

Spatio-temporal fusion for reliable moving vehicle classification in wireless sensor networks

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Abstract—One of the important tasks in sensor networks is classifying moving vehicles. Fusion of large amount of sensor measurements can improve network performance and reduce the consumption of sensor network resource. We study using continuous measurements of multiple sensor nodes to improve the classification performance by spatio-temporal fusion and fault detection. Time series decisions of single sensor node are aggregated to make a reliable classification estimation. A fusion center combines local classification decisions and evaluates the correctness of these decisions. A correctness status is sent back to each sensor node. Based on the status, sensor nodes can adjust their temporal fusion result. Simulation results demonstrate the validity of our method.

Index Terms—Wireless sensor networks, spatio-temporal fusion, fault detection, classification

I. INTRODUCTION

Wireless sensor networks (WSNs) are composed of a large number of tiny sensor nodes. These sensor nodes are densely deployed in the network covered area, and have limited communication, computation capability and storage capacity. Moving vehicle classification is an important task in WSNs[1][2]. Limitation of sensor nodes and interference of the observed environment make sensor's data prone to be faulty. Implementing reliable classification needs the collaboration of multiple sensor nodes. A lot of research focus on information fusion for moving vehicle classification in WSNs have been reported[3][4][5][6]. In this paper, we study fusion algorithm for reliable classification in WSNs.

Collaborative signal processing and fault management are crucial to reliable sensor network applications. In scenarios of moving object observation, densely deployed sensor nodes sample the phenomena periodically, measurements of distributed sensor nodes form a general observation of the moving object in space and time dimension[1][4]. Both the spatial and temporal sensor measurements can be utilized to improve sensor network performance[3][7]. Limitation of sensor nodes in sensing and communication and interference of observed environment make sensor's data prone to be faulty. To improve sensor network performance, fault management algorithm is necessary. Fault detection is an important way of fault management in WSNs. In many fault detection algorithms[8][9], a faulty sensor is usually detected and excluded in the processing procedure. However in some cases, sensors may be temporally faulty and the faulty information may be also useful. Moreover, Implementing fault detection and fusion both rely on

the collaboration of spatio-temporal sensor data[10][11][12]. Therefore, we intend to combine fusion and fault detection in one processing procedure.

We propose a scheme to implement fault detection in the fusion process, and make use of the fault detection result into the fusion procedure. Both spatial and temporal sensor data are used in the fusion process. Possibly faulty sensors can be detected at the fusion center based on classification decisions of multiple sensor nodes and the detection result can conduct subsequent temporal fusion at local sensor. We propose this method based on the spatio-temporal correlation nature of sensor measurements[13]. In a moving target observation event, classification decisions should be consistent in space and time dimension. Therefore we aggregate time series of local decisions to improve the reliability of local classification, then the local decisions of multiple sensors are fused at fusion center to decide the vehicle type. Fault detection is implemented at the fusion center by comparing the local decisions with the spatial fusion result. If a local decision is detected as faulty, it is obvious most other sensors have decisions different than it, its temporal fusion result may be unreliable. We use the fault detection results to adjust the temporal fusion of local sensors through Dempster-Shafer (DS) fusion framework. Only hard decision labels are communicated to the fusion center and the fusion center return a 1-bit status information to indicate the correctness of the local decision, each sensor can adjust its temporal fusion result without knowing local decisions of other sensors, so our method doesn't add much communication cost. The computation overhead is also low because the fusion and detection operation are simple. Simulation results show that the classification performance is improved based on our method.

The rest of this paper is organized as follows. Section II introduces the background of single moving vehicle classification problem. Section III presents the implementation of the spatio-temporal fusion and fault detection procedure. In section IV simulations and results are presented. Section V draws the conclusions.

