Equal-Gain Combination for adaptive distributed classification in Wireless Sensor Networks

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Abstract: A fault-tolerant classification system in Wireless Sensor Networks (WSNs) has recently been proposed. An adaptive redetection algorithm and an adaptive retransmission scheme were later developed to reduce the misclassification probability of the system when observations of sensors is highly noisy, and the transmission channel between the sensor and the fusion centre of the network is deeply faded, respectively. The observation and the received data are discarded if they are unreliable. However, they still have useful information. This work applies Equal-Gain Combination (EGC) techniques to utilise the unreliable data. Simulation results show that the new adaptive method with EGC outperforms the original one.

Keywords: EGC; equal-gain combination; WSNs; wireless sensor networks; adaptive distributed detection; fading channels; fault-tolerant.

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1 Introduction

Wireless Sensor Networks (WSNs) comprise many tiny, low-cost, battery-powered sensors in a small area (Akyildiz et al., 2002). The sensors observe environmental variations and then transmit the observation results to other sensors or a base station (Aldosari and Moura, 2004; D'Costa et al., 2004). The base station or a sensor, serving as a fusion centre, collects all observation results, and determines what phenomenon has occurred. The collection is realised using wireless communication technology, and a wireless network is built for multiple accesses. To lower the transmission burden, the observation result is typically denoted by a local decision which is made by the sensor, and which requires fewer bits than the observation result. The local decision is transmitted rather than the observation result. Hence, each sensor must be able to collect, 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 unrecognised 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 (Meyer and Weinert, 1986; Reibman and Nolte, 1990).

Wang et al. (2005) proposed Distributed Classification Fusion using Error-Correcting Codes (DCFECC) to solve this problem by combining the distributed detection theory (Varshney, 1997) with the concept of error-correcting codes in communication systems (MacWilliams and Sloane, 1977). 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 each sensor has its local decision rules. A local decision based on the rule is made from the observation 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.

Distributed Classification Fusion using Soft-decision Decoding (DCSD) (Wang et al., 2006) was later developed by improving DCFECC. DCSD adopts a symbol with L bits, instead of one bit, to represent the observation result at each sensor. The soft-decision decoding, instead of hard-decision decoding, is utilised to increase decoding accuracy. However, the misclassification probability remains high in the extreme case, i.e., very low SNRs (including OSNRs and CSNRs) because of large observation deviation and unreliable transmission channels. Pai et al. (2006, 2007) have developed an adaptive retransmission mechanism to resolve the low CSNR problem and then proposed an adaptive redetection algorithm to combat the low OSNR problem.

In the adaptive retransmission mechanism, the fusion centre calculates the channel reliability of each received detection result while making the final decision. When the final decision is not reliable, the received result with the lowest channel reliability is discarded and the sensor which has sent it will be asked to retransmit its detection result by the fusion centre. Similarly, if the observation result of the sensor is located in a unreliable range, it is discarded and the sensor makes another observation in the adaptive redetection mechanism. However, the unreliable observation result at the sensor and the unreliable received detection result at the fusion centre still contain information about the environment and the local decision, respectively. They should be utilised to increase the performance of the adaptive distributed classification system.

In this work, we apply Equal-Gain Combination (EGC) techniques (Brennan, 2003) for the utilisation of the unreliable data. A new observation result at a sensor is equally combined with the combined result of the previous observations. The combined observation result is then employed to decide whether another observation is necessary or not. If another observation is unnecessary, a local decision based on the combination result is made. The adaptive redetection scheme using the EGC technique needs a smaller number of observations and has a lower misclassification probability than the original one. Similarly, the channel reliability of the latest received local decision from the same sensor at the fusion centre is equally combined with the combined channel reliability of the previous received local decisions. The fusion centre then use the combined channel reliability to decide which sensor is selected for retransmission. Moreover, two methods are proposed to decide if the final decision can be made. The new adaptive retransmission algorithms needs less retransmission times and reach a misclassification probability close to the previous one under the same retransmission criteria.

The remainder of this work is organised as follows. Section 2 briefly addresses the distributed detection problem in WSNs and the previous work on the problem. Section 3 introduces the new adaptive redetection mechanism and the new adaptive retransmission scheme. Section 4 gives a performance evaluation of the proposed mechanism. Concluding remarks and suggestions for future work are given in Section 5.

