Cooperative Detection of Moving Targets in Wireless Sensor Network Based on Fuzzy Dynamic Weighted Majority Voting Decision Fusion

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Abstract—Multisensor data fusion has many military and civilian applications due to its statistical advantages. In this work, we propose a heuristic to enhance cooperative detection of moving targets within a region that is monitored by a wireless sensor network. This heuristic is based on fuzzy dynamic weighted majority voting for decision fusion. It fuses all the local decisions of the neighboring sensor nodes and determines the number and types of moving targets. A fuzzy logic weights each local decision based on the signal to noise ratio of the acoustic signal for target detection and the signal to noise ratio of the radio signal for sensor communication. The spatial correlation among the observations of neighboring sensor nodes is efficiently utilized. In addition, a finite state machine is proposed to reduce the detection false alarm and to estimate the best time at which the cluster decisions should be reported to the sink or gateway. Simulation results show that there is an optimal sensor number for distributed detection of a random process. This work is compared with the normal majority voting algorithm for hard decision fusion. It shows that the fuzzy weighted majority voting for decision fusion has less detection error than the normal majority voting.

I. INTRODUCTION

WIRELESS Sensor Network (WSN) is, by definition, a network of sensor nodes that spread across a geographical area, where each sensor node has a restricted computation capability, memory, wireless communication, and power supply. In general, the objective of WSNs is to monitor, control, or track objects, processes, or events [1]. Normally, the sensor nodes are densely deployed, self-organized, and cover a certain geographical area. Sensor nodes are automatically organized to bridge the gap between physical and digital world by detection, processing, and communicating information of the network covered area as in Fig. 1. In WSNs, observed data could be processed at the sensor node itself; distributed over the network; or at the gateway node. Most often, nodes are battery-powered which makes power the most significant constraints in WSNs. Power consumption, resulting from data transmission, is greater than power consumption, resulting from data processing. This motivates people to consider decentralized data processing algorithms more than the centralized ones [2], [3].

In distributed sensor network, each sensor node sends its local decision to the fusion center instead of sending the whole observation to save power and communication bandwidth as in Fig. 2. Recently, there are many researches in distributed detection and classification. However, most of these researches ignore the noises in the communication and observation channels and assume independent and identically distributed observations [4], [5]. In this paper, we consider the problem of decentralized classification of a Gaussian stochastic signal for cluster-based WSNs for non identically distributed observations.

Because of the path of the sensing measurement there will be a loss in the measurement power. this loss will make the SNR of the farther node poor. Ref. [6] assumed that all the measurement from different nodes were independent and identically distributed (i.i.d). It is known that in reality these sensing measurements will not be identically distributed because of the sensing channel loss. Fig. 8 shows that there is an optimal radius around each sensor node over which decisions should be fused to get the minimum detection error. Ref. [7] analyzed the performance of centralized detection of a stochastic gaussian signal in global power constrained wireless sensor networks. It is observed in Ref. [7] that, for global power constrained wireless sensor networks, there
is an optimal number of sensor nodes that minimize the detection fusion error probability, which depends on the signal to noise ratio for both the observation and the wireless communication channel. It is observed in this paper that even though the global power of the WSN is not constrained, there is an optimal number of sensor nodes for decision fusion to be performed. This is because of the decaying of the observed signal SNR as the target gets farther.

Weights for every local decision of each sensor node is computed based on the Signal to Noise Ratio (SNR) for both the sensed signal and the wireless radio signal. In WSN the Received Signal Strength Indication (RSSI) is used as a measure of the SNR of the wireless radio signal and the relative power of the acoustic signal emitted from the targets is used as a measure of the SNR of the acoustic signal.

A state machine is used to assure the detection and to determine the closest approach point and to determine the direction of motion of the target. The remainder of this paper is organized as follows. Section II formulates the problem mathematically. Section III describes the fuzzy logic weighting algorithm. The state machine is described in Section IV. Section V presents the simulation and results. And finally conclusions are described in section VI.

II. PROBLEM FORMULATION

The sensor nodes send either their observation or do some processing and send their decisions to a fusion center where a collective decision is made. In this research we relaxed the assumption that the independent observed signals from different sensors nodes is identically distributed. The observed signal to noise ratio depends on the distance between the target and the underlying sensor node. Assuming that the power of the independent noises for the neighbor sensor nodes are identical then the power of the observed signal will be poorer as the target be farther from the underlying sensor node. Based on this, there will be an optimal radius around the fusion center over which the fusion will be performed. Each local decision should be weighted to have a better contribution on the final decision to minimize the detection error probability. Suppose that a binary hypothesis testing situation where the hypothesis are denoted by $H_0$ and $H_1$. $H_1$ denotes the presence of the target signal. The target is modeled here as a zero-mean Gaussian stochastic process. The Gaussian observed signal is denoted by $S_n$. $S_n$ is characterized by its covariance matrix $S_n \sim N(0, \Sigma_n)$. $H_0$ denotes the noise $\nu$. $\nu$ is a white Gaussian noise characterized by its covariance matrix, $\nu \sim N(0, \Sigma_\nu)$, assuming that the noises are independent at different sensor nodes then $\sigma_\nu = \sigma_\nu^2 I$. So the observation vector for node $k$ is $X_k$ as in Fig. 2 can be written as follows:

$$H_1 : X_k = a_nS_k + \nu_k$$
$$H_0 : X_k = \nu_k, k = 1, \ldots, N$$

where $N$ is the number of sensor nodes and $a_n$ is the attenuation factor for the observation signal.

