Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/120311

A Collaborative Composite Event Detection Approach in Wireless Sensor Network Using Fuzzy Assisted Decision System

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Received: 9 Feb. 2018, Revised: 31 Mar. 2018, Accepted: 3 Apr. 2018
Published online: 1 May 2018

Abstract: Recently, in Wireless Sensor Networks (WSNs), several energy efficient event detection algorithms have been proposed that aim to minimize battery storage, energy consumption and to maximize the network lifetime by framing reduced fuzzy rules related to spatio-temporal properties for determining the event. Since sensors are prone to intermittent fault it would result to fault susceptible reading that generates false alarm event, which would lead to lack of conforming the event at a higher confidence rate. Hence, during decision making, the confidence level parameter of the sensor node is integrated by considering the spatio-temporal properties. In this paper, we demonstrate through collaborative techniques by setting hypothesis to confirm the composite event collected from the neighborhood nodes later the intelligent fuzzy decision system evaluates the rules with the composition of novel parameter confident factor, which results in higher event detection accuracy. This work is implemented in MATLAB and simulations are carried out under different network scenarios. The algorithm is evaluated with various metrics such as event detection accuracy, false positive rate, error rate of the event and energy consumption. Based on the results of the simulations, we conclude that our intelligent hypothesis based on the fuzzy decision system outperform than the well-established J48 decision tree classification algorithm

Keywords: Composite event detection, Energy efficiency, Fuzzy decision system, Hypothesis, Wireless sensor network.

1 Introduction

Recent advances in technology have paved the way to the small sized low power sensor devices. This has the capability to operate in wireless mode. The sensor network is well suited in a hostile rampant environment and it can be deployed in a high-density manner in harsh and unapproachable topographies like a desert, forest, mountains, oceans, etc. The sensor node has the capability of sensing the environment, performs the computation of sensed data and conveys the information through the wireless link to the remotely connected base station [1]. A group of nodes forms a cluster. Each cluster holds the cluster head and the cluster head is responsible for the complete communication within the group as well as with other clusters or to the sink node [2, 3].

Sensors are low-cost devices which come in the widest variety such as biochemical sensors, navigation sensors, seismic and pressure wave sensor and environmental parameter sensors, e.g., temperature, light, sound, humidity, wind and so on [2–5]. WSNs are self-organizable, the network can be rapidly deployed in any location which is also tolerable to fault, due to these versatile characteristics these networks of nodes can be utilized in a variety of applications, for instance, smart home, health monitoring system, observing environmental activities, battlefield application, habitat monitoring and high-end intense applications such as radiation system and nuclear threat detection system [4, 6].

Sensor networks are characterized by numerous constraints they are limited memory capacity, low processing capability, and severe energy constraints [7]. Hence it is a challenge to apply the system into near real-world applications. In addition to that as linguistic variables increases, in a fuzzy logic method. The rule base grows exponentially these would lead to additional burden to the processing node. In large-scale WSNs the scalability is another challenging factor in processing the

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event. The data come from the different set of nodes in the wide area. The algorithm should hold an effective computation. The sensor nodes are prone to intermittent fault due to this issue the false alarm may be raised that can lead to expensive transmission cost. In general, sensor nodes are tightly coupled to the environment. Certain events in the environment need to be monitored and detected in real-time. For example, tsunami detection, structural foundations, fire detection and so on. Event detection in WSNs has special characteristics which need to be measured from sensor reading data and need to be communicated the sink node as quick as possible. System reliability and the accuracy of detecting event should not be compromised.

An exceptional change in the environmental parameters is stated as an event. Events are classified as atomic and composite events [8]. An atomic event, e.g., the high humidity event represents a single event. The event is considered based on the observed value of humidity if the value crosses the specified threshold event is raised. A composite event holds the composition of multiple attributes. For example, fire event multiple attributes are required in the same region within a specified time interval to conclude the event. The composite event can be viewed as a composition of multiple atomic events connected with AND operator among the attributes.

The elementary idea of our proposed scheme is to detect the fire event in the building. According to the bureau of Indian standard the fire is classified as five different classes varies from class A to class E. The fire hazard directly affects the life of human begins and it destroys the valuable documents [9]. The cabin is monitored by a network of sensor nodes. The sensor nodes measures temperature, humidity, and smoke in the region. The data collection follows the standard IEEE 802.15.4 [10]. The fire event holds a multiple events. The sub-events temperature and smoke are observed continuously to conclude the occurrence of the fire event.