2 The previous works

Figure 1 depicts a WSN for distributed detection with N sensors deployed for collecting environment variation data and a fusion centre for making a final decision of detections. This network architecture is similar to the so-called SEnsor with Mobile Access (SENMA) (Yang and Tong, 2005; Tong et al., 2003), Message Ferry (Zhao and Ammar, 2003) and Data Mule (Shah et al., 2003). 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 centre would consume too much power, so a local decision, u_j, is made instead.

2.1 *Old adaptive redetection algorithm*

The DCFECC approach (Wang et al., 2005) designs an $M \times N$ code matrix $\mathbf{T}$ 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 lists an example of $\mathbf{T}$, which is the optimal code matrix found in Pai et al. (2008). Row i of the matrix represents 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 decision region at sensor j can be represented by a set of thresholds. Thus, a local decision rule associated with this threshold set can be performed to determine u_j when y_j is observed. Since the observation result around the threshold is not reliable, an unreliable range is defined around the threshold. For example, four hypotheses

H_1, H_2, H_3, and H_4, are detected and classified with $N = 10$ sensors and a fusion centre. 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. At each sensor, OSNR is defined as $-10 \times \log_{10} \sigma^2$. When $\sigma^2 = 0.6$ and channel noise is zero, the threshold, T_1, and the unreliable range, $U_1 = [T_1 - \tau_1 \, T_1 + \tau_1]$ of sensor 1 is illustrated in Figure 2. If the observation result falls in the unreliable range, it is discarded and another observation is taken. The whole process does not stop until the latest observation is not located in the unreliable range. The adaptive redetection scheme outperforms the non-adaptive algorithm by 2 dB.

Figure 1 Structure of a Wireless Sensor Network for distributed detection using N sensors

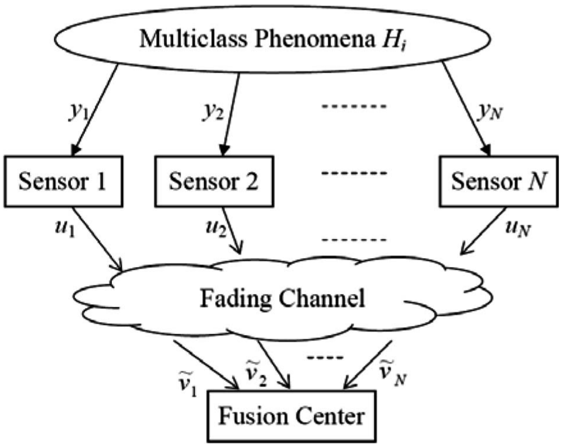


Table 1 The 4×10 optimal code matrix

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

Source: Pai et al. (2008)

2.2 *Old adaptive retransmission algorithm*

Distributed Classification Fusion using Soft-decision Decoding (DCSD) approach utilises soft decoding to improve the reliability of the final decisions (Wang et al., 2006). Set $\mathbf{u} = (u_1, u_2, \ldots, u_N)$. The local decision $\mathbf{u}$ is transmitted for the final decision to the fusion centre. When binary antipodal modulation is deployed, the received data at the fusion centre are $\tilde{\mathbf{v}} = (\tilde{v}_1, \tilde{v}_2, \ldots, \tilde{v}_N)$, where

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

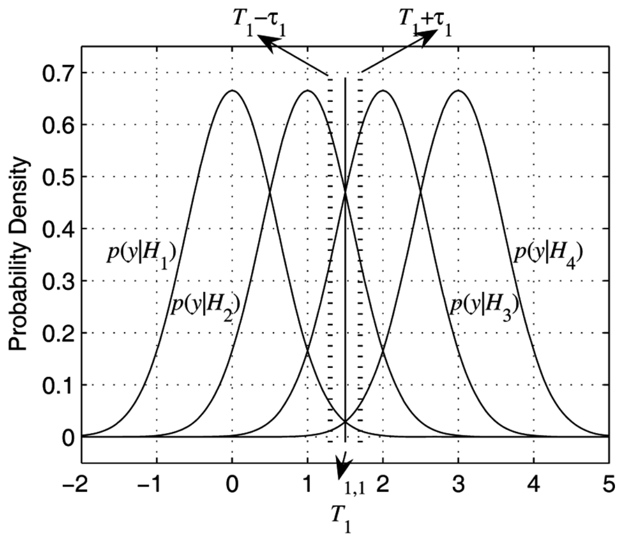
Notice that α_j is the attenuation factor, E_s is the total transmission energy per sensor, and n_j is the Additive White Gaussian Noise (AWGN) with the two-sided power spectral density $N_0/2$. The received data are decoded as hypothesis i if

