CERIAS Tech Report 2005-89

TIBFIT: TRUST INDEX BASED FAULT TOLERANCE FOR ARBITRARY DATA FAULTS IN SENSOR NETWORKS

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Abstract

Since sensor data gathering is the primary functionality of sensor networks, it is important to provide a fault tolerant method for reasoning about sensed events in the face of arbitrary failures of nodes sending in the event reports. In this paper, we propose a protocol called TIBFIT to diagnose and mask arbitrary node failures in an event-driven wireless sensor network. In our system model, sensor nodes are organized into clusters with rotating cluster heads. The nodes, including the cluster head, can fail in an arbitrary manner generating missed event reports, false reports, or wrong location reports. Correct nodes are also allowed to make occasional natural errors. Each node is assigned a trust index to indicate its track record in reporting past events correctly. The cluster head analyzes the event reports using the trust index and makes event decisions. TIBFIT is analyzed and simulated using the network simulator ns-2 and its coverage is evaluated with a varying number and varying intelligence of malicious nodes. We show that once TIBFIT gathers enough system state, accurate event detection is possible even if more than 50% of the network nodes are compromised.

Keywords: Sensor networks, secure and intrusion tolerant systems, trust index, arbitrary data faults, event aggregation.

1 Introduction

Recent innovations made in the fields of electronics and wireless communication have enabled the advent of sensor networks. These networks comprising of thousands of inexpensive sensor nodes can be set up with relative ease by placing the nodes in predefined locations manually or through the use of robots, as well as by random deployment of self-organizing nodes. A wide gamut of applications ranging from health, home, environmental to military and defense make use of sensor nodes for collection of appropriate data. The sensor nodes comprising of data collecting, processing, and transmitting units are very small in size and can be densely deployed owing to their low cost.

Sensor nodes have serious limitations in available resources, such as power, memory, and processing ability[2]. The sensor nodes and wireless links are prone to failure, while the network is also open to various malicious attacks. While significant research has been done in the areas of communication architecture, routing, and energy conservation in sensor networks, development of fault tolerance in this highly volatile scenario remains an interesting open research issue. Conventional fault tolerance and intrusion tolerance protocols do not translate well to the sensor network domain due to its large scale and the resource constraints on the sensor nodes.

In this paper we consider fault tolerance in an event driven model for sensing. An event driven model of behavior for sensing finds many applications in civilian, military as well as industrial scenarios. Examples could be seismic monitoring to detect and locate tremors in a given area, or military applications to sense any movement within a cordoned-off area. The inherent unreliability of sensor nodes makes fault tolerance in such an environment an important concern. The problem is essentially one of aggregating data from multiple sensor nodes to decide if an event has occurred and determining the location of the event, all in the face of natural and malicious failures in both the sensing nodes as well as the aggregating nodes. In particular, our approach looks at arbitrary faults in the sensor networks, whether natural or malicious. Natural arbitrary faults may arise suddenly and intermittently in sensor networks, thereby causing a node to miss reporting an event (missed alarms) or falsely reporting an event that has not occurred (false alarms). Malicious faults occur when some nodes in the network have been compromised by an adversary. This adversary can make the nodes send out corrupt information intended to adversely affect the data gathering role of the network. These malicious nodes, depending on their level of intelligence, may have some knowledge of how the network functions and be able to behave in a manner to try to escape detection.

The goal of the proposed TIBFIT protocol involves event detection and location determination in the presence of faulty sensor nodes, coupled with diagnosis and isolation of faulty or malicious nodes. The accuracy of the system is defined in terms of fraction of instances when an event occurrence is correctly detected, and its location determined within the given error bound.

The approach followed by the protocol is to maintain state of the sensing nodes in terms of their previous sensing capabilities, and use this information in making decisions involving those sensing nodes. Sensor nodes report the occurrence and location of events to a data aggregator (hereafter called a data sink), and remain silent otherwise. The data sink then decides on whether the event occurred and where based on the aggregated data. To determine the location of the event the data sink must aggregate all reports from nodes within the detection radius. The aggregation could be a simple voting scheme. However voting is a stateless approach and does not reflect on the past performances of the sensing nodes. TIBFIT introduces a new parameter called *trust index* for this purpose. The *Trust Index* (referred to as TI from here on) of a node is a quantitative measure of the fidelity of previous event reports of that node as seen by the data sink. In a system comprised of sensing nodes, the data sink assigns and maintains a TI for each node in its domain, and does voting in a stateful manner. As the system runs over a longer time, more state is built up concerning the performance of the associated sensing nodes, hence tolerance for faults also goes up accordingly. So while the simple voting approach falls apart when more than 50% of the nodes within detection range of the event are corrupted, TIBFIT can tolerate faults in a network with more than 50% of its nodes compromised after it has built up adequate state.

To demonstrate the effectiveness of TIBFIT, we use an event-driven simulation with ns-2. All nodes are considered liable to failure, whether natural or malicious. We group them into four categories: a) non-faulty nodes that naturally fault some percentage of the time; b) faulty nodes that err randomly; c) malicious nodes working independently that err occasionally and attempt to subvert the system but also try to remain undetected; d) malicious nodes that collaborate and err occasionally and attempt to subvert the system but also try to remain undetected. We show through simulation that TIBFIT is capable of accurately detecting and determining locations of events even when more than 50% of the network is compromised. Finally we also simulate a system that has a gradually increasing number of malicious nodes and analyze the accuracy of the system.

The main contributions of this paper are the following:

1. TIBFIT tolerates nodes that fail both naturally and maliciously, and makes decisions on event occurrence as well as location**.** Under several scenarios, accurate event determination and localization can be done even with more than 50% of the network compromised. We also demonstrate diagnosis and limited recovery in the system.