The fire event which comes under the category of dynamic event these events are usually unknown in advance. The dynamic event holds three major challenges to the WSNs environment they are complexity, mobility, and uncertainty. We have addressed the complexity and uncertainty challenges. The objective of this paper is to overcome the number of the fuzzy rule base in the fuzzy decision system, improving high detection rate by considering intermittent fault and reduce the transmission cost by transmitting the data packet in the shortest route.

The fuzzy logic takes a real-time decision when the data is not complete and it is well suited to the uncertainty environment [11]. The complete description of an environment can be obtained through the data fusion techniques [12] the fused data hold robust characteristics. A hypothesis is set to confirm the composite event which is compared along with the sensed node and neighborhood data based on that the confidence level of the sensed node. Subsequently, through the intelligent fuzzy decision system, the rules are judged and the substantiation of the event is resolved. The contribution of this paper is twofold. First, we present a higher accuracy of event detection with an intermittent fault by including confidence level of the sensor node as one of the parameters along with the event semantics into the fuzzy logic system. Second, we have designed a technique to route the event in the shortest path to the base station.

The remainder of this paper is structured as follows. Section 2 provides the brief discourse about the related work on the composite event detection problem. In Section 3, the problem statement, system model and assumptions are provided. The algorithm of the composite event model is depicted in Section 4 along with the fuzzy rules. Section 5 gives the performance indices that is used to evaluate the proposal. The experimental setup, simulation solutions and result analysis are presented in Section 6. Finally, Section 7 gives the concluding remarks of this work.

2 Related work

The different perspective methodology has been handled to solve the problem of event detection. The startup for event detection has utilized the threshold value. Upon exceeding the threshold level an alarm will be generated [13, 14]. In the article [15] hierarchical classification model was designed which comprised of four tiers–sensor-level, group level, and base-level. Sensor reading is read at a specific time on a sensor, these sample point readings are placed in the global sample set. The complexity increases in each level, these dispersals allows multiple sensors to collaborate on sensor node the detection and classification results are continuously refined at different levels, the highest level is base level, at this point event final decision of the classification is completed. Sung-Jib Yim et al. [16] have proposed double threshold which Collects data from the neighbor sensor node. Based on the sensor reading, it generates the binary hypothesis that results in two threshold values, three different groups are formed by holding the two-threshold value. The fixed threshold increases the accuracy and reduces the false alarm rate. An author of the paper [17, 18] uses an event tree formation.

In [17] Dynamic collaboration protocol framework was designed to determine the dynamic event through the event semantics, the node splits the event into sub-events. Furthermore, it is subdivided in terms of multi, single and partial attributes. The sub-events are ordered in time series and form an event tree. The event tree collaborates the reading of other sensor nodes in the network. In this architecture, there doesn't exist sink node, hence the event notification is transmitted to the destination node.

In paper [18] set of sensors monitor the area and tries to determine composite event which is a composition of atomic events. The event tree is generated, these nodes in the tree form the detection set. The nodes which are presented in the tree are represented by different color based on that color indication; it is involved in the computation and confirms the event. Machine learning techniques are also involved in the determination of event detection. Pattern matching is done at different points locally at the sensor node [19], at the base station [20, 21] and it is also distributed across the network [22–27]; it varies according to the scalability of the network size. Unsupervised general Hebbian algorithm [28] ensures the consecutive no of outliers detected. Upon the conformation, the algorithm enters into identification phase and computes the eigenvector. This scheme follows the concept of dimensionality reduction technique.

Since nodes are densely deployed in an environment, they may send redundant information, several works which were concentrated for getting rid of redundant information is discussed in [29–31]. Few previous works focus on distributed collaboration among neighbor nodes [32, 33]. Local collaboration and decision are used to make sensor readings more reliable. The properties of fuzzy logic are well-suited for providing solutions in the area such as clustering, MAC protocol, routing and QoS in WSNs. In the perspective of event detection, the author [34] collects data from a sensor node within its range and perform data fusion to overcome the uncertainty in the reading, fuzzy logic controller is employed to determine the confidence factor in the set of atomic events, the confidence factor is cross-checked with the threshold level, if the level exceeds event is concluded and the same is reported to the base station

In [35], the authors introduced the semantic and temporal constraint that exists in the network, which was analyzed by fuzzy logic and they concluded that the fuzziness value confirms the better event detection than the crisp value reading. Erroneous data have been perceived from nodes and it was tackled by using sliding window and clustering mechanism [36], the attribute values are estimated and event decision is performed by the fuzzy logic system. In D-FLER [37] the author combines the individual reading with the neighborhood reading and the algorithm is deployed to discriminate between the real fire data and the non fire data, the false alarm rate analysis was not carried out in D-FLER.