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

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

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

Figure 2 The threshold and the unreliable range at $\sigma = 0.6$ for sensor 1



Equation (2) is then equivalent to

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

Denote

$$\delta_i = \sum_{j=1}^{N} \left[\lambda_j - (-1)^{c_{i,j}}\right]^2.$$

The fusion centre decodes the received data as hypothesis $i_{\min}$ if $i_{\min} = \arg\min_i \delta_i$. Define

$$i_{\text{sec}} = \arg \min_{i, i \neq i_{\min}} \delta_i.$$

A smaller difference $\delta = \delta_{i_{\text{sec}}} - \delta_{i_{\min}}$ indicates that the received data are around the decision boundary, meaning that the decoding result has a higher error probability (MacWilliams and Sloane, 1977). Thus, retransmission of the local decision is necessary.

Define the channel reliability of the received local decision j as

$$\gamma_j = \left| \ln \frac{p(\tilde{v}_j \mid u_j = 0)}{p(\tilde{v}_j \mid u_j = 1)} \right|.$$

Because the retransmission should help the fusion centre to differentiate $\mathbf{c}_{i_{\min}}$ from $\mathbf{c}_{i_{\text{sec}}}$, only the sensor, j', with different symbols corresponding to these two codewords should be chosen, i.e., $c_{i_{\min}, j'} \neq c_{i_{\text{sec}}, j'}$. Therefore, the fusion centre discards the received local decision from sensor $j_{\min}$, where

$$j_{\min} = \arg \min_{j'} \gamma_{j'},$$

and ask it to retransmit its local decision. The retransmission process does not stop until δ is greater than a predefined threshold.

3 New adaptive schemes using EGC

3.1 New adaptive redetection

Assume that all observations of a sensor are identically independent distributed (i.i.d.) given H_i and have the same OSNR. According to Brennan (2003), EGC is the optimal method to combing two observations. Denote $y_j^d, d=1,2,\ldots$, as the dth observation of sensor j and

$$\bar{y}_j^d = \begin{cases} y_j^1 & \text{if } d=1 \\ \frac{1}{2}\left(y_j^d + \bar{y}_j^{d-1}\right) & \text{else} \end{cases}$$

as the combined observation result of sensor j in d observations. We propose an adaptive redetection algorithm for each sensor using the concept of EGC as follows:

Step 1: Define the allowed maximum number of observations as D and set the number of observations, d, to 0.

Step 2: The sensor makes an observation of the environment and sets $d=d+1$.

Step 3: If the combined observation result in d observations, i.e., $\bar{y}_j^d$ falls in the unreliable range and $d \le D$, go to Step 2. Otherwise, the sensor makes a local decision according to $\bar{y}_j^d$.

Step 4: The sensor transmits the local decision to the fusion centre.

Notably, all observations at each sensor may not be combine with equal weights. On the other hand, the new observation is equally combined with the combined result of previous observations. This adaptive mechanism is different from the original application of EGC, where all observations are equally combined, no adaptive mechanism is employed, and the number of observations is fixed. Furthermore, only the combined observation result must be saved at the sensor and an average operation for two values is conducted. Therefore, little extra cost over the old adaptive redetection in Section 2.1 is needed.