2. No nodes are considered immune to failure, whether they are sensing nodes or the data sink.
3. We have come up with an adversary model with increasing levels of sophistication and demonstrate the effectiveness of the protocol in each case.
4. The protocol is generic and can be applied to any data sensing and aggregation application in sensor networks.

The rest of the paper is organized as follows. First, we discuss the parameters of our system model in Section 2, we discuss TIBFIT design in Section 3, the simulation implementation and results in Section 4, the analysis of TIBFIT in Section5, related work in Section 6, and conclusions in Section 7.

2 System Model

All nodes in the network are identical and are arranged into disjoint clusters, each with a set of *cluster heads* (CHs), only one of which is active at any point in time. The CH serves as the data sink for its particular cluster. The nodes in a cluster are within one hop communication of the CH. The clusters themselves are formed randomly around the elected CHs. The CHs are rotated over time and CH election is based on energy-related parameters of the constituent nodes. In each cluster, the node that is chosen to be the CH knows the topology of the cluster. Nodes that are within the detection range of an event are called *event neighbors* for that event. This topology is illustrated in Figure 1.

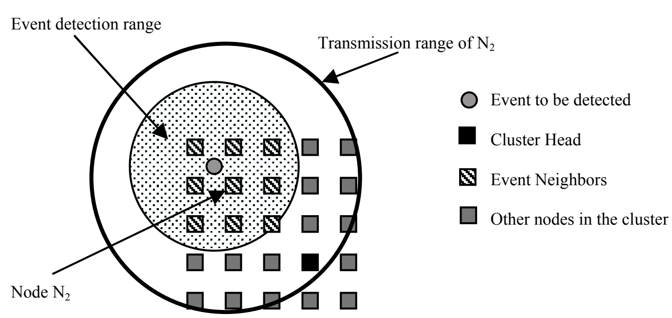

Figure 1: Event Detection

Figure 2: Hierarchy of fault behavior

When an event occurs, all the event neighbors are expected to report the occurrence of the event to the CH. The CH makes a decision on whether the event has occurred based on the reports received from the event neighbors and their *trust indices*. A detailed description of the TI model follows in Section 3.

The sensor network is deployed by placing the nodes randomly in the network. The nodes have the ability to determine their own locations. The locations of the nodes at a given time are known to the CHs, but not necessarily to non-CH nodes. The network could be stationary or mobile, as long as it is possible for the CH to estimate the positions of its cluster nodes during decision making. The sensor nodes function in an event-driven model, that is, they sense the environment for occurrence of a particular detection-level event and transmit data only if they sense such an event. We will assume that the event is typically detectable by multiple nodes, which makes our protocol practical. This assumption is not unreasonable for a large number of sensor deployments.

We adopt the low energy, adaptive hierarchical clustering protocol (LEACH), for cluster formation as well as CH election [3],[4]. This protocol architecture aids in the formation of self-organizing, dynamic clusters, with dynamically chosen CHs. Each node is assigned a probability of becoming a CH at the beginning of each round, which depends on the number of times it has been made CH previously and the energy available in the node. These properties help spread energy usage equally throughout the network. We have also incorporated the TI of the node as an additional parameter to be considered for CH election. The TI of the node has to be higher than a particular threshold value to ensure that only sufficiently trusted nodes can become CHs. This is not a property of the original LEACH protocol.

Each node independently decides if it wishes to be a CH. Once a node decides to become a CH, it broadcasts this information. Any node that receives advertisements from *n* different contending CHs affiliates itself with a single CH based on the strength of the signal received. If a node's TI is below a certain threshold, the central base station will cancel this node's effort to become a CH and re-initiate CH election.

We group event detection into two categories – binary event detection and event detection with location determination. Binary event detection leads to the system recognizing the occurrence of the event with a binary decision about whether it happened or not and not being concerned with the location of the event. An example could be detection of a forest fire based on the temperature reaching a critical threshold. Location determination is when the coordinates of the event are also reported by the sensing node. In the forest fire example, the sensor can detect environmental changes such as wind and variation in light intensity in a direction and estimate the location of the oncoming fire.

2.1 Failure Model

In sensor networks the reliability of the nodes can vary significantly, and this signifies one type of problem in dependably sensing the occurrence and location of an event. However, if a network is compromised where some nodes are replaced with an intruder's nodes, several other problems are created. We assume a fault model of increasing levels of sophistication as illustrated in Figure 2: Hierarchy of fault behavior. Four categories of sensing nodes are identified. *Correct nodes* are not assumed to be 100% accurate, but are expected to make errors within a specified bound referred to as *natural error rate. Faulty nodes* form the superset for nodes with natural or malicious failures. A faulty node can exhibit *naïve* behavior in terms of randomly sending out corrupt information following no specific pattern. The node lies arbitrarily, either in dropping an event report, falsely reporting an event, or reporting a faulty location (level 0). A *smart* faulty node is partially aware of the system model and tries to retain its TI at a reasonably high level where it estimates it will not be detected and isolated. Without collusion (level 1), the malicious nodes work independently. If a malicious node's TI is reaching a level at which it will either be dropped from the network or its vote has too little influence on the event decision, then the node will stop lying until its TI is raised sufficiently. *Smart* faulty nodes can also collude (level 2) in lying to ensure greater damage to the system. In our model, colluding nodes can lie and also function as regular nodes. They are assumed to be connected in a way that is undetectable by the reliable nodes in the network.

The four types of nodes give rise to the following failure scenarios. Missed alarms are where a node within sensing radius of an event does not report the event to the data sink within a specified time. False alarms are where a node either reports an event outside of its sensing radius or reports an event within its sensing radius that did not occur. Location faults are where a node reports an event but at the wrong location. It is assumed that the nodes will not continuously flood the network with packets, which would be the easiest way to corrupt the network and could only be solved by removing the offending nodes.