Numerous prevailing techniques reside for determining an event in the sensor network. Our work focuses on the collaborative automated version which performs an intelligent decision without the intervention of the human. As we are dealing with the event which occurs in real-world, surely uncertainties exist in the data, hence we have set the hypothesis and comparison analysis is performed with the fused value that results in a confidence parameter, To overcome the dynamic error confidence factor is additionally set along with the temporal and spatial parameter of the fuzzification module in this proposed protocol.

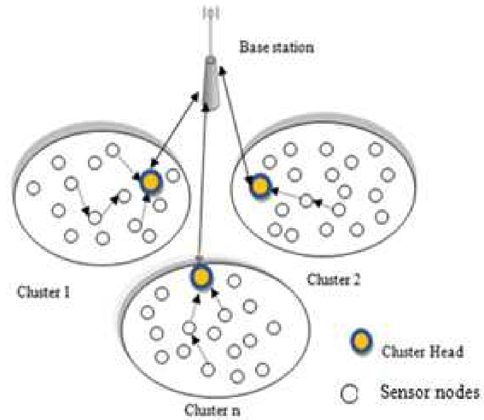

Fig. 1: Network Cluster Architecture.

3 System model and problem definition

In this paper, we have considered ‘n’ no of sensor nodes that forms a hierarchical network. The nodes are positioned in the fixed location; the position of the node plays vital role in the detection scenario. The network is segregated into a number of clusters as represented in Fig. 1. Each cluster nominates one of the nodes as Cluster Head (CH) in which it holds the major responsibilities. The CH manages the nodes within the cluster, communicates to the other CH in the network as well as to an active sink node. The default transmission range is t_{dr}. The data transmission between sensor nodes and their appropriate CHs is based on a multi-hop communication.

In the composite event detection model, the following notations are used which are represented in Table 1.

3.1 System assumption

The following assumptions are considered in the composite event detection model.

- Sensor nodes are heterogeneous (supports with different sensing capability).
- Each sensor node holds the node id.
- Sensor nodes are prone to failure.
- Mobility of sensor nodes is static in the event detection model.
- Wireless broadcast is used for communication and Radio Links are symmetric.
- All sensor nodes are loaded with initial energy without variation.

3.2 Problem statement

Due to the inherent characteristics of sensor nodes, Uncertainty exists in sensor measurements and nodes are

Table 1: Notations.

Sl.no	Symbols	Description
1	N_n	Neighborhood nodes in the detection window D_n
2	D_n	Detection window $DR_{\min}$ and $DR_{\min}$
3	S_{nr}	Neighborhood nodes sensor reading
4	$\overline{x_i*}$	Mean of sensor node of ith epoch
5	$\overline{x}$	Grand mean
6	A	Probability ratio
7	K	No of neighbor nodes in D_n
8	y_p	The number of true positive (classified correctly as an event)
9	y_n	The number of true negative (classified correctly as normal event)
10	n_p	The number of false positive (classified incorrectly as an event)
11	n_n	The number of false negative (classified incorrectly as normal event)
12	C.F.	Confidence factor

prone to intermittent fault. As a result of the fault, false alert is generated and it is addressed towards the base station. False alarm will drag the precious energy resource and bandwidth is wasted. To distinguish the false alarm, it is necessary to sustain the event in near real time with the highest confidence rate. The uncertainty nature of sensor reading is handled by fuzzy model. The fuzzy decision unit takes decisions and confirms the fire event in an environment.

4 Composite event detection Model

The proposed model deals with the composite event by collaborating the reading of neighborhood sensed nodes that exist in the detection window which satisfies the spatial and temporal property. This model works with a livelihood of two different Modules. In Module1 statistically evaluates the confidence level of the sensor node. The second model deals with the fuzzy decision system to confirm the composite event in the determined sensor area.