II. PROBLEM FORMULATION

We consider the scenario of a single vehicle moving through an observed area. The sensor nodes are grouped as clusters and the cluster heads act as fusion centers to perform spatial fusion. Assume a cluster of n sensor nodes $\{S_i, i = 1, \dots, n\}$

participate in the classification process. Some modalities of signals emitted by a moving vehicle, such as acoustic, seismic or infrared, can be sampled by the sensor nodes. Distributed sensor nodes observe the object continuously. The measurement of S_i at time t denoted as $x_i(t)$ is modeled as:

$$x_i(t) = s_i(t) + n_i(t), \quad (1)$$

where $s_i(t)$ is the emitted signal of a moving vehicle measured at location of S_i , $n_i(t)$ is additive Gaussian noise. Processing unit of sensor node can extract time or frequency domain features and use these features to distinguish vehicle type. Let X_i denote an l -dimensional feature vector extracted by sensor node i from a period of raw samples. Assume there are M types of vehicles, C_j denotes the j th type of vehicle, the likelihood probability of X_i committed to C_j is

$$p(X_i|C_j) = \frac{1}{(2\pi)^{d/2}|\Sigma_j|^{1/2}} \exp(-\frac{1}{2}(X_i - \mu_j)^T \Sigma_j^{-1} (X_i - \mu_j)), \quad (2)$$

where $j = 1, \dots, M$, μ_j and Σ_j are mean and covariance of C_j . Each sensor node makes a classification decision locally through the maximum a posteriori (MAP) rule:

$$u = \arg \max_{j=1, \dots, M} p(C_j|X_i), \quad (3)$$

and

$$D_i = g(u). \quad (4)$$

where $p(C_j|X_i)$ is the posterior probability of C_j , D_i is a decision label, function $g(u)$ output an M -dimensional vector with only the u th element is 1 and others are 0.

If these sensor nodes are reliable, observations of the same object may have consistent classification results. However, faults are always inevitable in WSNs. There are many types of faults. [10] presents a taxonomy of classification of faults in sensor networks. In this study, we assume the sensor hardware and the signal processing algorithms are fault tolerant and communication links between sensor nodes and fusion center are reliable. We only consider the faults caused by random measurement noise, the sensor decisions are randomly faulty with probability d .

III. SPATIO-TEMPORAL FUSION AND FAULT DETECTION

The basic concept of our algorithm is to detect and correct decision faults when fusing the sensor data in space and time domain to achieve reliable classification. The procedure includes temporal fusion, temporal updating and spatial fusion. Fig. 1 shows the signal processing procedure at local sensor node and the fusion center.

A. Temporal fusion

In the temporal fusion step, each block of T decisions are combined at local sensor node to improve local classification performance. The decision label of node S_i at time t derived from (4) is denoted as $D_{i,t}$, which is an M -dimensional vector, the block includes decision labels from time $(k-1)T+1$ to

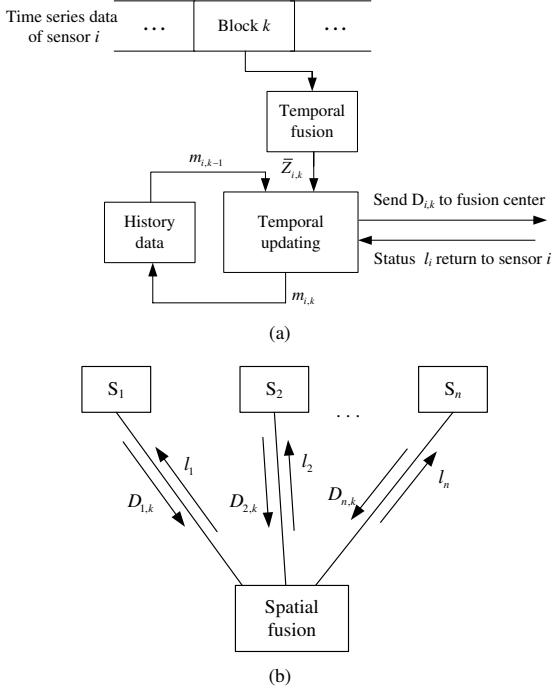


Fig. 1. (a) Temporal processing in local sensor, (b) Framework of spatial fusion

kT . Let $\bar{Z}_{i,k}$ denote the temporal fusion result of the k th block of node S_i . Averaging of the labels are computed

$$\bar{Z}_{i,k} = \frac{1}{T} \sum_{t=(k-1)T+1}^{kT} D_{i,t}. \quad (5)$$

Note that $\bar{Z}_{i,k}$ need not to be a hard label. The hard decision label $D_{i,k}$ will be given in the temporal updating step.