3 Basic Design

The goal of the TIBFIT protocol is to determine whether an event has occurred from analyzing reports from the event neighbors. Event reports may be incorrect due to either natural errors in the correct nodes or lying malicious nodes. This can cause missed event reports, false reports, or wrong location reports. To combat these anomalies, each node is assigned a TI, maintained at the CH, to indicate its track record in reporting past events correctly.

The TI is a real number between zero and one and is initially set to one. For each report a node makes that is deemed incorrect by the CH, the node's TI is decreased. Similarly, for each report a node makes that is deemed correct by the CH, the node's TI is increased. Thus correctly functioning nodes will have a TI approaching one while faulty and malicious nodes will have a lower TI.

We assume that correct nodes are allowed to make occasional errors due to natural causes. The rate of these errors is denoted the natural error rate (NER). The TI is decremented exponentially. Nodes that make mistakes are penalized more for earlier mistakes, and find it more difficult to regain their previous trust levels. This is considered better than a linear model where a node that lies 50% of the time would still have maximum trust index. If a node errs more frequently than its NER its index decreases, while if it errs less frequently then its index increases.

The TI is calculated as follows. Let the natural error rate be f_r (<1). A variable v is maintained for each node at the CH. Each time a node makes a report deemed to be faulty by the CH its v is incremented by the expression $1-f_r$. Each time a node makes a report deemed to be correct by the CH its v is decreased by f_r if v is larger than zero. The TI is calculated as

$$TI = e^{-\lambda v}$$

where λ is a proportionality constant that is application dependent. An uncompromised node's TI is expected to remain at the same value. It can be expected to suffer a fault at the rate of one per every $1/f_r$ events and the expected change in v is:

$$E[\Delta v] = (1 - f_r) - \left(\frac{1}{f_r} - 1\right) * f_r = 0$$

The design of the protocol is explained next by successively relaxing some simplifying assumptions.

3.1 Binary Events

Assumptions: Let us initially assume that event reports are binary in nature simply specifying whether the event has occurred or not. All the nodes in the cluster, say k, are event neighbors for any event detected by the cluster.

A sensing node can detect the occurrence of an event perfectly for events that happen within a radius r_s surrounding the node.

After the CH receives the first event report it determines that an event could have happened, if confirmed by a suitable number of other nodes from the cluster. The CH is aware of the *k* event neighbors for the event. The CH then waits for a predefined interval of time T_{out} for event reports to be received from these nodes. After T_{out} has elapsed, the CH partitions the event neighbors into two sets *R* and *NR* based on whether they have reported the occurrence of the event or not, respectively. The trust indices of each group are summed and the group with the higher cumulative TI (CTI) wins out. The trust index values of nodes in the *winning* group are increased while the index values of nodes in the *losing* group are decreased according to the formula given above. A faulty node can generate both false alarms and missed alarms. It should be noted that a smaller group of reliable nodes can win the vote against a larger group of unreliable nodes based on the higher TI that the correct nodes have *earned* over past events.

It is evident that we do not need a TI model for a system with faulty nodes in the minority. A simple voting would suffice to mask the decision of the faulty nodes. However, consider a system where the density of faulty nodes increases over time. Examples could be batteries of the nodes dying out with time, or existing nodes being compromised by adversaries. The faulty nodes which have been in operation for a while would have had their TIs reduced to low values. Hence even when the total number of faulty nodes is in a majority, their CTI may still be lower than that of the correct nodes. Hence, TIBFIT can lead to correct aggregation as well as diagnosis even with more than 50% of the nodes compromised. It is obvious that if the initial condition consists of faulty nodes being in the majority, then the protocol will be unsuccessful in tolerating faults. We use this state-aware attribute of the protocol in dealing with malicious nodes of levels 0, 1, and 2 (refer to failure model in Section 2.1). After time, the system can identify a faulty node when its TI falls below a certain threshold. It can then be removed from the network.

3.2 Location Determination

In this section we build on the previous model by adding location details to the event reports. The event report consists of location in terms of (r, Θ) with respect to that node. The nodes do not sense the location of the event perfectly and the CH must determine the actual location of the event.

Simplifying Assumptions: Let us assume there is a time difference of at least T_{out} between any two events to avoid overlapping event neighbors. A correct event report sent in by a sensing node reports the location of an event to within a radius r_{error} surrounding the event.

Once time T_{out} has elapsed after the first event report, let there be k other reports that have come in from the nodes in the cluster during this time T_{out}. The CH performs a clustering algorithm that groups these k event reports into a number of *event clusters* based on the locations indicated by the reports. Each event cluster represents a possible location where the event could have occurred, as indicated by the reports. The clustering algorithm is a heuristic based on K-Means, so as to minimize the sum of squares error [14].

Goal of the algorithm presented below is to organize the event reports into disjoint event clusters of radius $r_{error.}$ Let C be the set of all event clusters consisting of elements $\{C_1, C_2 \ldots C_r\}$. Let $\{c_1, c_2 \ldots c_r\}$ be the centers around which the event clusters $\{C_1, C_2 \ldots C_r\}$ are formed. Distance(c_i, c_j) > r_{error} for every C_i, C_j that is an element of C. C_k.*cg* (Center of gravity) denotes the average location indicated by all event reports in cluster C_k.

Event clusters are created using the following procedure.

(1) The clustering algorithm is started once T_{out} has elapsed after the first event report. The set of all event reports in this time T_{out} is referred to as E. The distances between each pair of event reports are computed and sorted in a 2D array.

(2) Let E_1 and E_2 be event reports from the set E with the greatest distance between them. Event clusters C_1 and C_2 are created with E_1 and E_2 as centers, and C1, C2 are added to C.