We further assume that all hypotheses, H_i, are equally likely to occur. Let U_j be the unreliable range for senor j. The probability that the $(d+1)$th observation, $d=1,2,\ldots,D-1$, is necessary for sensor j after d observations can be represented by

$$P_j^r(d) = \Pr\{\bar{y}_j^1 \in U_j, \bar{y}_j^2 \in U_j, \ldots, \bar{y}_j^d \in U_j\}.$$

Therefore, the expected number of observations for sensor j can be calculated by

$$O_j = 1 \times (1 - P_j^r(1)) + 2 \times P_j^r(1)\left(1 - P_j^r(2)\right) + \cdots + D \times \prod_{d=1}^{D-1} P_j^r(d).$$

Define C_{ij} and W_{ij} as the range which sensor j will make a correct and wrong local decision given H_i, respectively, if $\bar{y}_j^d$ is located in. Notably, both C_{ij} and W_{ij} are reliable ranges. The probabilities that the local decision of sensor j is correct and wrong after $d < D$ observations can be computed by

$$P_j^c(d) = \frac{1}{M}\sum_{i=1}^{M} \Pr\{\bar{y}_j^1 \in U_j, \ldots, \bar{y}_j^d \in C_{ij} \mid H_i\}$$

and

$$P_j^e(d) = \frac{1}{M}\sum_{i=1}^{M} \Pr\{\bar{y}_j^1 \in U_j, \ldots, \bar{y}_j^d \in W_{ij} \mid H_i\},$$

respectively. When $d=D$, no unreliable ranges are effective since the sensor must make a decision. Let C'_{ij} and W'_{ij} be the range which sensor j will make a correct and wrong local decision given H_i, respectively, when no reliable ranges are defined. The probabilities that the local decision of sensor j is correct and wrong after D observations can be computed by

$$P_j^c(D) = \frac{1}{M}\sum_{i=1}^{M} \Pr\{\bar{y}_j^1 \in U_j, \ldots, \bar{y}_j^d \in C'_{ij} \mid H_i\}$$

and

$$P_j^e(D) = \frac{1}{M}\sum_{i=1}^{M} \Pr\{\bar{y}_j^1 \in U_j, \ldots, \bar{y}_j^d \in W'_{ij} \mid H_i\},$$

Consequently, the probabilities that the the local decision of sensor j is correct and wrong can be found by

$$P_j^c = P_j^c(1) + P_j^r(1)P_j^c(2) + \cdots + \prod_{d=1}^{D-1} P_j^r(d)P_j^c(D)$$

and

$$P_j^e = P_j^e(1) + P_j^r(1)P_j^e(2) + \cdots + \prod_{d=1}^{D-1} P_j^r(d)P_j^e(D).$$

In the example of Section 2.1, the ranges, C_{11} and C'_{11}, that sensor 1 will make a correct local decision given H_1 are $[-\infty\ T_1 - \tau_1)$ and $[-\infty\ T_1)$, respectively. On the other hand, the ranges, W_{11} and W'_{11}, that sensor 1 will make a wrong local decision given H_1 are $[T_1 + \tau_1\ \infty]$ and $[T_1\ \infty]$, respectively. Similarly, C_{ij}, C'_{ij}, W_{ij} and W'_{ij} for all i and j can be defined/found. Therefore, O_j, P_j^c, and P_j^e can be calculated numerically according the pdfs of H_i, $i=1,2,3,4$.

3.2 New adaptive retransmission

Denote $\tilde{v}_j^{r_j}$, $r_j=1,2,\ldots$, as the r_jth received local decision from sensor j at the fusion centre and

$$\bar{\lambda}_j^{r_j} = \ln \frac{\sum_{b_u=0}^{1} p(\tilde{v}_j^1, \ldots, \tilde{v}_j^{r_j} \mid u_j = b_u)p(u_j = b_u \mid c_{i,j} = 0)}{\sum_{b_u=0}^{1} p(\tilde{v}_j^1, \ldots, \tilde{v}_j^{r_j} \mid u_j = b_u)p(u_j = b_u \mid c_{k,j} = 1)}$$

as the combined bit log-likelihood ratio of the received local decision j at the fusion centre. Assume that all received local decisions from sensor j at the fusion centre are i.i.d. given its local decision, u_j. That is,

$$p(\tilde{v}_j^1, \ldots, \tilde{v}_j^{r_j} \mid u_j) = p(\tilde{v}_j^1 \mid u_j) \cdots p(\tilde{v}_j^{r_j} \mid u_j). \tag{3}$$

The combined bit log-likelihood ratio can be rewritten as

$$\bar{\lambda}_j^{r_j} = \ln \frac{\sum_{b_u=0}^{1} \prod_{k=1}^{r_j} p(\tilde{v}_j^k \mid u_j = b_u) p(u_j = b_u \mid c_{i,j} = 0)}{\sum_{b_u=0}^{1} \prod_{k=1}^{r_j} p(\tilde{v}_j^k \mid u_j = b_u) p(u_j = b_u \mid c_{k,j} = 1)}.$$