4.1 Determining the Confidence Factor (C.F.)

The spatial and temporal semantics are considered to determine the condent factor of the node. The condence factor is evaluated by taking the reading from the environment. In this Module, one way ANOVA method is used to determine the mean, variance between values extracted in the time interval of ti, which holds the time period of 60 seconds slot for per interval, each node records the measurement value and save temporarily in its memory location Upon raising an alarm, Detection window of size $DR_{\min}$ and $DR_{\max}$ is constructed. The nodes in the detection range are identified as neighborhood nodes. The vector of measured reading $S_{nr} = [S_{i1}, S_{i2}, \ldots, S_{in}]$ is collected from the time period of K.

$$K = E_a(t) - 5 \text{ epochs}.$$

$E_{ai}(t)$ indicates the event raised at the node i at the time t, the recent 5 slot is the assumed time periods fixed in this model. We assume that measures in each set S_{ij} are independent.

$$S_{ij} = \mu + \tau_j + \varepsilon_{ij},$$

where $j =$ no. of neighbors in the detection window and $i = 1, \ldots, |S_j|$.

The variable S_{ij} holds the sum of three components: The μ denotes the grand mean of sensor reading, τ_j is the deviation of individual neighbor mean from the overall mean, random error term ε_{ij}, its reflects variability within each sensor node. Therefore, there are n_k measurements, which can be represented in matrix form. The measurement, analysis of this module includes two stages. In the first stage descriptive analysis of measurement distribution is calculated. The Second stage performs the hypothesis testing with analysis of variance and it statistically analyzed Tukey test [38].

Algorithm 1

Case 1: Network Deployment /Reformation of network scenario
for all nodes in the network **do**
    Set default unity value to the Confident factor parameter.
    Save the parameter value locally in the sensors memory location.
end for
Case 2: Upon raising event alarm
Execute the Algorithm 2 which considers the spatio-temporal semantics.
Evaluate the Confident factor.
Update the Confident factor parameter

Initially all the nodes in the deployed environment hold the parameter Confident factor. The default value 1 is assigned to the parameter. Algorithm 1 represents the setting up the parameter value of Confident factor which varies by two different cases.

4.1.1 Sensor's measurement analysis

The measurement analysis is observed for the variant reading within the each sensor node and across the neighborhood nodes that exists in the coverage of detection window.

$$ss_{\text{tot}} = \sum_{i=1}^{n} \sum_{j=1}^{k} (s_{ij} - \overline{x})^2 \tag{1}$$

$$ss_{\text{among}} = k\sum_{i=1}^{n}(\overline{x_i*} - \overline{x})^2 \quad (2)$$

$$ss_{\text{within}} = \sum\sum(s_{ij} - \overline{x_i*})^2 \quad (3)$$

$$F = \frac{MS_{\text{between}}}{MS_{\text{within}}}; \quad MS_{\text{between}} = \frac{ss_{\text{among}}}{n-1} \quad (4)$$

$$MS_{\text{within}} = \frac{ss_{\text{within}}}{nk-n} \quad (5)$$

where
ss_{tot}—Total Sum of squares of n sets
ss_{among}—Sum of squares between the sensor nodes
ss_{within}—Sum of squares within the sensor nodes

4.1.2 Hypothesis testing

To improve the conclusion and to reduce Type I error, i.e. upon true condition rejecting the null hypothesis is controlled by setting up a hypothesis. The null hypothesis states that no fluctuation exists in the sensor measurement. Hence it states that there is no significant mean difference in the sensor for last epochs. Upon selection of null hypothesis C.F. of the event, sensed node is not updated, it retains the same C.F.

$$H0: \quad \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_J$$
$$HA: \quad \mu_1 \neq \mu_2 \neq \mu_3 \neq \cdots \neq \mu_J$$

The hypothesis is rejected if the F calculated from the measures is greater than the critical value of the T distribution for probability $\alpha = 0.5$. The alternative indicates that there exists a variation in the reading; hence the Confidence Factor C.F. is decreased by 0.1 values.

4.2 Fuzzy decision system

Fuzzy logic is a mathematical tool that forms as similar of human reasoning that approximates the decision and efficiently handles the uncertainty and ambiguity that exists in the environment. It is well suited to take decision on sensor network because it can tolerate the imprecise reading of the sensor node, does not require high speed processor and data are stored in the form of membership function which requires less memory.

Fig. 2 represents the fuzzy decision system of the composite event detection model. The decision is taken by the fuzzy logic system by using the fuzzy set. Three main modules are involved fuzzification, decision making defuzzification. Mamdani model is applied in the inference procedure.

