Retransmission rate for each sensor at OSNR = 20 dB, CSNR = 0 dB, and $T = 10$ when sensor 2 has a random fault using the load-balanced algorithm.

network has a random fault, *i.e.*, it sends out 0 or 1 to the fusion center with the same probability, all sensor still have the same transmission load as in Fig. 10. Notably, the adaptive retransmission scheme using the load-balanced algorithm had almost the same misclassification probability and retransmission times as that using the load-unbalanced algorithm. Figs. 11 to 14 reveal that the performance and retransmission rate of the load-balanced algorithm were close to those of the load-unbalanced algorithm.

6. CONCLUSIONS AND FUTURE WORKS

This work presents an adaptive retransmission mechanism to combat the poor transmission channel in wireless sensor networks. In this mechanism, the fusion center

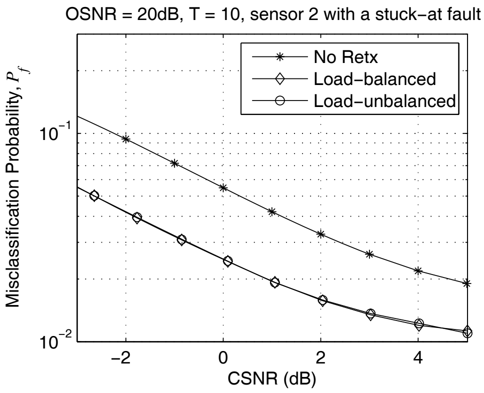

Fig. 11. Comparison of the load-balanced and load-unbalanced algorithms in P_f at OSNR = 20 dB when sensor 2 has a stuck-at fault.

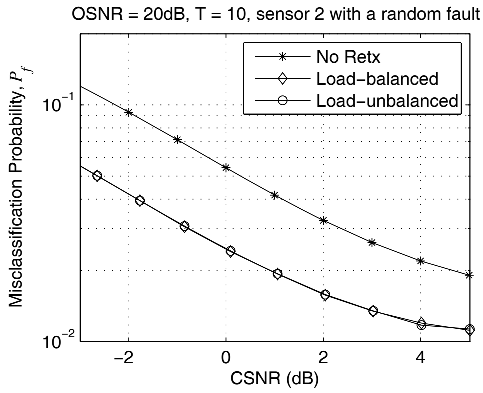

Fig. 12. Comparison of the load-balanced and load-unbalanced algorithms in P_f at OSNR = 20 dB when sensor 2 has a random fault.

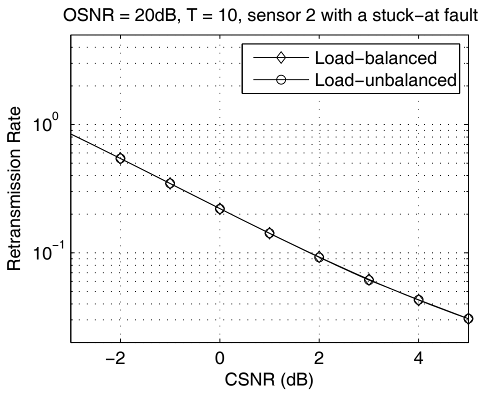

Fig. 13. Comparison of the load-balanced and load-unbalanced algorithms in the retransmission rate at OSNR = 20 dB when sensor 2 has a stuck-at fault.

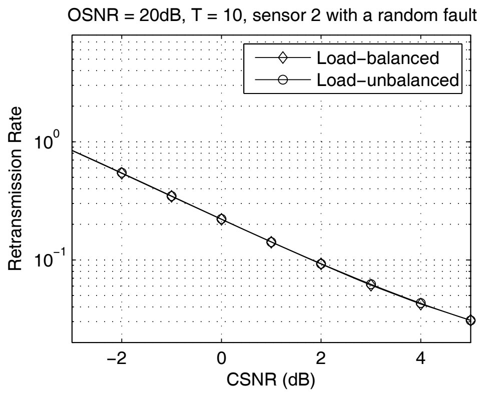

Fig. 14. Comparison of the load-balanced and load-unbalanced algorithms in the retransmission rate at OSNR = 20 dB when sensor 2 has a random fault.

selects the sensor to retransmit its local decision according to the reliability of the received local decision, instead of randomly. This adaptive selection mechanism can reduce the misclassification probability with even fewer retransmissions than the random selection mechanism.

An adaptive retransmission algorithm with balanced load is also proposed to combat the load-unbalanced problem of the adaptive retransmission approach in wireless sensor networks with faulty sensors. In this load-balanced algorithm, the fusion center selects the sensor randomly. The selected sensor then makes 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. This load-balanced algorithm can give all sensors the same transmission load with little performance loss compared to the previous adaptive mechanism.

Future work will be to theoretically prove the asymptotical performance of the proposed mechanism. That is, the tendency of the misclassification probability, P_f, when the difference Δ goes to infinity, will be investigated. Moreover, the relationship among Δ, T, and P_f should be studied in details. Finally, one sensor per selection/retransmission may not be efficient when $\Delta \ll T$. Additional future work will be to determine the optimal number of sensors per selection/retransmission.

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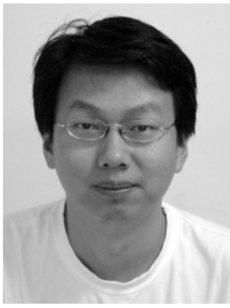

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