A Reputation Based Tactical Fusion Approach in Wireless Sensor Networks

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Abstract

To address the issues of the coexistence of the noisy signal channels, the vulnerability of sensor nodes and the limited coverage redundancy of monitoring, which is very common in actual application scenarios, a new decision fusion approach for distributed detection in wireless sensor networks is developed in this paper. A reputation weight is given to every sensor node by the fusion center when fusing their local decisions which then is modified according to the global decision to grade the reliability of the sensing nodes. By adopting this approach, the noise in the signal channels and the potential damage of the sensor nodes that may affect the accuracy of the sensing result are taken into account. Meanwhile, by using the reputation strategy, less sensor nodes are required to monitor the region of interest to achieve the accuracy of sensing, which can greatly save the energy consumption of the networks. The advantages of proposed fusion strategy are demonstrated by simulation results.

Keywords: Reputation, Distributed Detection, Wireless Sensor Network, Decision Fusion

1. Introduction

As a result of recent advances in micro-electro-mechanical systems technology, wireless communications, and digital electronics, the rapid development of low-cost, low-power, multifunctional sensor nodes that are small in size and communicate wirelessly in short distances lead to the prosperity of wireless sensor networks (WSNs) [1]. Because of its inherent properties, WSN is extremely suitable for the application of distributed detection, such as sensing environment, monitoring intrusions, detecting forest fire, tracking patients and etc. Therefore, a lot of efforts have been devoted to the field of distributed detection in wireless sensor networks and there is considerable amount of literature trying to optimize the decision fusion algorithm.

However, no existing work has yet covered the situation where the noisy signal channels, the potential broken sensor nodes and the limited coverage redundancy of monitoring coexist, which is quite common in actual application scenarios. In practice, noise is an inevitable factor of the telecommunication, and much literature has focused on improving the detection rate under the interference of channel noise. Meanwhile, the pursuit of cheap hardware components leads to the vulnerability of sensor nodes. Faults can be caused by physical damages, software mistakes, and resource depletion [2]. The limited resource constraints of nodes such as energy (battery power), memory, computational capacity and communication bandwidth make the sensing data unreliable and inaccurate, especially when battery power is exhausted [3]. Finally, although WSNs are supposed to be deployed randomly in high density, due to limited range of sensors, the number of sensor nodes that monitor a specific area can’t be very large. In most application, the number of nodes responsible for an event occurring in a specific area should be no more than two hundred.

To address the issue mentioned above, a new decision fusion approach for distributed detection in wireless sensor networks is developed in this paper. The fusion center stores a reputation weight table which indicates the reliability of every local sensor node which sends binary decisions to the fusion center. If the binary decision of a local sensor node consists with that of the fused decision, the value of its reputation weight is increased. Otherwise, it is decreased. Nodes whose reputation weight decreases to a certain value will be permanently excluded from the candidate fusion pool, as their decisions are untrustworthy because of physical damage or heavy interference. The reputation weight effectively takes into account of the signal channels noise and the potential damage of the sensor nodes without much communication or computation cost. At the same time, through the reputation strategy, less sensor nodes are required to monitor the region of interest to achieve the accuracy of sensing, which greatly save the limited energy of the networks.
The rest of this paper is organized as follows: Section 2 presents related work. Section 3 gives the system formulation. The detail of the reputation-based decision fusion approach is described in Section 4. Section 5 presents performance simulation of the proposed method. Finally, the conclusion is given in Section 6.

2. Related works

The field of distributed detection had been studied even before the emergence of WSNs [4]. The classical approach to this problem is to assume a signal model and frame it as a hypothesis test: whether or not a target is present. This approach was widely used in fusion algorithms during the 1980s by surveillance systems (e.g., radars). References [5] and [6] present the optimum decision fusion rule under the conditional independence assumption. Decision fusion with correlated observations has been studied in references [7-9]. However, neither the premises of knowing exactly the detection probability of every sensor node nor the requirement for computation capacity and communication bandwidth is satisfied in WSNs.

With the rise of WSNs, quite a few of decision fusion methods are proposed or improved, aiming at the issue of distributed detection with constrained system resources. In [10] a fusion rule call “counting rule” where the fusion center employs the total number of detections reported by local sensors for hypothesis testing is proposed. It greatly reduced the computation complexity of the fusing process proposed in [6]. A modified “counting rule” is presented in [11], in which the number of sensor nodes and the ideal wireless channels are no longer necessary prior knowledge. However, in order to achieve an agreeable detection probability, the number of local sensor nodes that monitor whether or not an event occurs is no less than 1000. In WSNs, due to the limited sensing range of nodes, this requirement is difficult to satisfy. Besides, it is a waste of resources to maintain a redundancy of more than 1000 in most applications. Katenka et al. propose an local vote decision fusion algorithm in [12], in which sensors first correct their decisions using decisions of neighboring sensors, and then make a collective decision as a network. Although it increases the detection probability, more communication overhead was introduced. In [13], Guerriero et al. draw the idea of mobile fusion center which counts the number of binary decisions reported by local sensors from anomaly detection community. A Bayesian data fusion approach is developed in [14], in which generalized likelihood ratio test is used to make the decision fusion. Yet perfect communication channels between the local sensors and the fusion center are compulsory in these strategies. In [15], a soft decision fusion rule was proposed, where each local sensor obtains a soft-decision (a value between 0 and 1) rather than a binary decision (0 or 1). By this way, the confidence weight of local sensor node was introduced to assists the fusion center to achieve better performance. However, the confidence weight only counts when the local node normally works. If the local node is damaged, the confidence weight lost its point. Still this approach can be integrated with the decision fusion algorithm propose in this paper to achieve better performance.