4.2.1 Fuzzification

The following parameters stated in Table 2 act as inputs: the fuzzifier unit temperature (t), change in temperature (Δt), smoke (s), change in smoke (Δs). Confident Factor (C.F.). The Confident factor is evaluated by variance module by considering the semantic of spatial and temporal property. As the number of parameter increases, the fuzzy rule will multiply in term of exponential factor hence to reduce the no of rules in first phase the spatial and temporal semantics are evaluated and it is set to the single parameter. The fuzzifier unit converts the crisp input into a fuzzified set. All these variables hold three

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Algorithm 2 Determining Confidence factor based on spatial and temporal semantics.

for $\forall N_n \in D_n$ **do**
  $T_{\text{Loc}} \leftarrow$ collect data for k periods
//Calculate the variance of the sensor reading
  for each epoch k **do**
    $\overline{x_i^*} = \frac{1}{k}(s_{i1} + s_{i1} + \cdots + s_{ik})$
  end for
//Calculate the grand mean of sensor reading that exists in the detection window DR_{min} and DR_{max}.

$$\overline{x} = \frac{1}{|k*n|}\left(\sum_{i=1}^{n}\sum_{j=1}^{k} s_{ij}\right)$$

end for
The parameters are evaluated using Tukey test by using Eqs. (1)–(5).
$T \leftarrow d.f.(ss_{\text{among}}, ss_{\text{within}})$.
if $F > T$ **then**
//Variation in sensor's measurement reading
  Accept the (H_a) alternative hypothesis
  C.F. $\leftarrow$ C.F.-0.1
else
//No variation in sensors measurement reading
  Accept the (H_0) null hypothesis
  C.F. $\leftarrow$C.F.
end if

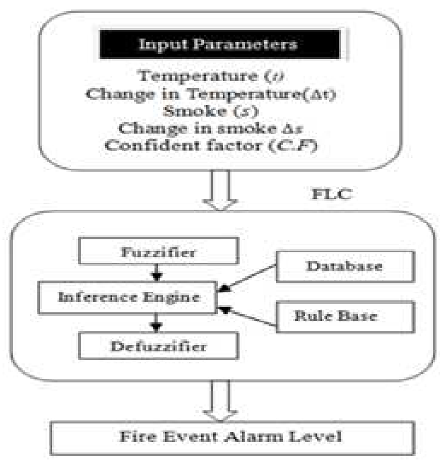


Fig. 2: Fuzzy Decision system.

Table 2: Input parameter for fuzzy unit.

Input parameter	Range
Temp. $t, \Delta t$	[0–100]
Smoke $s, \Delta s$	[0–0.2]
C.F.	[0–1]
Note: 1. Linguistic Term set: Low (L), Medium (M), High (H) 2. Membership Function: Triangular	

different linguistic variable namely low, medium and high. Triangular and trapezoidal membership function $\mu(x)$ are used in the determination of event occurrence. Table 2.

4.2.2 Fuzzy inference rules

Fuzzy rules are formed by representing the human knowledge by forming a natural language expression. If ...then rules that forms the relationship between the input and output. An implication statement is represented in Rule$_1$. Compound rules can be formed by applying conjunctive, disjunction and negative operator to the antecedent which is represented in Rule$_2$ these rules are formed by considering n antecedent input with 1 output that indicates the level of fire in the chamber. The antecedents establish the rule weight. Degree of Membership (DOM) value of the linguistic set lies between the values of zero and one.

Rule$_1$: IF antecedent$_1$ THEN consequent.

Rule$_2$: IF $A_1 \cup A_2 \cup \cdots \cap A_{n-1} \cap A_n$ THEN consequent

According to composite event detection model the spatial and temporal properties are taken along with a confidence factor of the node. The ultimate goal is to reduce the false alarm rate; thus, by taking into account the spatial property parameter distance is used to analysis the fire occurrence. Totally depending upon the single sensor reading and proceeding with the confirmation of the event would lead to fault, instead in addition to the reported node the spatial coverage location with distance linguistic variable claim the strongest confirmation of the event. Further the false alarm rate, time factor is also taken into consideration. The antecedent part is analyzed first by applying the fuzzy operator between the multi-input parameters. In the next step the result of the antecedent part will reflects in the confirmation of fire detection in the location.

The input vector is framed as $X = (x_1, x_2, x_3, x_4, x_5)^T$, where, x_i corresponds to the multi-input parameter; $i \in [1-5]$.

Table 2 represents the input parameters, term set, membership function and the universe of discourse U. The firing strength of the rule is determined by equation.

$$\alpha_i = \min\left(\mu^i_{x_1}(x_1)\,\mu^i_{x_2}(x_2)\,\mu^i_{x_3}(x_3), \mu^i_{x_4}(x_4)\,\mu^i_{x_5}(x_5)\right) \quad (6)$$

Composite event detection rule base is represented in Table 3. Centroid method is used in defuzzification block.

Table 3: Rule base for CED.