(3) Condition for any event report E_k to form a separate event cluster is that Distance (E_k, c_i) > r_{error} for every C_i that is an element of C. The set E is iterated through and the set of all cluster centers are identified, so that the remaining event reports are at a distance of less than r_{error} from at least one element in C, i.e., the remaining event reports cannot form separate event clusters.

(4) Once the initial set of clusters in C are formed, remaining event reports in E are added to one of the clusters in C based on which cluster center it is nearest to. C_k.*cg* for the clusters are updated appropriately.

(5) If the centers of two or more clusters lie within r_{error} of each other the clustering algorithm is repeated by forming a new cluster center at the weighted average of these centers. The rounds are executed until no changes in cluster constituency take place.

The final elements in C represent the set of all events. $C_k.cg$ represents the location of the event *k*. The event neighbors can be determined for the location determined and a determination of whether an event has occurred is made based on the trust indices of the associated nodes as in Section 3.1. This design successfully throws out event reports from nodes which make a localization error of more than r_{error}.

3.3 Concurrent Events

Additions: In this section we build on the previous model by assuming that multiple events can occur within T_{out} of each other (referred to as concurrent events from here on). We however assume that concurrent events cannot occur closer than a distance of r_{error}.

(1) When the CH receives the first event report *E1*, a symbolic circle of radius r_{error} is drawn around it. A new timer $E1.T_{out}$ is started for the associated event reports from other event neighbors to come in. All subsequent events that lie within r_{error} of *E1* reported within time T_{out} are added to the same circle.

(2) If any subsequent event report E_k received lies outside this circle, a new circle of radius r_{error} is formed with this event report E_k as its center. Associated $E_k.T_{out}$ is started.

(3) Once time $E_k.T_{out}$ has passed from the reception of event report E_k that is the center of a circle, all the event reports inside this circle are put into a group and the clustering algorithm described in the previous section is performed on them to determine the location of the event.

(4) However if one or more other circles overlap with this circle, then the CH must wait until time T_{out} has elapsed for all such overlapping circles. The clustering algorithm is performed on the union of all event reports in all the overlapping circles to determine the event clusters and thus how many events have actually occurred.

3.4 Unreliable Cluster Heads

Though the CHs are chosen based on high TI values, it is still possible for a selected CH to fail. To combat this problem we assign two additional shadow cluster heads (SCH) to each cluster such that the SCHs can monitor all input and output traffic associated with the selected CH. The SCHs themselves may be considered as reliable as they are chosen based on the fact that they have the highest trust indices amongst all nodes that are closest to the CH. The SCHs listen in to the communication going in and out of the CH and perform all the functions as the CH except transmitting the aggregated event reports to the base station. On perceiving a wrong conclusion being drawn at the CH based on the input data, the SCHs also send the result of their own computations to the base station. The base station, on receiving data from all CHs in the cluster, does a simple voting to arrive at the right conclusion. It also prompts CH election in that cluster to pick a new CH and reduces the TI of the previous faulty CH.

TIBFIT can also be extended to scenarios where the sensing nodes are more than one hop away from the data sink. The data sink still needs to know the location of the constituent node and reliable data dissemination primitive needs to be introduced to ensure that the data sent out by the sensing nodes reliably reach the data sink without alteration [15],[16].

4 Simulation

The TIBFIT protocol is simulated using the *network simulator – ns-2[6]*. A sensing radius of 20 units is considered. Events are generated at regular time intervals by the *event generator,* using a uniform random variable to generate X and Y coordinates uniformly distributed in the network. The event generator informs the event neighbors of the event and its location.

We run three different experiments. In experiment 1 we show the accuracy of the binary event model versus percentage of the network compromised by level 0 faulty nodes. In experiment 2 we show the accuracy of the location event model versus percentage of the network compromised by level 0, 1, and 2 faulty nodes. In experiment 3 we show the accuracy of the location event model versus time, where the percentage of the network compromised increases linearly over time.

For each simulation we use either the TIBFIT system that uses the trust index, or we use the baseline system, which uses majority voting to make event decisions. Experiments are run with faulty nodes belonging to only one level for a given experiment. The accuracy of the system is the fraction of instances when an event occurrence is correctly detected, and its location determined within the given error bound. In all experiments, accuracy of the system is measured against percentage of compromised nodes in the network.

4.1 Experiment 1 – Binary Events

A cluster of ten nodes is formed, and all nodes are considered event neighbors for every randomized event. Level 0 faulty nodes are used for the fault model, generating both missed alarms and false alarms. The CH makes a decision regarding occurrence of the event based on the data forwarded to it from the sensing nodes.

Type of Event		Binary Event Model	
Independent Variable		Percentage Faulty Nodes: varied from 40%-90%	
	Correct Nodes	Faulty Nodes	
Fault Model	NER=0,1, and 5%	Level 0: Missed alarm 50%, False alarm 0,10, and 75%	
Size of Network		Number of Event Neighbors	Events per Measurement
10 sensing nodes, 1 event generator, and 1 CH		10	100
Lambda (λ)	0.1	Fault rate (f_r)	Equal to NER

Table 1: Parameters for Experiment 1

For this experiment we started simulations with 40% of the network compromised. As Section 5 shows, even for the baseline system, the probability of failure with less than 40% of the network compromised is very small, and therefore not simulated. All faulty nodes in these simulations miss alarms with a 50% error rate.