B. Temporal updating

The temporal updating step updates the k th block of temporal fusion result $\bar{Z}_{i,k}$ based on previous temporal updating result $D_{i,k-1}$ and its status l_i to generate the k th temporal updating result $D_{i,k}$. The status l_i that sent back by the fusion center indicates the consistency of $D_{i,k-1}$ with the spatial fusion result. Intuitively, if $l_i = 1$, we think $D_{i,k-1}$ is correct, otherwise it is faulty.

We use DS theory[14] to implement temporal updating. DS theory is an appropriate method to deal with and represent uncertain information. The frame of discernment is defined as $C_\Theta = \{C_1, \dots, C_M\}$. Denote $m_{i,k-1}(C)$ as the basic probability assignment (BPA) function of $D_{i,k-1}$. Let C_j denote the class that has the maximum decision value, i.e. for any $j \neq m, 1 \leq j, m \leq M$, there are $D_{i,k-1}(C_j) > D_{i,k-1}(C_m)$.

The BPAs of $D_{i,k-1}$ are defined as:

$$\begin{aligned} m_{i,k-1}(C_j) &= \begin{cases} D_{i,k-1}(C_j) & l_i = 1, \\ 0 & l_i = 0. \end{cases} \\ m_{i,k-1}(C_j^C) &= \begin{cases} 0 & l_i = 1, \\ D_{i,k-1}(C_j) & l_i = 0. \end{cases} \\ m_{i,k-1}(C_m) &= D_{i,k-1}(C_m) \quad m = 1, \dots, M, \Theta, \quad m \neq j, \end{aligned} \quad (6)$$

where $C_j^C = C_\Theta \setminus C_j$ is the complement of C_j . Define $m_{i,k}(C)$ as the BPA function of $\bar{Z}_{i,k}$:

$$\begin{aligned} m_{i,k}(C_m) &= \bar{Z}_{i,k}(C_m) \quad m = 1, \dots, M \\ m_{i,k}(C_\Theta) &= 0. \end{aligned} \quad (7)$$

To avoid evidence conflict between $m_{i,k-1}$ and $m_{i,k}$, we use the combination rule proposed by Yager[15] to allocate the conflict evidence to the frame of discernment C_Θ :

$$\begin{aligned} m_i(C_j) &= \sum_{A \cap B = C_j} m_{i,k-1}(A)m_{i,k}(B) \\ m_i(C_\Theta) &= m_{i,k-1}(C_\Theta)m_{i,k}(C_\Theta) + \sum_{A \cap B = \emptyset} m_{i,k-1}(A)m_{i,k}(B). \end{aligned} \quad (8)$$

The local decision $D_{i,k}$ is made by:

$$u_{i,k} = \arg \max_{j=1, \dots, M, \Theta} m_i(C_j), \quad (9)$$

and

$$D_{i,k} = g(u_{i,k}). \quad (10)$$

After decision making, we send $D_{i,k}$ to the fusion center based on the following principle:

- 1) If $C_j, j = 1, \dots, M$ has the maximum element in m_i , node S_i sends $D_{i,k}$ to the fusion center to perform spatial fusion.
- 2) If $m_i(C_\Theta) > m_i(C_j)$ for all $j = 1, \dots, M$ or there are more than one classes have the maximum decision value, S_i does not send $D_{i,k}$ to the fusion center and the status l_i is set to be 1. S_i will combine the next block of temporal fusion result to make a valid decision.

C. Spatial fusion and fault detection

Fusion center receives the temporal updating results $\{D_{i,k}; i = 1, \dots, n\}$ of each sensor and perform spatial fusion. The final decision is made based on:

$$u_s = \arg \max_{j=1, \dots, M} \sum_{i=1}^n D_{i,k}, \quad (11)$$

and

$$D_k = \begin{cases} g(u_s) & \text{if } |u_s| = 1 \\ g(M+1) & \text{otherwise,} \end{cases} \quad (12)$$

where D_k is $(M+1)$ -dimensional and $|\cdot|$ denotes the cardinality. After spatial fusion, the fusion center use D_k to evaluate the correctness of $D_{i,k}$ and send a status l_i return to sensor i to indicate the correctness. If $D_{i,k}$ is judged as faulty, a status $l_i = 0$ will return, otherwise, $l_i = 1$.