Rule no.	Input t	Δt	s	Δt	C.F.	Output FDL
1	L	L	L	L	L	Low
2	L	M	L	M	L	Low
3	L	H	L	H	L	Low
4	M	L	M	L	L	Low
5	M	M	M	M	L	Low
6	M	H	M	H	L	High
7	H	L	H	L	L	Low
8	H	M	H	M	L	High
9	H	H	H	H	L	High
⋮	⋮	⋮	⋮	⋮	⋮	⋮
125	L	L	L	L	M	Low
126	M	L	M	L	M	Low
127	H	L	H	L	M	Medium
128	L	M	L	M	M	Low
129	M	M	M	M	M	Medium
130	H	M	H	M	M	High
131	L	H	L	H	M	Medium
⋮	⋮	⋮	⋮	⋮	⋮	⋮
152	H	H	H	H	M	High
	L	L	L	L	H	Low
	M	L	M	L	H	Low
189	H	L	H	L	H	High
⋮	⋮	⋮	⋮	⋮	⋮	⋮
238	L	M	L	M	H	Low
239	M	M	M	M	H	High
240	H	M	H	M	H	High
241	L	H	L	H	H	High
242	M	H	M	H	H	High
243	H	H	H	H	H	High

The output parameter is Fire_detectionLevel; The linguistic variables for Fire_detectionLevel is represented as

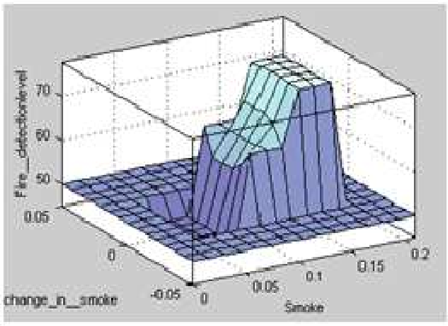
$$T(FDL) = \{\text{Low (L)}, \text{ Medium (M)}, \text{ High (H)}\}$$

5 Performance indices

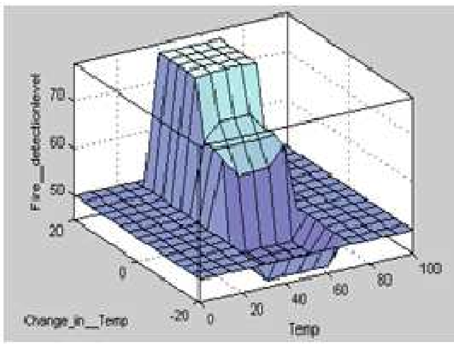
In this proposed work, different performance indices such as energy consumption and event detection accuracy level of the proposed design are evaluated for the composite fuzzy decision unit and the evaluated results is compared with J48 decision tree.

5.1 Energy consumption

The energy Consumption uses the rst order radio model in which, during idle and sleep period the energy consumption is eliminated. To transmit l bit of message for a distance d the $E_{tx}(l,d)$ and $E_{rx}(l)$ is evaluated by Eqs. (1)–(2) respectively. Based on a threshold level, i.e



(a) Smoke parameter.



(b) Temp. parameter.

Fig. 3: Surface view.

the distance between the sender and receiver is less than d_{th} the free space model is used or in the alternative case multipath fading model is used.

$$E_{tx}(l,d) = \begin{cases} l * E_{\text{elect}} + l * \varepsilon_{fs} * d^2; d < d_{th} \\ l * E_{elect} + l * \varepsilon_{mp} * d^2; d > d_{th} \end{cases} \tag{7}$$

$$E_{rx}(l) = l * E_{\text{elect}} \tag{8}$$

where,
ε_{fs}—Amplification factor for free space
ε_{mp}—Amplification factor for multipath radio model
l—Data Bit
d—Node Distance
E_{elect}—Energy consumption per bit of Transmitter unit/ Receiver unit.

5.2 Event Detection Accuracy (EDA)

Composite event detection model raises two different possible outcomes. On the occurrence of the event, an alarm is generated otherwise alarm is not initiated. The event detection accuracy is measured by the EDA formula which is evaluated based on the formula

$$EDA = \frac{y_p}{y_p + y_n + n_p + n_n} \tag{9}$$

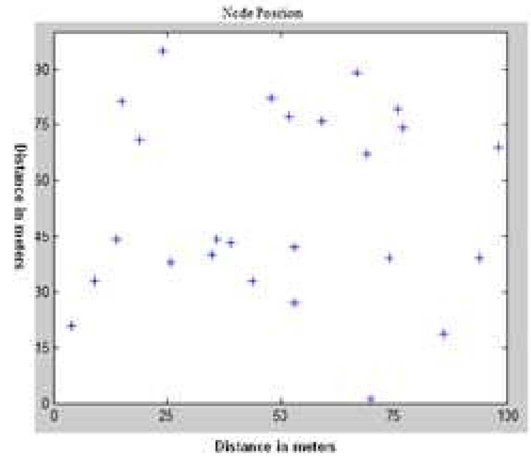


Fig. 4: 25 Nodes position in (x,y) co-ordinates.

