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Event Location Estimation in Binary Wireless Sensor Network

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ABSTRACT: The accuracy of event localization in wireless sensor network is relying largely on the reliable contribution of sensors in the field. Collecting sensor data in real time should provide meaningful insight. Many deployment scenarios have noted faulty sensor readings. Localization performance degrades due to error in reporting by sensors. Real time sensitive applications must be fault resilient. This work explores the localizing of an event in the binary sensor networks in presence of faulty sensors. To improve localization accuracy and to identify false alarm, spatial and temporal aspect is embodied. Proposed algorithm consists of preprocessing and localization phase. Preprocessing phase filters outlier noises using local neighborhood information. The readings from close neighborhood of a sensor are used to approximate its fitness. Localization phase takes input from preprocessing and estimates the location of an event using median of all the readings and approximating local information. Proposed algorithm requires low computation and communication overheads. Simulation results show that the proposed algorithm is efficient.

Keywords: Wireless Sensor Network, Fault Resilient, Event Localization, Binary Sensor, Data Fault

I. INTRODUCTION

Localization in wireless sensor networks (WSN) is one of the key aspects which have gained vast attention. This is due to a spectrum of potential applications in several areas like habitat monitoring, surveillance and target detection. Localization of sensors and events is also considerably different from the application perspective. In sensor localization, knowing the location of the sensor helps in routing and solving queries related to the target. In event localization, the location of event is essential for quick response in critical application scenarios [1]. For many applications it is crucial to know the accurate location of the event in order to detect and track a variety of physical entities.

A WSN has a number of sensor nodes mainly performing sensing, data processing and communication. Sensor nodes are set up to observe distinct events of concern. Sensors are restricted by resources such as computing, storage, energy and communication capabilities [2]. So sensor resource utilization should be minimized. Sensor nodes are intended to function in abandoned and unfavorable condition for long periods of time e.g. deployed in a surveillance area to detect probable targets [3]. From security perspective, there is an increased likelihood of a malicious attacker altering the sensor measurements. In applications like monitoring large environmental areas, false alarm generated by sensors may prove expensive to response team by visiting fraudulent location instead of authentic. So it is crucial that any event detection algorithm exhibits fault resilient feature in order to reduce the impact of misbehaving nodes.

Instead of transmitting raw data, binary data can be effectively used to facilitate low communication bandwidth. Energy conservation ultimately results in increasing the lifetime of system which is also a design concern of WSN [4]. Use of sensors to record binary decisions will require less storage and sensors can transfer data to Fusion Centre (FC) with fewer burdens on communication channel. Binary sensors find its appropriate use when it has to jot down only presence or absence of an event [5]. Event location is determined if the position of the sensors is known which produces binary data. The accuracy of event location estimate can be improved if the space and time domain are considered. Analysis of multiple sets of binary decisions gathered over time can increase the event location estimate [6]. Certain factors will dominate the accuracy of location like process of generating binary outcome, estimating the location based on these outcomes, the number of time frames being observed and noise in the binary data. A maximum likelihood (ML) approach established on multi frame binary data is presented in [7]. The deterministic algorithms are usually observed with a habit of getting stuck to a local maximum value leading to large estimation errors.

A set of sensors at different geographical locations send the information about an arbitrary incident to FC. Each of the sensors obtains information about the related phenomenon and transmits it to FC. The FC takes decision based on the received information. Earlier research about event location estimation was based on the belief that number of sensors which send the data to FC is noise free. This faith, however, may come out incorrect. So the location estimation of an event which was based on the sensor location knowledge would account to inaccuracy. For example, consider the scenario where a WSN is used to detect fire in a forest. Since the objective is to determine whether a fire has occurred or not, binary sensors can be adopted for this situation. Assuming that the location of sensors is known to FC, the binary sensors will sense the fire phenomenon. Once it crosses the sensing threshold, it will send the report to the FC. The FC will now decide event location based on the sensors who observed the phenomenon. However, interpretation of event location based on sensors' actual position would lead to localization errors as sensors were assumed to be noise free which can be an ideal situation. Involvement of faulty data in location estimation affects the results badly. So faulty sensor nodes detection and isolation must be done before event positioning as faults in sensors would introduce fault in event localization [8].