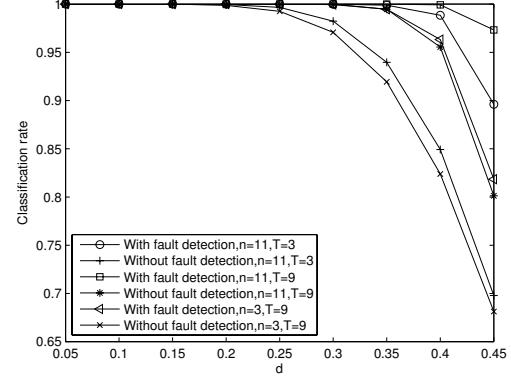


Fig. 2. Classification rate comparison of fusion with and without fault detection

IV. SIMULATION

This section presents the simulation results to illustrate the performance of our algorithm. We simulate n sensor nodes that generate M -dimensional hard decision labels, where the labels are randomly faulty with probability d . In the simulation, the number of classes M is set to be 2. Our simulation results are averaged over 50 runs. At each run, 2000 decision labels per node are generated.

Define n_c as the number of correct classification decisions that were made by the fusion center, n_f is the number of faulty decisions. Classification rate p_c is defined as:

$$p_c = \frac{n_c}{n_c + n_f}. \quad (13)$$

Fig. 2 compares the classification rate of our method with spatio-temporal fusion method that without fault detection. The spatio-temporal fusion method that without fault detection is computing average of each block of labels at the temporal fusion step and making a decision, and sending the decision to the fusion center to perform spatial fusion. Fig. 2 shows our method performs better than the method without fault detection for different n and T .

Fig. 3 and Fig. 4 study how the block length T and number of sensor node n impact classification performance. Fig. 3 shows the classification rate as a function of the sensor fault probability d for $T = 3, 5, 9, 15$ and $n = 3, 15$, respectively. We can see that our method has higher classification rate for all the T and n when $d \leq 0.2$, and increasing T and n both can improve the classification performance. Therefore, T can be increased to diminish the need of number of sensors that participate in the fusion process, and increasing n can reduce decision delay. Fig. 4 investigates the relationship of classification rate with n . Fig. 4 also shows that the classification rate is improved along with increasing n . The improvement is diminished when n reaches a certain extent.

There are three operations in our method that can ensure reliable classification: temporal fusion, temporal updating and

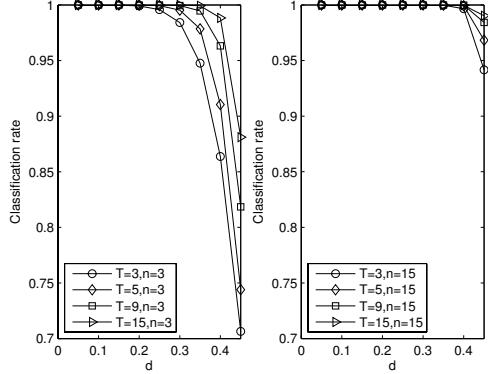


Fig. 3. Classification rate with respect of d for $T = 3, 5, 9, 15$ and $n = 3, 15$