$$a_n = \frac{1}{10^{\alpha p_i}} \tag{1}$$

where $p_i$ is the distance between sensor node $i$ and the moving vehicle. $\alpha$ is the attenuation factor for unit distance [8]. The value of $\alpha$ is determined by the Atmospheric Sound Absorption Calculator [9]. The problem is to define the minimum $p_i$ for each sensor node to have a beneficial contribution in the decision fusion.

$$Z_k = b_kX_k + \omega_k$$
$$Z_k = b_ka_nS_k + b_k\nu_k + \omega_k$$

Where $Z_n$ is the radio received signal, $\omega_s$ is the receiver white Gaussian noise $\omega \sim N(0, \sigma_\omega^2 I)$, and $b_n$ is the attenuation factor of the radio signal. Based on the above the covariance matrices for both the noise and the original signal will be changed as the following:

$$\Sigma_z = b_k^2\sigma_z^2 \Sigma_s + b_k^2\sigma_\omega^2 I + \sigma_z^2 I \tag{2}$$

$$\Sigma_\omega = (b_k^2\sigma_\omega^2 + \sigma_\omega^2) I \tag{3}$$

Thus the decision variable for the optimal fusion rules is as follows:

$$T(z) = z^T(\Sigma_\omega^{-1} - \Sigma_z^{-1})z$$
$$= z^T((b_k^2\sigma_\omega^2 + \sigma_\omega^2) I^{-1} - (b_k^2\sigma_z^2 \Sigma_s + b_k^2\sigma_\omega^2 I + \sigma_z^2 I)^{-1})z$$

The decision will be based on comparing the decision variable $T$ with a certain threshold. According to the above equations the distance between the two distributions will be

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decreased, because the attenuation factors $a_n$ and $b_n$ are both less than one. This makes the decision accuracy declines as the attenuation factors decrease. Thus, each local decision should be weighted according to the signal to noise ratio for both acoustic signal and the wireless radio signal. Therefore we use fuzzy logic to weigh the each local decision to get use from human logic.

III. Fuzzy Logic Inference

Fuzzy logic inference is a simple approach to solving problem rather than attempting to model it mathematically. Empirically, the fuzzy logic inference depends on human’s experience more than the technical understanding of the problem. As in Fig. 3, fuzzy logic inference consists of three stages:

1) Fuzzification: map any input to a degree of membership in one or more membership functions. The input variable is evaluated in terms of the linguistic condition.
2) Fuzzy inference: fuzzy inference is the calculation of the fuzzy output.
3) Defuzzification: defuzzification is to convert the fuzzy output to a crisp output.

IV. Fuzzy Weighted Majority Voting

Majority voting is a simple way to combine decisions of several classifiers or decision makers to improve the recognition process. We refer the reader to [10] to understand how and why the majority voting can improve the recognition process. A fuzzy logic is used for weighting the local decisions according to both, observation SNR as well as wireless radio signal to noise ratio SNR to minimize the decision fusion probability of error. Fuzzy logic is applied in decision fusion to get help from the human logic. The fuzzy decision weighting is consist of two inputs: The relative sensing signal power ($SP$) and the relative Received Signal Strength Indication ($RSSI$) of the wireless radio signal ($RP$). The three membership functions of the two fuzzy logic inputs $SP$ and $RP$ are shown in Fig. 4. The inputs are defined by the following membership functions: $C$ (Close), $M$ (Medium), and $F$ (Far). The output of the fuzzy logic, the weight of each local decision $W$, is defined by four membership functions very low ($VL$), low ($L$), Medium ($M$), High ($H$), and Very High ($VH$). Fig. 5 shows these membership functions. The fuzzy logic rules are deduced as in Table I. The Centroid method is used for defuzzification. $W$ is shown as a function of $SP$ and $RP$ in Fig. 6.
TABLE I
FUZZY RULES FOR FUZZY WEIGHTING