True positive (y_p): Generates an alarm for the event occurrence in the setup environment. False positive (n_p): faultily generates an alarm for a normal value. False negative (n_n): On the occurrence of the event alarm not generated. True negative (y_n): alarm appropriately not generated for an occurrence of an event.

$$\text{True positive rate} = \frac{y_p}{y_p + n_p} \tag{10}$$

$$\text{False Positive rate} = \frac{y_n}{y_n + n_n} \tag{11}$$

The parameter true positive rate and false positive rate reflect the event accuracy which is analyzed and plotted in terms of ROC curve.

6 Experimental setup and results analysis

To determine the composite event detection, four differently sized set up of nodes are deployed. The test bed is created by varying the no of consisting of 10, 25, 35, and 50. Fig. 3 shows the surface view with respect to smoke and temperature parameters, while Fig. 4 represents the location (x,y) which holds 25 sensor nodes setup.

In this proposed experiment, Xbee S2 modules provide the endpoint connectivity. By making use of the XCTU software one of the node is configured as coordinator node and other nodes act as an end device. The nodes are battery powered using 1.5 V AA batteries. The sensors are continuously monitored and on the occurrence of the event, it is reported to the Base station.

6.1 Results and analysis

Parameter values used for the proposed composite event detection model are given in Table 4. In the proposed work,

Table 4: Simulation Parameters.

Parameter	Values
Network Topology	
Network Size	100×100 m
No. of Nodes	40
BS Location	50×50 m
Node distribution	Fixed
PHY /MAC Layer	IEEE 802.15.4
Radio Model	
Energy Model	Battery
Operating channel	2.4 GHz
Baud rate (BD) bps	115,200 bps
Data bits	8
Bandwidth	1 Mbps
Energy	
E_{elec}	50 nJ/bit 0.0013 pJ/bit/m4
$\varepsilon_{fs}s$	10 nJ/bit/m2
ε_{amp}	0.0013 pJ/bit/m4
E_{DA}	5 nJ/bit/Message

Table 5: Comparison indices for setup of 25 sensor nodes.

Sl.No.	Indices	J48 Decision Tree	CED
1	Accuracy %	0.95	0.98
2	Error rate	0.05	0.02
3	False positive Rate	0.04	0.035
4	Energy Consumption (8 Faulty Nodes)	1.35 V	1.2 V

analysis is performed in term of energy of the node after deploying the fuzzy decision unit and the false alarm rate are evaluated. The evaluated value is compared with J48 decision tree.

6.1.1 Case A: Considering neighborhood

Different setup is considered by varying the sensor nodes in the range of 25, 40 and 50 in the network. A setup of 25 nodes with 2 clusters is analyzed and represented in Table 5. By considering the reading of the neighborhood nodes the Confidence Level is evaluated, the hypothesis works well as the no of neighborhood nodes increases the decision of the CED shows the slight improvement in the result. The results given in Table 5 and plotted in Figs. 5, 6 and 7 show that the indices perform well; it is also further proved that the proposed model with the hypothesized decision of neighborhood perform better than the J48 decision tree.

6.1.2 Case B: Analysis with faulty sensor nodes

The network is intentionally deployed with the composition of accurate as well as with the faulty sensor nodes. An analysis for the robustness of the proposed model is measured by considering the faulty nodes.

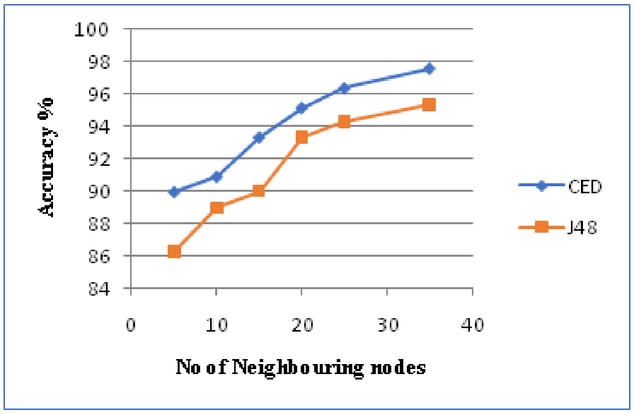


Fig. 5: Plot of Event accuracy.