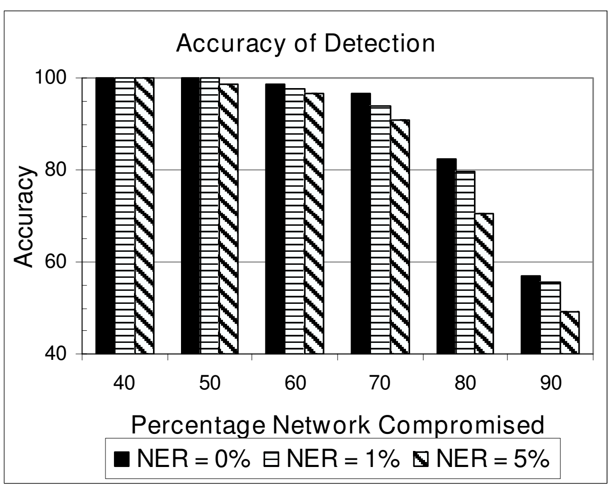

Figure 3: 50% accurate faulty Nodes, missed alarms only

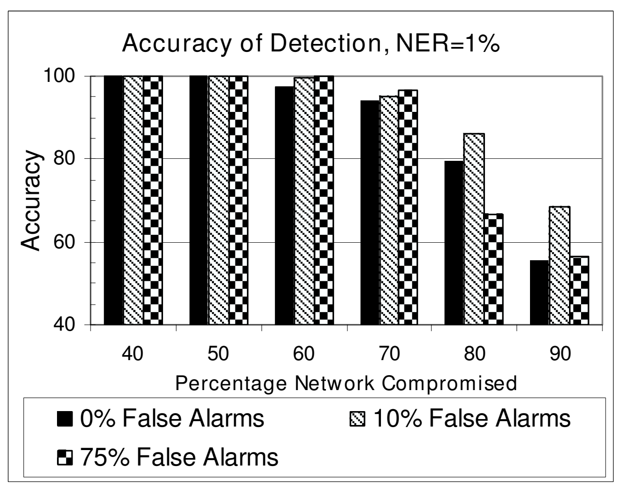

Figure 4: 50% accurate faulty nodes, missed alarms and false alarms

The results in Figure 3 include only missed alarms. The most noteworthy result from this experiment is that the network can have 70% of its nodes compromised and still maintain over 85% accuracy. This result is superior to the analytical results shown in Figure 12 in Section 5.

Figure 4 shows the simulation with both false alarms and missed alarms from faulty nodes. All correct nodes have 1% NER. Again, the network performance starts to degrade with 70% faulty nodes. The interesting result is that 75% false alarms shows the best accuracy when less than 80% of the network is compromised, indicating that the excessive false alarms lower faulty nodes TIs and therefore increase system reliability. At 80% faulty nodes with 75% false alarms, accuracy falls dramatically, as the system is no longer able to tolerate the excessive false alarms. 10% false alarms maintains the highest accuracy at this point, indicating that occasional false alarms lower faulty nodes' trust indices enough to outperform 0% false alarms.

4.2 Experiment 2 – Location Determination Model

In the second type of simulation, 100 nodes are placed uniformly in a 100X100 grid, and these nodes are considered stationary. The CHs and event generator are the other entities present in the network. The CH decides on both the occurrence of the event as well as its location. The network is a single cluster, and the CH knows the positions of all 100 nodes. All nodes can reach the CH in a single hop. For location estimation r_{error} = 5 units. Table 2 shows various experimental parameters for this experiment. Due to the *ns-2* wireless model, correct nodes' packets are naturally dropped less than 1% of the time.

<table>
<tr><td colspan="2">Type of Event</td><td colspan="2">Location Determination Model, concurrent or single</td></tr>
<tr><td colspan="2">Independent Variable</td><td colspan="2">Percentage Faulty Nodes: varied from 10%-58%</td></tr>
<tr><td></td><td>Correct Nodes</td><td colspan="2">Faulty Nodes</td></tr>
<tr><td>Fault Model</td><td>Std deviation is 1.6 or 2.0, or 99% and 95% location accuracy</td><td colspan="2">Level 0, 1, 2: Std deviation is 4.25 or 6.0, or 50% and 30% location accuracy, drop packets 25% of the time</td></tr>
<tr><td colspan="2">Size of Network</td><td>Number of Event Neighbors</td><td>Events per Measurement</td></tr>
<tr><td colspan="2">100 sensing nodes, 5 CH, and 1 event generator</td><td>Varies on event location</td><td>100, run 3 times</td></tr>
<tr><td>Lambda (λ)</td><td>0.25 (TIBFIT) or 0 (baseline)</td><td>Fault rate (f_r)</td><td>0.1</td></tr>
</table>

Table 2:Parameters for Experiment 2

A lower threshold (*lowerTI*) of 0.5 is used for level 1 and level 2 nodes to ensure their trust indices do not fall too low. If they reach the lower threshold they behave like a correct node until they reach an upper threshold (*upper*TI) of 0.8, after which they begin erring again. Each node reports an event with error in both the X and Y directions as dictated by a Gaussian random variable (rv) with standard deviation σ. The error percentage indicated in Table 2 is calculated as the joint probability distribution of the two Gaussian rv's, which is Rayleigh distributed, and it indicates the probability a node reports a event more than 5 units away from the actual event location. The standard deviation for a correct node is much less than that for a faulty node. Level 1 nodes work independently, while level 2 nodes collude with each other and all either send the event report for the same location or do not send the event report.

This experiment initialized a network with a percentage of the network compromised by Level 0, 1, or 2 malicious nodes. 58% was the upper limit for the compromised network as past this point the system did not work with much accuracy. Simulations are run with both concurrent and single events. The legend format for all the result figures from this point on is "*Lvl M W-Z [TIBFIT or Baseline]*", where M is the type of malicious node used, W is the standard deviation of the correct nodes, Z is the standard deviation of the malicious nodes, and the final parameter is whether the TIBFIT or the baseline model was used.

The results in Figure 5 show that at low percentages of the network compromised, the TIBFIT system and the baseline system perform similarly. However, after 40% of the network is compromised, the TIBFIT model performs better than the baseline model by at least 7% percent, and by as much as 20% percent. More importantly, TIBFIT has accuracy near 80% even with faulty nodes having errors 70% of the time. A consequence of the execution of the network with TIBFIT is that the trust index values of the faulty nodes continue to decrease and once they reach a threshold, the nodes can be removed from the network, thus eliminating them from causing future damage.