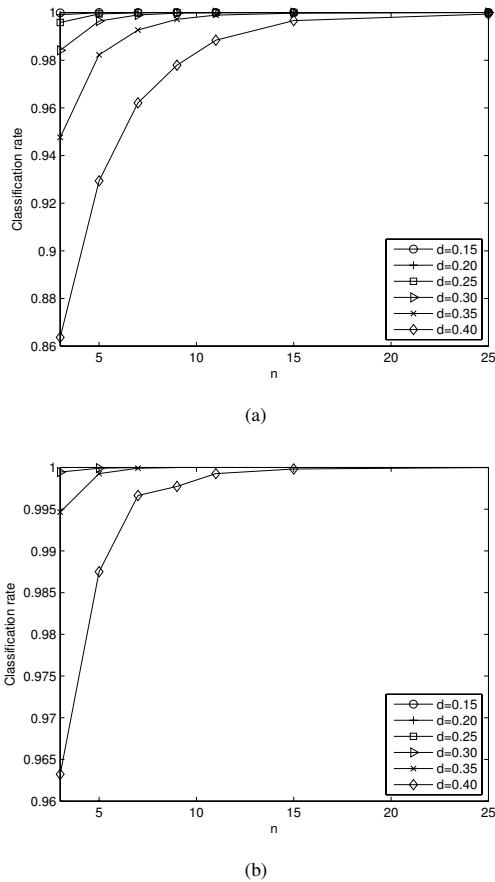


Fig. 4. Classification rate with respect of n , (a) $T = 3$, (b) $T = 9$

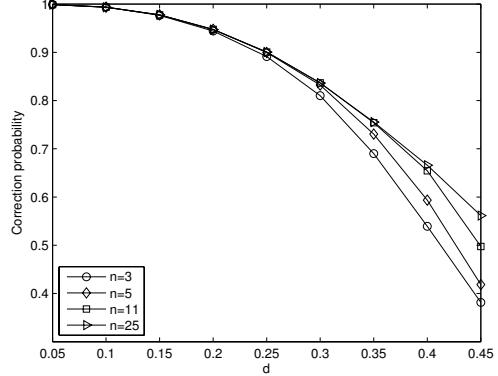


Fig. 5. Fault correction probability of temporal fusion and temporal updating for different n , $T = 3$

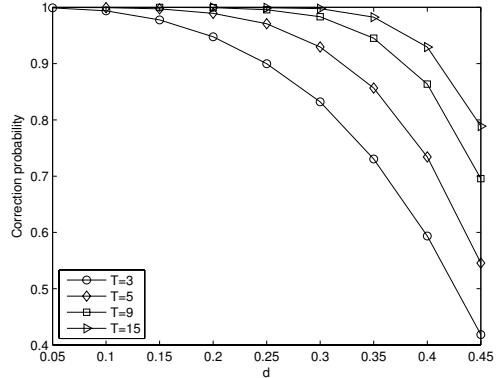


Fig. 6. Fault correction probability of temporal fusion and temporal updating for different T , $n = 5$

spatial fusion. Temporal fusion combine a series of local decisions to improve the classification reliability. Temporal updating amend the temporal fusion result based on the previous temporal updating result and its correctness status. Consequently, faults of local decisions can be corrected. Fig. 5 and Fig. 6 show the fault correction capability of the temporal fusion and updating steps for different T and n , respectively. The fault correction probability p_{fc}^t is defined as the ratio of the number of faulty decision labels $D_{i,t}$ that were corrected to the number of all the faulty $D_{i,t,s}$. The correction probability exhibits similar trend as classification rate and is greatly improved by increasing T . Fig. 7 shows the fault detection probability p_{FD} of the fusion center for different n . The fault detection probability is defined as the ratio of the number of faulty reports that sent to the fusion center to the number of faulty reports detected by the fusion center. The results show that p_{FD} is improved along with increasing n . Although the temporal fault correction probability and spatial fault detection probability are limited with respect of large d , combining

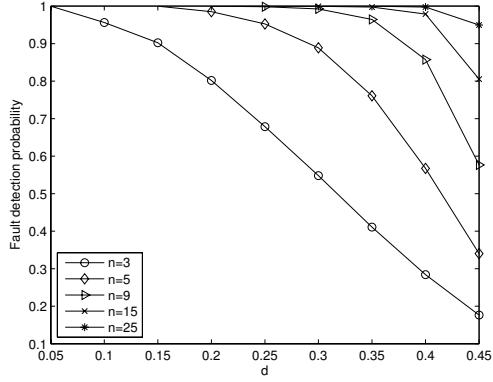


Fig. 7. Fault detection probability of spatial fusion for different n , $T = 3$

the three steps together still can achieve better classification performance.

V. CONCLUSIONS

This paper studies a method for reliable classification in WSNs. We implement fault detection and correction in a spatio-temporal fusion process. Possibly faulty sensors are detected after spatial fusion and the detection result is used to conduct following temporal fusion procedure. Faults can be corrected in the temporal fusion, temporal updating and spatial fusion steps. Simulation results show that spatio-temporal fusion with fault detection has better classification performance than the fusion method without fault detection, and increasing T and n can both improve the classification performance.

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