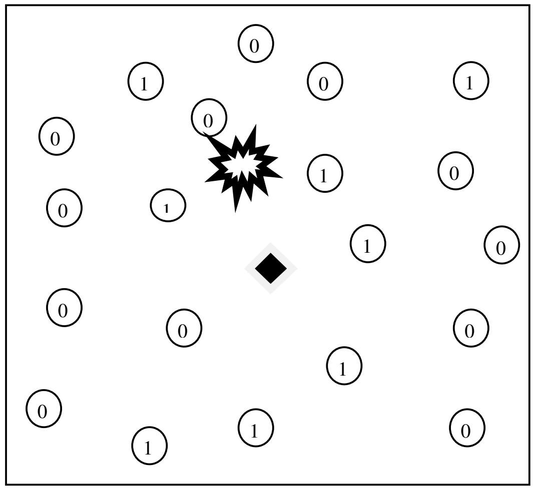

Fig. 1. Random Binary sensor deployment with actual and deviated event location.

Actual Event location   Non alarmed Sensor

Deviated Event location   Alarmed Sensor

An example of a Binary Wireless Sensor Network (BWSN) showing actual event location that deviate from an estimated event location due to faulty sensors is shown in figure 1. Faulty sensors that send data to FC will be responsible for deviating actual event location. In figure 1, binary sensors are deployed randomly over a field. The sensor sends a bit value '1' on detecting an event, otherwise it remains silent. The circle with '0' value is a sensor which does not detect the event. The circle with '1' value is a sensor which detects the event. The FC will determine event location based on some estimation algorithm. The estimated event location is not close to an actual location due to noise in the data sent by sensors. The noise in the data needs to be eliminated before sending the data to the estimator. This will reduce the localization error.

In this paper, the problem of event localization with binary observations in the presence of faulty sensors is discussed. Section II highlights various localization aspects from literature. In Section III gaps observed from the literature are put up. Section IV gives an overview of mathematical model. Section V describes a fault resilient event localization algorithm for binary sensors. In section VI simulation results are discussed followed by conclusion of paper in section VII.

II. LITERATURE SURVEY

The location estimation of random phenomenon based on noisy sensor observations in real time critical applications is a conventional problem. The event to be localized can be single or multiple. To localize an event, it first needs to be detected. Numerous strategies have been created to tackle the source confinement issue in WSN. These strategies fall under centralized or decentralized category. Centralized estimators collect the data from sensors at FC. The FC has to ascertain the validity of the data. In decentralized scenarios, the sensors cooperate with each other to determine source location. So it is also known as cooperative location estimation.

Source Localization of a chemical substance using Maximum Likelihood Estimator(MLE) for binary sensors at FC is presented by authors. The collection of data is processed using MLE and Real time approximated MLE. Approximated MLE exhibits reduced time complexity so it can be utilized for real time applications [9]. An event detection and isolation problem for large WSN using distributed approach is discussed by authors in [11]. The approach assumes that events will influence only nodes falling in events vicinity, so observations from these sensor nodes will be considered. The paper describes sensing model, event model, measurement model in detail. The parameters average time to false alarm and false isolation are proposed. The existing centralized technique are analyzed and compared to that of distributed.

Evetrack is a 3 stage event localizing scheme which starts by identifying outliers followed by event detection and localization. The distributed method localizes global and composite event. It proposes event report packet consisting of information about events and nodes. The outlier detection model incorporates hyper-ellipsoidal model. The clustering algorithm defines the boundary of a cluster using distance metric. The data samples outside boundary are considered as outliers. The outliers which exhibit relationship in time and space domain are recorded as event. Simulation results of proposed scheme are compared with existing scheme for outlier detection and event detection and identification which shows significant improvement [11].