Moreover, let

$$\bar{\delta}_i = \sum_{j=1}^{N} \left[\bar{\lambda}_j^{r_j} - (-1)^{c_{i,j}}\right]^2.$$

Thus, the fusion centre decodes the received data as hypothesis $\bar{\imath}_{\min}$ if $\bar{\imath}_{\min} = \arg\min_i \bar{\delta}_i$. Define

$$\bar{\imath}_{\mathrm{sec}} = \arg \min_{i, i \neq \bar{\imath}_{\min}} \bar{\delta}_i$$

and

$$\bar{\delta} = \bar{\delta}_{\bar{\imath}_{\mathrm{sec}}} - \bar{\delta}_{\bar{\imath}_{\min}}.$$

Finally, let

$$\bar{\gamma}_j^{r_j} = \left| \ln \frac{p(\tilde{v}_j^1, \ldots, \tilde{v}_j^{r_j} \mid u_j = 0)}{p(\tilde{v}_j^1, \ldots, \tilde{v}_j^{r_j} \mid u_j = 1)} \right|$$

as the combined channel reliability of the received local decision j at the fusion centre. According equation (3),

$$\begin{aligned} \bar{\gamma}_j^{r_j} &= \left| \ln \frac{\prod_{k=1}^{r_j} p(\tilde{v}_j^k \mid u_j = 0)}{\prod_{k=1}^{r_j} p(\tilde{v}_j^k \mid u_j = 1)} \right| \\ &= \left| \sum_{k=1}^{r_j} \ln \frac{p(\tilde{v}_j^k \mid u_j = 0)}{p(\tilde{v}_j^k \mid u_j = 1)} \right|. \end{aligned}$$

From the above equation, we can find that $\bar{\gamma}_j^{r_j}$ is calculated based on the summation of all logarithmic terms with the same weight, which is the concept of the EGC.

According the above derivation, an adaptive retransmission algorithm for the fusion centre is developed as follows:

Step 1: Define the allowed maximum number of transmission for sensor j as R and the acceptable channel reliability as Γ. Set $r_j = 1$, for $j = 1, 2, \ldots, N$. Ask all sensors transmit their local decisions. Compute $\bar{\lambda}_j^{r_j}$, for $j = 1, 2, \ldots, N$.

Step 2: Compute $\bar{\delta}_i$, $i = 1, 2, \ldots, M$.

Step 3: Calculate $\bar{\imath}_{\min}$, $\bar{\imath}_{\mathrm{sec}}$ and $\bar{\delta}$.

Step 4: If $\bar{\delta}$ is lower than a threshold Δ and some $\bar{\gamma}_j^{r_j}$ is less than Γ, the fusion centre asks sensor $\bar{\jmath}_{\min}$ to retransmit its local decision and set $r_{\bar{\jmath}_{\min}} = r_{\bar{\jmath}_{\min}} + 1$, where

$$\bar{\jmath}_{\min} = \arg \min_{j', r_{j'} \leq R} \bar{\gamma}_{j'}^{r_{j'}}.$$

Calculate $\bar{\lambda}_{\bar{\jmath}_{\min}}^{r_{\bar{\jmath}_{\min}}}$. Go to Step 2. Otherwise, the fusion centre decodes the received local decisions as $H_{\bar{\imath}_{\min}}$.

Notably, in Step 1, the allowed maximum number of transmissions is set because the sensor has limited power and the power for a local decision cannot be infinite in practice. The acceptable channel reliability is defined for avoiding useless retransmissions due to low OSNRs. Furthermore, the fusion centre must have enough storage to save R received local decisions for each sensor such that $\bar{\lambda}_j^{r_j}$ can be calculated accordingly. However, if the fusion centre is a sensor with limited complexity, such storage may be too huge.