Dynamic sensor threshold is suggested in [16], where selection of threshold is based on a recently proposed statistical metric for multiple testing problems. In [17], the a mathematical model is set up to study distributed detection in WSNs using IEEE 802.15.4 protocol. Distributed detection and energy-efficient routing are jointly optimized in [18], which is carried out in fusion center that pre-computes the routes as a function of the geographic location to be monitored. By formulating and solving a multi-objective optimization problem, reference [19] tries to obtain the optimal decision thresholds for local sensors.
3. System description

As shown in Figure 1, we assume that a number of sensors are deployed in the region of interest (ROI), which is a square area whose edge length is e, whose area is $e^2$. The locations of sensor nodes are independent identically distributed (i.i.d.) and follow a uniform distribution in the ROI:

$$f(x, y) = \begin{cases} \frac{1}{b^2} & -\frac{b}{2} \leq x, y \leq \frac{b}{2} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

In the above equation, for $i = 1, \ldots, N$, $(x_i, y_i)$ denotes the coordinates of sensor. The location of the target, represented by its coordinates, is independent of the positions of sensors, and follows the same uniform distribution within the ROI as that described in (1).

We assume that the signal power emitted by the target decays isotropically. We assume that noises at the local sensors are i.i.d. and follow standard Gaussian distribution. All the sensors use an identical local threshold for a likelihood ratio test, and to obtain a local decision. Under hypothesis (target presence), the probability of detection at sensor is a function of its receiver’s SNR, which is a function of the signal strength at a reference distance, the distance from the target, and the threshold.

For a local sensor $i$, the binary hypothesis testing problem is:

$$H_1 : s_i = a_i + n_i$$
$$H_0 : s_i = n_i$$

(2)

where $s_i$ is the received signal, $a_i$ is the signal amplitude.

4. Decision fusion algorithm

As the system model is based on binary decision fusion, a quick review of Neyman-Pearson criterion is presented here. A binary hypothesis testing problem is based on two hypotheses: $H_0$ indicating signal absent while $H_1$ indicating signal present. It is assumed that there are $n$ randomly distributed sensor nodes which are independent to each other when conditioned on hypotheses, and have probability distributions under both hypotheses. Each local sensor node $i$ processes its observation $y_i$ and makes its decision based on a local threshold $\tau$. 
\[ I_i = \begin{cases} 1, & LR_i(y_i) = \frac{P(y_i | H_i)}{P(y_i | H_0)} \geq \tau \\ 0, & \text{otherwise} \end{cases} \]

(3)

According to the Neyman-Pearson criterion, maximizing the global detection probability (GDP) under the condition that the global false alarm probability (GFAP) is below a certain value is the goal. Chair-Varshney fusion rule presents the optimal decision fusion rule

\[ D = \sum_{i=1}^{N} I_i \ln \frac{p_{d_i}}{p_{f_i}} + (1 - I_i) \ln \frac{1 - p_{f_i}}{1 - p_{j_0}} \]

(4)

However, at each local sensor node, it is very difficult to calculate \( p_{d_i} \). Thus a simpler decision fusion rule call counting rule was proposed

\[ D = \sum_{i=1}^{N} I_i I_{H_i} \geq T \]

(5)

Although the counting rule is simple enough to be adopted in the WSNs, it takes neither the vulnerability of sensor nodes nor the noise in the communication channels into consideration. To solve this problem, we introduce the reputation weight of local sensor nodes into the decision fusion rule.

\[ D = \sum_{i=1}^{N} I_i \alpha_i I_{H_i} \geq T \]

(6)

Where \( \alpha_i \) is the reputation weight of local node \( i (i=1, 2, 3, \cdots, N) \).