The authors propose a distributed scheme for event detection in WSN. Various architectures to detect the event and algorithmic approaches are discussed and a comparative analysis is presented. The authors implement pattern recognition approach in distributed scenario for fence surveillance application. The parameters like detection accuracy and energy consumption are evaluated to test the efficiency of proposed algorithm. The results show that lifetime of the network has increased as per node energy consumption is reduced. The detection accuracy of distributed event detection for different deployment scenarios is analyzed. It is found that real world deployment of proposed system improves accuracy as compared to others [12].

Cluster of sensors is formed to detect the target in presence of noise. The cluster head determines the area in which the target is present by analyzing the output of binary sensors. The algorithm employs sensor wakeup strategy in case the information at cluster head about target positioning is not enough. Depending upon the area of probable target, the number of sensors is woke up. The localization error is studied in two ways. First the sensors monitoring the area are not faulty and secondly when some of them are faulty due to noise. Theoretical validation of the proposed scheme is done. It does not consider error in sensors. Results indicate that localization error will be less when the additional round of sensor wake up is performed thereby taking information about target for more sensors. Miss probability parameter performance is improved as compared to existing approaches [13].

The energy levels are representative of isotropic signal intensity attenuation. Energy parameter is used to decide the quantization threshold and convert it into one bit data. Position based Maximum Likelihood Estimator (P-MLE) and Position based Cramer-Rao lower bound estimator are derived. P-MLE is compared with MLE and former is found to be more accurate [14].

Multiple sources recognition in binary sensor network environment is tested using iterative fuzzy C-Means algorithm (IFCM). Elfes's binary sensing model is used as it is more realistic as compared to simple binary sensing model. Binary sensor is implemented using Neyman Pearson criterion. The IFCM algorithm removes false positive instances followed by FCM to compute cluster centers which indicate source position. Simulation results were compared for FCM and IFCM algorithm for localization error parameter with respect to varying number of nodes, false alarm probability. IFCM outperforms FCM in all cases. The nodes are deployed in uniform, random and hexagon pattern [15].

Event detection results are severely suffered by noise in the data. Dependencies among observed attributes can be depicted with Bayesian network. Correlating attributes with respect to time and space domain can reduce the impact of false alarm and hence increase accuracy [16]. Convergence properties of Bayesian techniques are used to estimate source location. The search for source is carried out in an environment which is divided into cells and posterior probability of each cell is approximated to locate the source [17].

Subtract on Negative Add on Positive (SNAP) finds location of the event using only binary sensor node information. The primary concept is that the base station builds a matrix by adding ±1 using binary observations. The matrix used is a square matrix with fixed size and the sensor is in the middle cell of the matrix. Sensors which are alarmed will add 1 and those not will subtract 1. After adding each sensor's input, the estimated location of the event is the cell where maximum value lies. A version of SNAP algorithm is Add on Positive (AP) algorithm. It only utilizes the alarmed sensors ' input to build the likelihood matrix. In three significant stages, the SNAP algorithm operates namely grid formation, likelihood matrix construction and maximization. Although it is a simple algorithm, it uses the observation of all sensors irrespective of its data errors. Data faults present in the sensors are ignored to calculate event position which makes this estimator less accurate. The algorithm is energy efficient as only single bits must be transferred to the sink for the building of the likelihood matrix [18].

III. GAP ANALYSIS

Literature survey discusses about existing event localization techniques in wireless sensor network which use either binary sensor or conventional sensor. The output of the binary sensor differs from the conventional sensor. Data faults in binary sensor may lead to dubiety. So if this incorrect data is taken into account while finding out event location, it may deviate from the actual location. Following aspects must be focused while presenting a localization solution.

- Taking advantage of possible correlations among outcome of sensors.
- Determining fitness of sensor before using its outcome.

IV. MATHEMATICAL OVERVIEW

An event localization scenario discussed in section 1 is considered where the objective is to estimate the location of the event. The objective is to achieve more accuracy in the presence of faulty sensors in the network. The model in this paper hereby assumes following things.

- Assume an event with undetermined location that emits energy into a two-dimensional area.
- A large number of sensors are deployed in the environment and the FC is aware of the location of all the sensors.
- The sensors are binary in nature. They are capable to detect only the emission of source when signal received at the sensor is greater than a predetermined threshold and it will send binary value '1' to the FC.