We may assume that the OSNR is high when we compute $\bar{\lambda}_j^{r_j}$ to solve this problem. When the OSNR is large, the local decisions of all sensor are correct with very high probabilites, i.e.,

$$\begin{aligned} &p(u_j = 0 \mid c_{i,j} = 0) \approx p(u_j = 1 \mid c_{i,j} = 1) \approx 1 \quad \text{and} \\ &p(u_j = 1 \mid c_{i,j} = 0) \approx p(u_j = 0 \mid c_{i,j} = 1) \approx 0. \end{aligned}$$

Thus, $\bar{\lambda}_j^{r_j}$ can be approximated by

$$\begin{aligned} \bar{\lambda}_j^{r_j} &\approx \ln \frac{\prod_{k=1}^{r_j} p(\tilde{v}_j^k \mid u_j = b_u)}{\prod_{k=1}^{r_j} p(\tilde{v}_j^k \mid u_j = b_u)} \\ &= \sum_{k=1}^{r_j} \frac{p(\tilde{v}_j^k \mid u_j = b_u)}{p(\tilde{v}_j^k \mid u_j = b_u)} \\ &\approx \sum_{k=1}^{r_j} \lambda_j^k \\ &= \bar{\lambda}_j^{r_j - 1} + \lambda_j^{r_j}, \end{aligned} \tag{4}$$

where

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

That is, the combined bit log-likelihood ratio of the received local decision j is approximated using the EGC at the fusion centre. Consequently, the fusion only needs to save $\bar{\lambda}_j^{r_j}$ instead of all received local decisions from sensor j.

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 2.1, a fusion centre 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 σ^2 and means 0, 1, 2, and 3, respectively. The attenuation factors α_j in (1) had identical and independent Rayleigh distributions with $E[\alpha_j^2] = 1$. Furthermore, CSNR is $10 \times \log_{10}(E_s/N_0)$. The code matrix in Table 1 was used.

In the first set of simulations, Figure 3 shows performance comparison between the old and new adaptive redetection algorithms when $\tau = 0.4$, $D = \infty$, and CSNR = 10 dB. The OSNR is normalised by the average number of observations per sensor for fair comparison in Figure 3(a). That is,

$$\text{OSNR} = -10 \times \log_{10} \sigma^2 + 10 \times \log_{10} \overline{O}, \qquad (5)$$

where

$$\overline{O} = \frac{1}{N} \sum_{j=1}^{N} O_j.$$

The new adaptive redetection mechanism outperforms the old mechanism, especially in low OSNRs. The average number of detection for the new algorithm is slightly higher than the old one. Less than 1.8 detections per sensor is required.

Figure 4 illustrates performance comparison among the old (denoted by Old ART) and new adaptive retransmission algorithms when $\Delta = 4$, $R = \infty$, $\Gamma = 5$, and OSNR = 0 dB. The CSNR is also normalised as the OSNR in equation (5). Two new adaptive retransmission algorithms are included: one calculates $\overline{\lambda}_j^{r_j}$ without any approximation and the other use the approximation in equation (4) (denoted by ART-EGC and ART-EGC^2, respectively). The new adaptive retransmission algorithms outperform the old mechanism. The average numbers of transmissions are less than three transmissions per sensor.

5 Conclusions

This work presents a new adaptive redetection and two new adaptive retransmission algorithms to combat noisy observation environment and imperfect channels in WSN.

Figure 3 In the case of $\tau = 0.4$, $D = \infty$, and CSNR = 10 dB, performance comparison between the old and new adaptive redetection algorithms (denoted by Old ARD and ARD-EGC) in: (a) the misclassification probability and (b) the number of detections