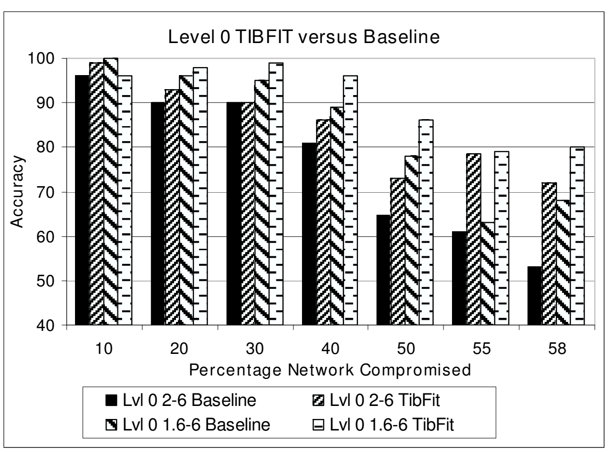

Figure 5: Level 0 faulty nodes

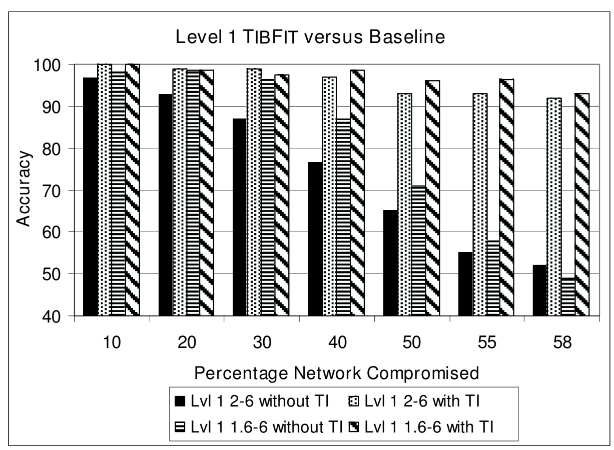

Figure 6: Level 1 malicious nodes

The second graph for location estimation, shown in Figure 6, is for level 1 nodes. The result shows that even with 58% of the network compromised, TIBFIT's accuracy remains over 90%. In contrast, the baseline model falls well below that level once the network reaches 40% malicious nodes. The reason for this trend is that the level 1 nodes lie with the intention to keep them from being detected. In effect, the trust index forces the malicious nodes to lie less frequently and therefore helps to improve the accuracy of the event determination.

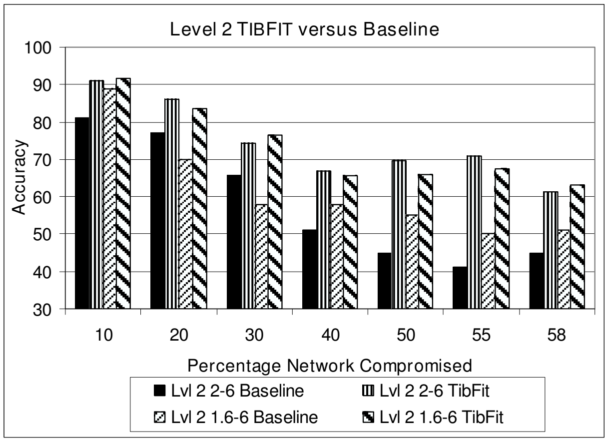

Figure 7: Level 2 malicious nodes

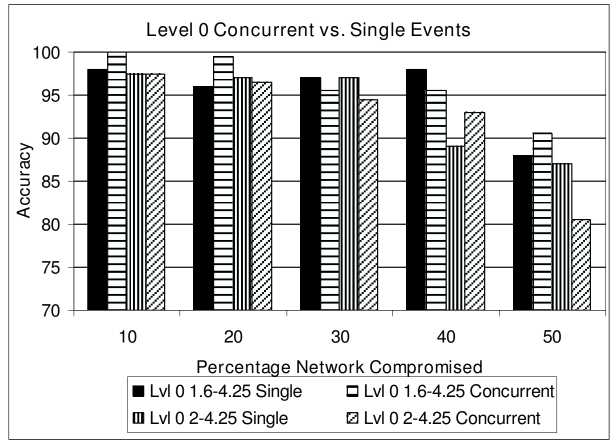

Figure 8. Concurrent Events

Figure 7 shows results for level 2 malicious nodes. It shows that these nodes dramatically reduce the accuracy of the network, although the TIBFIT still outperforms the baseline model. It is clear from this figure that even the trust index has trouble tolerating level 2 type faults due to the collaborative nature of the nodes.

Figure 8 shows level 0 nodes with concurrent events compared to single events, both simulations using TIBFIT. The concurrent events occur with uniform distribution simultaneously, although never within r_{error} of each other. The graph indicates that tolerating concurrent events does not significantly alter the success of the nodes in accurate detection of events.

4.3 Experiment 3 – Decay of Network

The next simulation increases the percentage of the network compromised by malicious nodes linearly over time. The network is initialized with 5% of the network compromised by level 0 faulty nodes. After every 50 events 5% more of the network is compromised until 75% of the network is compromised.

Figure 9 and Figure 10 show that over time TIBFIT outperforms the baseline model in all cases. This occurs because the trust indices of the faulty nodes decrease over time and the system can then handle the transition of some correct nodes to faulty nodes. It is important to compare only the lines with the same standard deviation parameters, because for some time the baseline model with 1.6-4.25 outperforms the TIBFIT 2-4.25 case, although after a longer period of time the TIBFIT line does better, even though it has a higher fault rate in its correct nodes. What is also notable is that the TIBFIT network maintains nearly 80% accuracy even with 60% of the network compromised.