The sensors present in the region of influence of an event will detect the event and those outside will not. The propagation model used is isotropic which decreases monotonically as distance increases. This model is same as used in [7].

$$A_i^2 = \frac{g_i p_o^{'}}{\left(\frac{D_i}{D_0}\right)^n} = \frac{g p_o^{'}}{\left(\frac{D_i}{1}\right)^n} = \frac{p_o}{D_i^n} \qquad (1)$$

Where signal amplitude at the i^{th} sensor is A_i , g_i is the gain at the i^{th} sensor. The power $p_o^{'}$ is emitted by the source measured at a distance D_o and n is the power decay exponent. For simplicity it is assumed that $g_i = g$ for i=1..N and $D_o = 1$ m. The product of power emitted by source $p_o^{'}$ and gain g is p_o. The Euclidean distance D_i between i^{th} sensor and the source is given by

$$D_i = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2} \qquad (2)$$

Where $(x_i - x_s)$ and $(y_i - y_s)$ represent coordinates of i^{th} sensor and the source respectively. The sensors are assumed to be at least D_o meters away from the source at every time instant.

$$S_i = A_i + w_i \qquad (3)$$

Additive Gaussian noise corrupts the signal amplitude A_i at every i^{th} sensor. Since w_i follows a Gaussian distribution, following assumption follows.

$$w_i \sim N(0, \sigma^2) \qquad (4)$$

for $i = 1..N$. The source emits a signal which is measured by sensors at each sampling instant.

V. EVENT LOCATION ESTIMATION (ELE) ALGORITHM

In BWSN, monitoring applications are event triggered. So when sensor readings cross threshold, it initiates the communication between sensor node and sink. But sensor nodes are highly susceptible to errors due to their simple nature. For a multitude of reasons, these faults can happen. Ambiguity in sensor outcome is ascertained to be significant cause for the inaccuracy in event location estimation. So a need arises to have event localization scheme which eliminates faulty sensors and considers only healthy sensor contribution in the process of estimating event location. This paper proposes a scheme which is fault resilient. The proposed algorithm for event location estimation consists of two phases, (i) Preprocessing, (ii) Localize

The first is preprocessing phase which differentiates between normal reading and error reading. It identifies the faulty sensors and eliminates them in estimation process to increase accuracy. The second phase localize determines whether the event has occurred or not and if occurred it assesses the location of the event.

A. Preprocessing

Each sensor typically gets an energy reading from the environment about the phenomenon that can be temperature, acoustic signal, vibration, etc. Sensors transmit binary value '1' when the observed reading is above the preset threshold. The FC receives readings from all such sensors which might be healthy or faulty. So a preprocessing algorithm identifies these faulty sensors exploiting spatial and temporal information about them. FC maintains a database about neighbors of each sensor and it also records the sensor output at each time frame. The preprocessing method is depicted with flowchart in Fig. 2. The flowchart shows the process to determine health status of sensor.