<table>
<thead>
<tr>
<th>Index</th>
<th>Input 1 SP</th>
<th>Operator</th>
<th>Input 2 RP</th>
<th>Rule weight</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>C</td>
<td>and</td>
<td>C</td>
<td>1</td>
<td>VH</td>
</tr>
<tr>
<td>2</td>
<td>F</td>
<td>and</td>
<td>F</td>
<td>1</td>
<td>VL</td>
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<tr>
<td>3</td>
<td>M</td>
<td>and</td>
<td>M</td>
<td>1</td>
<td>M</td>
</tr>
<tr>
<td>4</td>
<td>C</td>
<td>and</td>
<td>F</td>
<td>1</td>
<td>M</td>
</tr>
<tr>
<td>5</td>
<td>F</td>
<td>and</td>
<td>C</td>
<td>1</td>
<td>M</td>
</tr>
<tr>
<td>6</td>
<td>M</td>
<td>and</td>
<td>F</td>
<td>1</td>
<td>L</td>
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<tr>
<td>7</td>
<td>F</td>
<td>and</td>
<td>M</td>
<td>1</td>
<td>L</td>
</tr>
<tr>
<td>8</td>
<td>M</td>
<td>and</td>
<td>C</td>
<td>1</td>
<td>H</td>
</tr>
<tr>
<td>9</td>
<td>C</td>
<td>and</td>
<td>M</td>
<td>1</td>
<td>H</td>
</tr>
</tbody>
</table>

V. STATE MACHINE DECISION MAKING

The position and the speed of each target will not be estimated in this paper. However, the position and speed of the group will be estimated based on the propagation of the acoustic signal without association. Each cluster head will keep track of the state of the targets and decide whether the targets are closing or going far from the fusion center according to the power of the acoustic signal for each sensor node at each time step. Although cluster head takes the decision every time step, it just sends its decision to the gateway or sink one time. The best time is when the targets are as close as possible to the cluster center. This time will be determined by the state machine as in Fig. 7. We grouped sensor nodes to two groups: group one, and group two. Group one is the \( J \) sensor nodes with the highest acoustic signal power. Group two is the closest \( J \) sensor nodes to the cluster center. Suppose \( \xi \) is the difference of the sum of the acoustic power of group one and group two.

\[
\xi = \sum_{1}^{J} P_{\text{groupOne}} - \sum_{1}^{J} P_{\text{groupTwo}} \tag{4}
\]

Then, if \( \xi \) is decreasing, then the vehicles are closing toward the center of the cluster. If \( \xi \) is increasing, then the vehicles are going far away from the center of the cluster. By this we can know the direction and the position of the vehicles in that specific cluster and tracking \( \xi \) with time will lower the detection false alarm, because of the motion detection besides the acoustic signal detection. The speed can be estimated from the rate of the difference \( \Delta \), where \( \Delta = \xi_{i} - \xi_{i-1} \). In ideal cases, If the targets are heading toward the center of the cluster then \( \Delta \) sign will not change. In reality, because of the noise and the random motion of the vehicles, the sign of \( \Delta \) may fluctuate. Therefore, we introduced the four counting states as in Fig. 7. These four counters \( \{CIF, CIC, CTF, CTC\} \) will be reset in any transition to any other state. State Count_To_Get_Far counts the number of time steps that \( \Delta \) has the negative sign. If the counter \( (CIF) \) is greater than \( (L) \) the state will be changed to Count_To_Get_Far state, and the same for other states. \( \{K, L, M, N\} \) are determined experimentally. The state machine is tracking the region of the high acoustic power. This will enable the fusion center to know if these detection are false or not from the changing of the region of the highest acoustic power. This algorithm can be applied for position estimation, speed estimation, as well as target tracking.

VI. SIMULATION AND RESULTS

Simulation environment for one network cluster region with dimensions \((300 \times 300)\) is developed using Matlab. Vehicle motion is modeled as a Gaussian Markov mobility model. Simulation of the acoustic signal of two different vehicles is based on real sounds. Local decision for each sensor node is taken by multi-hypothesis testing after a feature vector is extracted based on the distribution of the spectrum of the acoustic signal. Classification decision and acoustic power is sent to the cluster head where the decision fusion is performed. All the local decisions are fused by a fuzzy weighted majority voting decision fusion algorithm. In the classical majority voting algorithm, all the local decisions of the sensor nodes have the same weight regardless of the observation SNR and wireless RSSI. While in the fuzzy weighted majority voting decision fusion algorithm, each local decision of the sensor node has been assigned a different weight based on the observation SNR and wireless RSSI. The result of simulation is show in Fig. 8. The fuzzy majority voting achieves less minimal point of detection error average than the normal majority voting. Since farther sensor nodes will have less weight, this makes sharing many sensor nodes with the highest acoustic signal more effective.
nodes in the decision will not increase the error in the fuzzy majority voting. This means that, if the optimal number of the involved sensor nodes in the decision fusion is unknown or can’t be determined, the least detection can be obtained if the fuzzy weighted majority voting decision fusion is used. The correct fuzzy rules are deduced based on experiment results. Thus the rules should be changed as the network parameters change. Fig.9 shows the detection error average for four different densities. To have the detection error decrease as the number of sensors increases until having the least detection error, the right fuzzy logic rules should be deduced.

VII. CONCLUSIONS

A new on-line decision fusion method is developed for moving targets in wireless sensor networks. Where fuzzy logic determines the weights for each local decision based on the signal to noise ratios for the sensing signals and the wireless radio signals. This is also integrated with a state machine to help in deciding when to take the best decision for the whole cluster and to know the direction and speed of the targets. Simulation results demonstrate the efficiency of this method. however, it is computationally more expensive than the classical majority voting method.

REFERENCES