4.1 Initialization

The reputation weight of every local node is stored at the fusion center node. For node \( i \), we give it an initial value of \( \alpha_i (t_0) \) while the global threshold of fusion decision is set \( T_0 \). After the initialization, we can obtain the GPFA and GDP of the network as below.

\[ P_{fa} = \sum_{i=2}^{N} \binom{N}{i} p_{j_0}^i (1 - p_{j_0})^{N-i} \]

(7)

\[ P_d = \sum_{i=2}^{N} \binom{N}{i} p_{d_i}^i (1 - p_{d_i})^{N-i} \]

(8)

4.2 Reputation and threshold update

At the \( k_{th} \) update, fusion center firstly figures out the global decision using the global decision fusion rule. Then the decisions of all local nodes are compared with global decision, by which the
reputation of local nodes will be updated. Those local nodes whose decisions conform to the global
decision are rewarded reputation promotion, while the others suffer relegation.

\[
\alpha_i(t_{k+1}) = \begin{cases} 
\alpha_i(t_k) + r, I_i = D_k \\
\alpha_i(t_k) - r, I_i \neq D_k 
\end{cases}
\] (9)

After this, global threshold should be updated as below

\[
T_{k+1} = \frac{\sum_{i=1}^{N} \alpha_i(t_{k+1})}{\sum_{i=1}^{N} \alpha_i(t_k)} T_k
\] (10)

There are three advantages that we can enjoy when we choose to store the reputation of local nodes
in the fusion center. Firstly, the healthy status local nodes and the communication channels can be both
taken into consideration. Secondly, this strategy minimizes the amount of data to be transferred. Finally,
fusion centers usually possess better power supply and computation ability than local sensors, thus
assigning the responsibility of storing and updating the local node reputation to fusion centers makes
the whole network more energy-efficient and enjoys longer life-time.

5. Simulation Results

The performance of the proposed decision fusion rule is evaluated as follows. We assume the case
of N sensors with Gaussian distributed observations, i.e.,

\[
P(y_i | H_0) = \frac{1}{\sqrt{2\pi}} e^{-y_i^2/2}
\] (11)

\[
P(y_i | H_1) = \frac{1}{\sqrt{2\pi}} e^{-(y_i-t_i)^2/2}
\] (12)

To achieve desired GFAP at the fusion center, a threshold of

\[
T_0 = \sqrt{n} \phi^{-1}(GFAP)
\] (13)

is needed at the fusion center, where the \( \phi \) function is defined as

\[
\phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz
\] (14)

The corresponding GDP is given by

\[
GDP = \phi\left(\frac{t_0 - ns}{\sqrt{n}}\right)
\] (15)
The decision rule of each local sensor is given by

\[
I_i = \begin{cases} 
1, & \text{if } y_i < t_i \\
0, & \text{if } y_i \geq t_i 
\end{cases}
\]  \quad (16)

And the corresponding false alarm and detection probabilities are

\[
pf_i = \phi(t_i) \quad (17)
\]

\[
pd_i = \phi(t_i - s_i) \quad (18)
\]

Where the \(t_i\) sensor threshold is determined according to the sensor false alarm probability.

Figure 2 shows the comparison between the proposed decision fusion method and counting rule fusion method in the case of two hundred identical sensors (\(N=200\)). Neither damaged nodes nor communication channel interference was taken into consideration here. Simulation results demonstrate that there is no significant difference between the proposed decision fusion method and counting rule fusion method if we ignore the influence of damaged nodes and communication channel interference.

![Figure 2. Comparison of GDP as a function of GFAP (ROC curve)](image)

Then we cut down the total number of sensor nodes and raise the SNR which means the introduction of communication channel interference. Still, damaged nodes are not taken into consideration here. As expected, the result shows that the counting rule suffers greater performance drop than the proposed method. Because of the help of reputation weight, the proposed decision fusion method enjoys better interference-tolerance to channel noise.

![Figure 3. Comparison of GDP as a function of GFAP (ROC curve) with N=50, SNR=−1](image)

In Figure 4, the performance comparison between propose method and counting rule in the case of potential damaged nodes is presented. Out of the total 200 sensor nodes, 10 random sensor nodes are set to be damaged which send incorrect local decision to the fusion center. Simulation result demonstrates that the incorrect data sent by damaged nodes greatly affects the performance of counting rule decision fusion method. However, the proposed method is able to avoid this performance drop by
heuristic self-learn automatically.

![Figure 4](image-url)  
**Figure 4.** Comparison of GDP as a function of GFAP (ROC curve) between propose method and counting rule with 10 damaged one out of 200 sensor nodes

The tolerance performance of the proposed decision fusion method under potential damaged nodes risks is also evaluated. Out of a total of N sensor nodes, k is damaged. Here we set N=200, and k=0, 15, 30. The result of the comparison is presented in Figure 5.

![Figure 5](image-url)  
**Figure 5.** Comparison of GDP as a function of GFAP (ROC curve) between propose method in the case of different number of damaged sensor nodes

6. Conclusion

In this paper, a reputation based decision fusion method is proposed to address the issues that widely exist in current literature. Reputation weight of every local sensor node is introduced to solve the inaccuracy led by damaged nodes and channel noise. Meanwhile, the proposed approach also effectively reduces the requirement of coverage redundancy. The proposed method is compared with counting rule decision fusion method and the advantages mentioned above are demonstrated by simulation results. Sincerely we hope our work may contribute to the practical use of distributed detection in wireless sensor network.

References