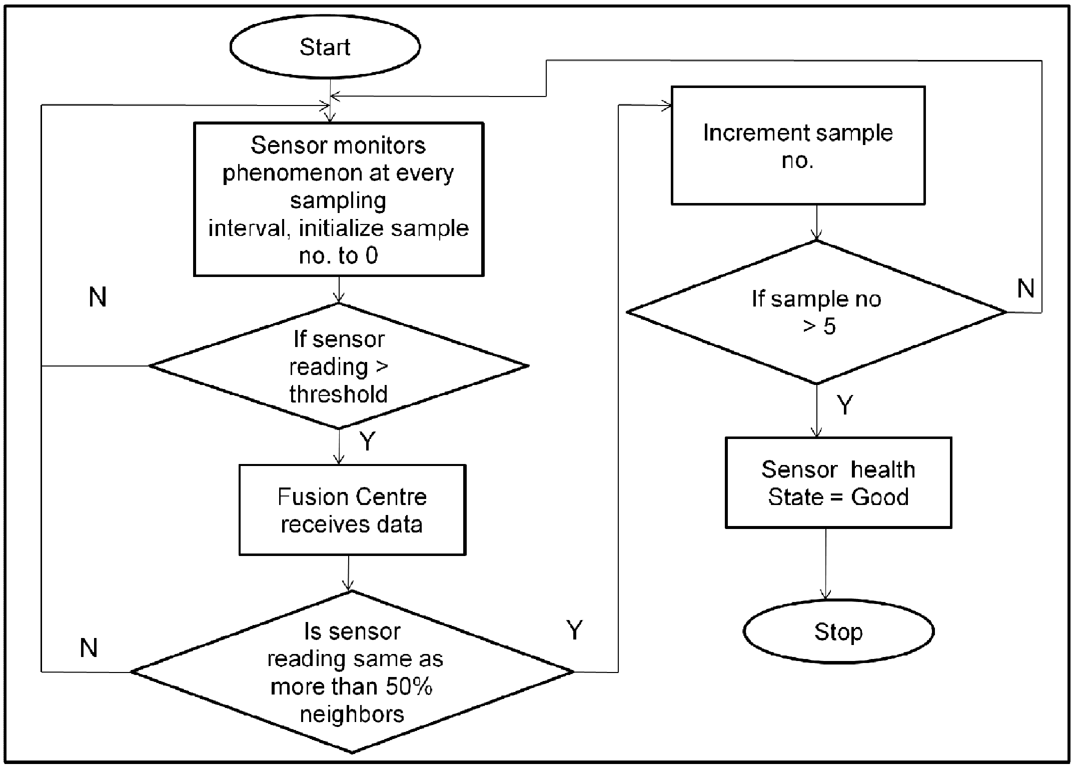

Fig. 2. Flowchart to determine health status of sensor.

Every sensor will be evaluated for its health status using this method at the FC. Here sensor reading of only five consecutive sampling intervals is considered. This is the centralized method which makes use of neighbor readings in space domain and consecutive sampling interval readings in time domain. The number of sampling intervals to be monitored can be increased depending upon the nature of application. If the application will not be affected much by the delay in response due to triggering of event, then observation of more sampling interval can be done. In real time critical application, it has to be kept less to get quick result. But if more samples are analyzed, the accuracy in identifying healthy sensors will be more.

B. Localize

Preprocessing phase identifies faulty sensors. So the readings from these faulty sensors are ignored in the localize phase. All alarmed sensor nodes which are fit are treated with equal weight in localize phase. FC calculates average number of neighbors for the sensor.

Localize process consists of following steps.

1. FC receives information from all alarmed sensors.
2. FC discards readings from faulty sensors.
3. Determine whether the event has occurred or not using spatial data.
4. If (total number of healthy sensors) > (50% average number of neighbors) then
5. { Event Detected.
6. Compute arithmetic mean of location coordinates of all healthy sensors

   to estimate event location.

   }
7. Else
8. Event not detected.
9. End if.

Binary sensors data faults can be categorized into false positive and false negative readings. False positive readings are outlier instances as neighboring sensors do not report the occurrence of event. On the contrary, sensors remaining silent despite being in the region of influence of the event are said to be false negative. The ELE algorithm is robust to false positive sensor readings although it consider readings from all alarmed sensors. The robustness is by virtue of the fact that the proposed algorithm is able to differentiate healthy and faulty alarmed sensors.

VI. RESULTS AND DISCUSSION

This section presents the result of simulation done using proposed ELE algorithm and existing SNAP [18] algorithm. The experiment is carried out on the NS2 simulator. Table 1 lists the simulation parameter and its values. Sensor nodes are deployed in a random manner. Random occurrence of events is observed for 100 simulation runs.

Table 1: Simulation Parameters.