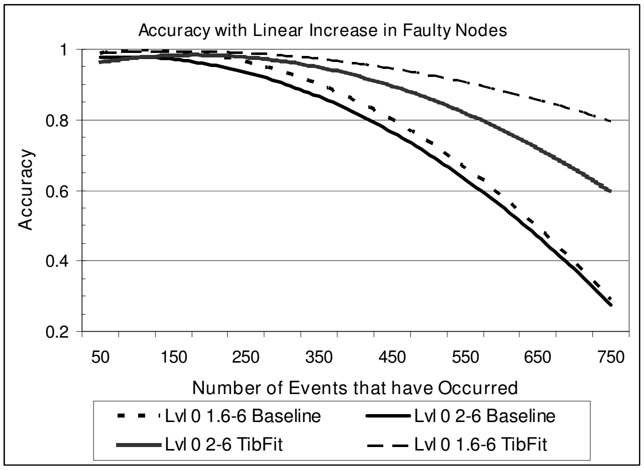

Figure 9: Linear increase in faulty nodes

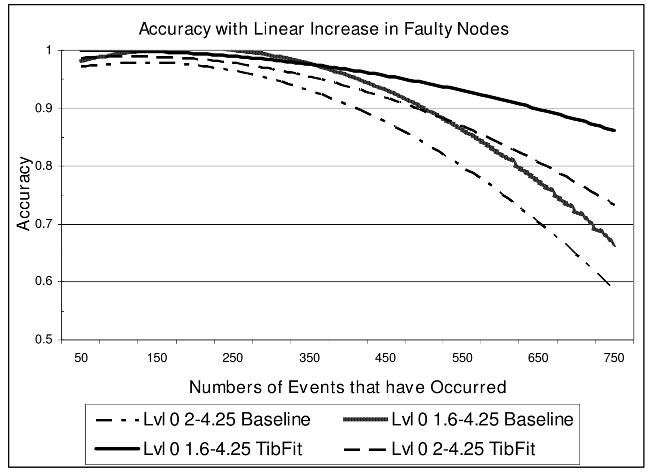

Figure 10: Linear increase in faulty Nodes

5 Mathematical analysis

In this section we analyze the probability associated with the CH successfully identifying a binary event in the presence of faulty nodes.

Consider a baseline model with no trust indices assigned to the nodes. Let us assume that there are *N* event neighbors, of which *m* are faulty. The probability of a successful report from a correct node is *p*, and the probability of a successful report from a faulty node is *q*. Let **X** be the random variable that is the number of correct reports from correct nodes, and **Y** be the random variable indicating the same for the faulty nodes. They are defined thus:

$$P\{\overline{X}=k\}=\binom{N-m}{k}*p^k(1-p)^{N-m-k}\text{, and likewise for } \overline{\mathrm{Y}}: P\{\overline{Y}=k\}=\binom{m}{k}*q^k(1-q)^{m-k}$$

The probability that the N-m correct nodes correctly make k or more reports is therefore the sum of the probabilities from *k* to *N*-*m*, and from *k* to *m* for faulty nodes. Define the random variable **Z**=**X**+**Y**. We wish to know that probability that **Z** has a majority of the *N* votes, or that an event is successfully identified (or rejected). Therefore, we find the following expressions:

$$P(success) = P\left(\overline{Z} \geq \left\lfloor \frac{N}{2} \right\rfloor + 1\right) = \sum_{j=1}^{\lceil N/2 \rceil} P\left(\overline{Z} = \left\lfloor \frac{N}{2} \right\rfloor + j\right)$$

Let $i = \left\lfloor \frac{N}{2} \right\rfloor + j - k$

$$P(success) = \sum_{j=1}^{\lceil N/2 \rceil} \left(\sum_{k=\left\lfloor \frac{N}{2} \right\rfloor + j - m}^{\min\left(\left\lfloor \frac{N}{2} \right\rfloor + j, N-m\right)} \left(\binom{N-m}{k} * p^k (1-p)^{N-m-k} * \left(\binom{m}{i} * q^i (1-q)^{m-i} \right) \right) \right) \quad m \leq N-m$$

$$P(success) = \sum_{j=1}^{\lceil N/2 \rceil} \left(\sum_{k=\left\lfloor \frac{N}{2} \right\rfloor + j - (N-m)}^{\min\left(\left\lfloor \frac{N}{2} \right\rfloor + j, m\right)} \left(\binom{m}{k} * q^k (1-q)^{m-k} * \left(\binom{N-m}{i} * p^i (1-p)^{N-m-i} \right) \right) \right) \quad m > N-m$$

This expression maps to Figure 11 for N=10, q=0.5, and p=0.99,0.95,0.90,0.85 (the plots are in order from the top to the bottom).

Figure 12. Expected accuracy of the network as the percentage of faulty nodes increases

Figure 13. Variation of k with different λ values

The accuracy begins to fall off steeply once fifty percent of the network is compromised. The CTI can tolerate both an increase in faulty nodes over time and more initial nodes being faulty, and will therefore outperform this baseline case. We will show how the CTI performs over time.

Consider the TIBFIT model. Assume the network initializes with N nodes with 1 faulty node and N-1 correct nodes. We will corrupt the nodes in the network at a linear rate of (1/k) and show how the system still functions with 100% accuracy till N-3 nodes are corrupted, thereby outperforming the baseline case which drops in accuracy once 50% of the nodes in the system are compromised. Without loss of generality, let us assume that

N is odd. We also make the simplifying assumption that correct nodes are always correct and the faulty nodes always fail. Let $CTI_{correct}$ be the CTI of the set of correct nodes and CTI_{faulty} be the CTI of the set of faulty nodes.