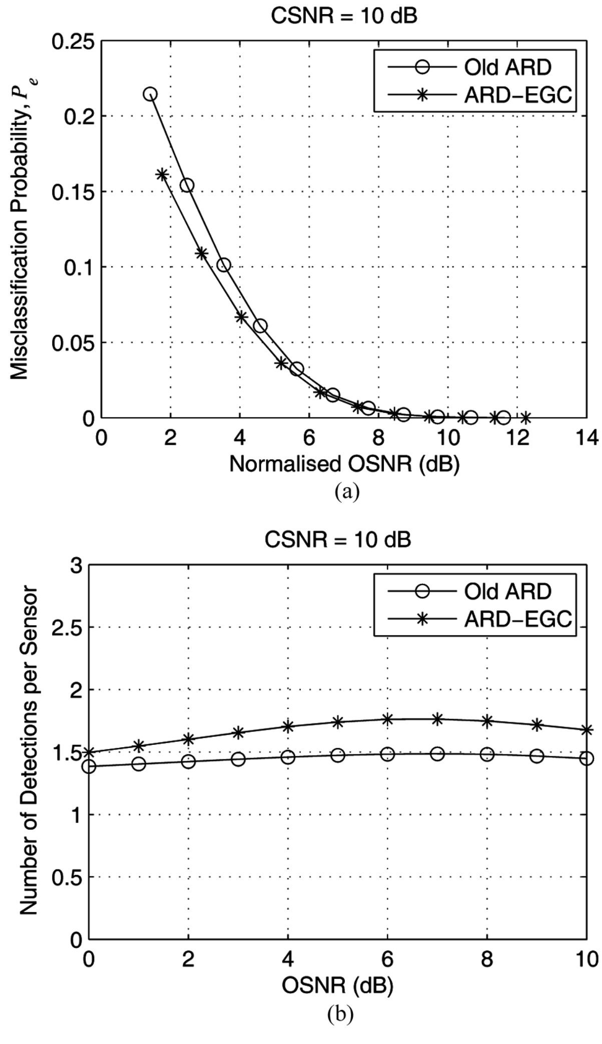
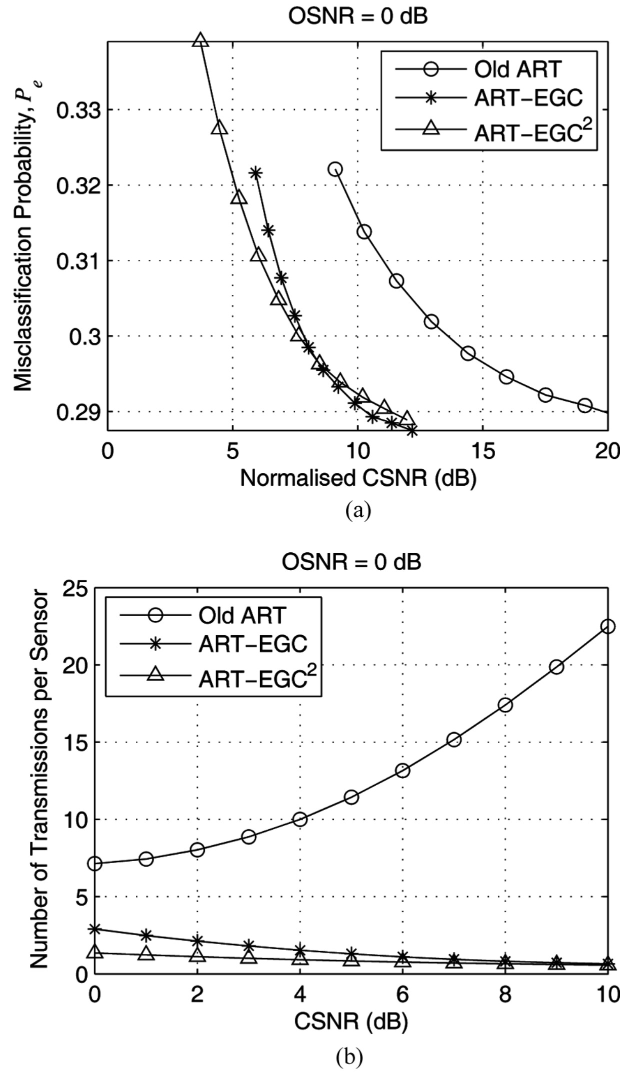


Figure 4 In the case of $\Delta = 4$, $R = \infty$, $\Gamma = 5$, and OSNR = 0 dB, performance comparison between the old and two new adaptive retransmission algorithms (denoted by Old ART, ART-EGC, and ART-EGC^2, respectively) in: (a) the misclassification probability and (b) the number of detections



These new algorithms are developed according to the EGC technique. All observations at a sensor are linearly combined for making a local decision or deciding another observation in the redetection algorithm. All received local decisions from a sensor at the fusion centre are also combined according the concept of the EGC in both the retransmission algorithms but the two algorithms use different combination techniques for deciding another transmission. Simulation results show the new adaptive redetection and retransmission algorithms outperform the old ones.

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