Parameter	Value
Simulator	NS2
MAC	802.11
Simulation time	20s
Sensor Deployment area	1200x800 m^2
Number of nodes	100
Fault model	Normal random variable
Transmission range	40m

In every simulation run, the distance between the actual location of event and estimated location is calculated using Euclidean distance formula. Proposed and existing algorithms are evaluated and the values obtained are averaged for all scenarios. The difference in the actual and estimation location of event is the distance estimation error. The event localization accuracy for proposed and existing algorithm is calculated and it is observed that the proposed algorithm shows nearer location of event than existing algorithm. The accuracy plot of both algorithms is shown in Fig. 3. The ELE algorithm shows an improvement of 4.32% over existing SNAP algorithm. The ELE algorithm shows more accuracy due to the fact that it eliminates the readings from faulty sensors in its preprocessing stage.

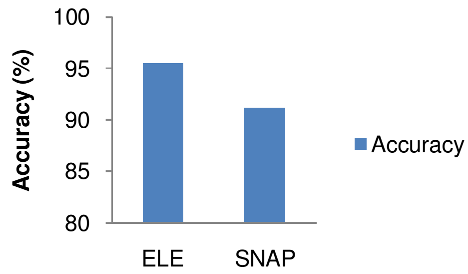

Fig. 3. Performance comparison of proposed and existing algorithm.

An alarmed sensor outside the event influence region is an outlier. Such instances of binary sensors in the network are successfully ignored. The nodes in the event influence region might be suffering from stuck-at 0 and reverse status faults. Without modeling the expected sensor behavior, it is very difficult to detect data faults. Spatial relation amongst the sensors can hint about the health status of a sensor. Since it is utilized in ELE algorithm, it leads us to differentiate between healthy and faulty sensors. If certain change in a physical phenomenon which is being sensed is measured across successive samples and this rate of change is above a predefined threshold then it is a case of fault. ELE algorithm has pondered on this notion in its preprocessing stage which delivered promising results.

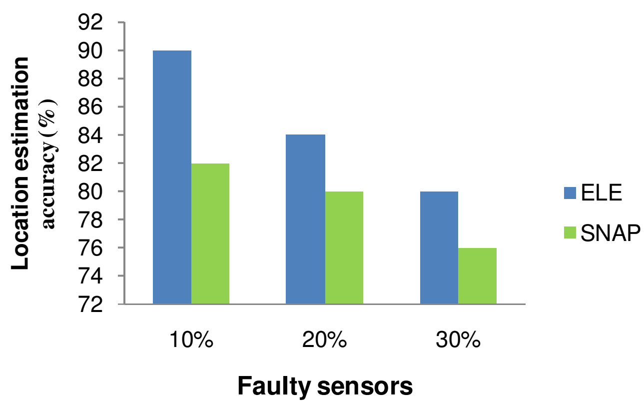

Fig. 4. Event Location accuracy for varying number of faulty sensors.

Sensor may remain silent for many sampling intervals as if stuck to the value 0 or it might be showing reverse value for the time being as reverse status. These faults occur when sensor gets stuck to a specific value due to some fault like overheating, depletion of energy or some malfunctioning [19]. Inconsistency in the readings from sensors in the vicinity of event raises a question mark. It is difficult to comment on the health status of these sensors. So when the number of faulty sensors in the network increases, the performance of both the algorithms should be analyzed. Figure 4 shows the localization performance by varying number of faulty sensors in the network. It is observed that the location estimation accuracy decrease with the increase in the number of faulty sensors for both the algorithms. But in every variation, it is observed that ELE outperforms SNAP. The different type and amount of faults are handled well in ELE and it maintains high level of accuracy even when large number of faulty sensors exists.

VII. CONCLUSION AND FUTURE OUTLOOK

Estimation errors are dominated by the effect of sensor data accuracy. This work is centered on binary sensors where sensors output is one of the two possible values based on the testing with respect to threshold. Binary sensors provide very little information, still they can deliver astonishing performance in many application related to locating the event. The proposed work accomplishes high location accuracy by focusing on improving the resilience to faults. Intelligent use of spatial temporal information in presence of large number of faults facilitates selection of good sensors which reduces estimation errors and improves accuracy. When number of events are more than one, there influence region might intersect each other. Sensor nodes can also be impacted by more than one event. An algorithm to detect all the events along with their location is left as a future work.

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