After every k rounds a good node is compromised. After $(N\text{-}2)*k$ rounds, total number of correct nodes is 3, and faulty nodes is N-3. $CTI_{correct}$ is 3 as correct nodes are always correct and each have a TI of one. After the first faulty report, the TI of a node becomes $e^{(-\lambda)}$. Therefore after k rounds, the TI of the faulty node would be $e^{(-k\lambda)}$. So, CTI_{faulty} for (N–3) faulty nodes when the newest addition to the faulty set has made k errors would be $e^{-k\lambda}+e^{-2k\lambda}+\ldots+e^{-(N-2)k\lambda}$.

For the system to be 100% accurate, CTI of correct nodes ($CTI_{correct}$) should always be greater than CTI of faulty nodes (CTI_{faulty}). For a correct node to be corrupted, CTI_{faulty} should be infinitesimally close to 1, so that $CTI_{correct}$ -1 > CTI_{faulty}+1 (a node is transferred from the good side to the bad side). We have the following expression:

$$3-1>1+e^{-k\lambda}+e^{-2k\lambda}+\ldots+e^{-(N-2)k\lambda}, \qquad \text{or} \qquad 2=\frac{1-e^{(N-1)k\lambda}}{1-e^{-k\lambda}}\rightarrow 0=e^{-k\lambda(N-1)}-2e^{-k\lambda}+1,$$

which can be solved with computational mathematics software. Figure 14 shows this expression for several different λ values. Wherever a given line crosses the x-axis that is the value of k and the number of rounds after which a good node can be made into a faulty node. What is of note is that as λ increases the number of rounds needed increases. It is for this reason we chose λ=0.25 for our simulations, so that we could create a fair number of data points but without needing a very large number of events to show the beneficial effects of TIBFIT.

The upper limit on k is the k necessary to make three good nodes tolerate an additional failure. We stop the analysis at two because once the system has two good nodes left then the sum of the faulty nodes' trust indices must be less than zero to allow the addition of a bad node, which is impossible. When there are 3 good nodes left in the system, then 3 > CTI_{faulty} , where CTI_{faulty} = 3-ε, ε>0. After k_{max} rounds from this state, let us assume that one more correct node can be transferred to the faulty side. Therefore after k_{max} rounds the value of CTI_{faulty} should be = 1- ε before the transfer. Solving $3*e^{-k_{max}\lambda}$ =1- ε gives us $k_{\max}=\frac{1}{\lambda}\ln 3$ as $\varepsilon\rightarrow 0$. Hence, the maximum number of rounds needed to tolerate another faulty node is $\frac{1}{\lambda}\ln 3$.

6 Related Work

As in any sensor networks problem, we require a great deal of related material to ensure that our model accounts for the many challenges of creating a functioning wireless sensor network. For instance, [18] gives an algorithm that guarantees reliable and fairly accurate output from different types of sensors when at most k out of n sensors are faulty. [17] gives a fault tolerant way of averaging sensor data, and the author also gives a control process to deal with individual sensor failures. [19] deals with multi-sensor data fusion and assumes that the biggest loss in sensor network efficiency is from sensor readings. They propose a method of handling sensor failures through substitution of another on-board sensor. One sensor network problem we can solve is where a network is attempting to track a mobile sensor node that is transmitting a signal as it moves throughout the network. [20], [21], and [22] provide techniques of localization for finding node position, such as triangulation and lateration. Nodes within sensing range of this mobile node must be able to determine the location of this node. Location determination efforts with directional antennas can aid in finding the location of such a mobile node. In [13] it is shown that given signal strength and attenuation model one can estimate sensor location. Given enough fixed anchor nodes Bagchi *et al.* present a technique for finding an unknown node within some range of error [12].

There appears to be a dearth of existing work related to our specific topic. Schaeffer *et al.* discuss decision making concerned with propagating an alert through a network [7]. They set a threshold for event propagation, where if a node hears more than n nodes announce an alert then that node sounds the alert. They analyze the characteristics of this network with false alarms and missed alarms, where the evaluation is on whether the event notification reaches some data sink. They address natural faults exclusively and do not consider cases with faulty nodes colluding.

Wagner discusses aggregation of data in a sensor network and malicious intruders in [10]. The paper does a statistical evaluation of what may happen in the presence of an omniscient adversary. The author suggests trimming, or removing data outliers, as a good means of dealing with averaging of sensor data. The author also mentions that the count problem, the problem of gathering binary votes on a decision, is statistically secure. However, he implies that more than half of the network compromised clearly makes the count break down.

Koo shows an upper bound on the tolerance of a broadcast decision process as approximately $1/\pi$ of the network as compromised nodes [1]. This model is proven theoretically with arbitrarily powerful malicious nodes.

7 Conclusions

We present a protocol called TIBFIT that maintains state for event decisions in a sensor network. This protocol can handle both binary event detection and event location estimation with high accuracy in the face of natural and malicious nodes failures within the network. We implement a TI-based protocol that outperforms the standard voting scheme for event detection. We also define two types of intelligent malicious fault models that can disrupt a network, and find that using TIBFIT malicious nodes acting independently are successfully tolerated although not completely diagnosed. Additionally, random faults with no intelligent behavior are successfully tolerated and diagnosed, so they may be removed from the system once their TI has fallen below a certain threshold. The accuracy of TIBFIT in a system of colluding nodes is not as high as against the other two fault models. Colluding nodes can disrupt a system once their numbers are sufficiently large and while TIBFIT outperforms the baseline voting scheme, it does not maintain a very robust network.

There still remains much work to be done with this protocol. We would like to further explore the impact of different system parameters on performance. We would also like to make TIBFIT more robust against level 2 malicious nodes. Another step would be to explore more types of intelligent models involving different levels of collusion and decision-sharing amongst malicious nodes. Ultimately, we would like to implement the protocol in hardware such as the Berkeley motes.

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