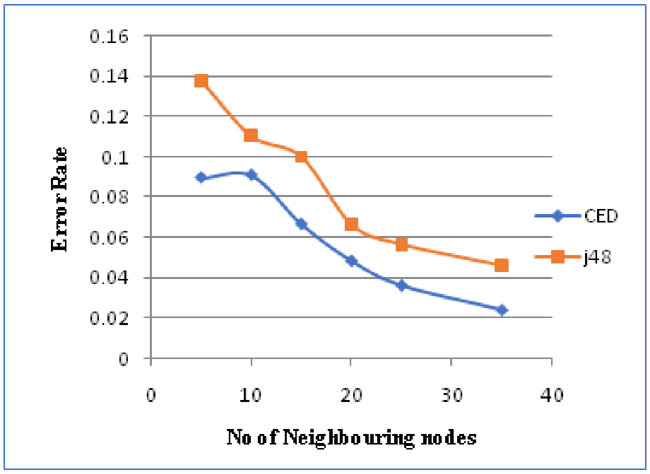


Fig. 6: Plot of Error Rate.

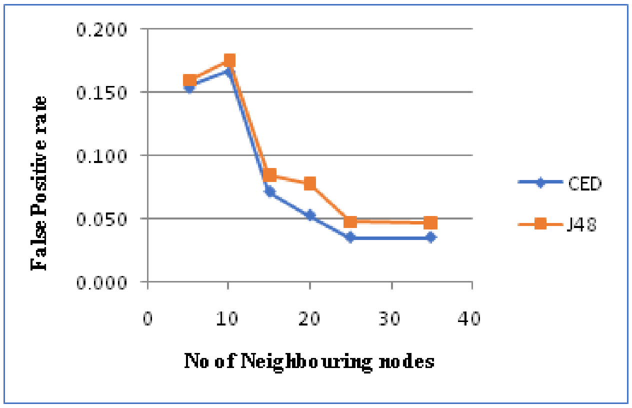


Fig. 7: Plot of False Positive Rate.

Fig. 8 represents the remaining energy level of the nodes. In multiples of 5 the faulty nodes are introduced. As the no of faulty nodes increase the energy level retains in the linear fashion for the CED algorithm. The parameter True positive rate vs. false positive rate reflects

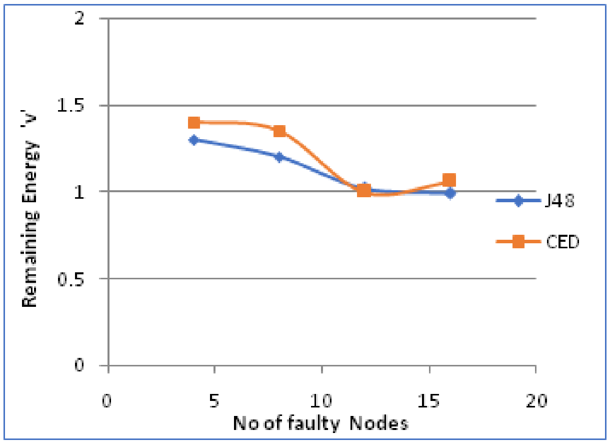


Fig. 8: Plot of Energy Level.

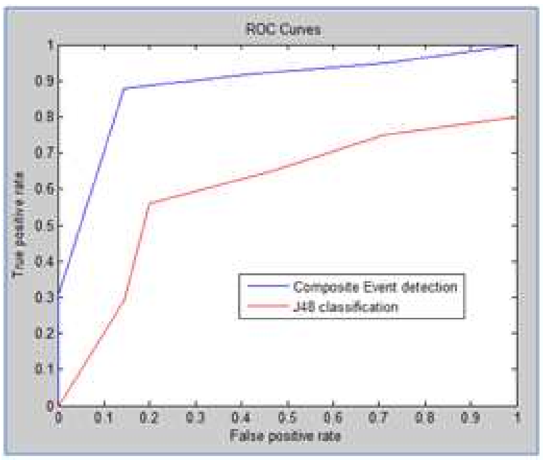


Fig. 9: ROC Curve.

the event accuracy which is analyzed in Fig. 9 and it is plotted in terms of ROC curve.

7 Conclusion

Sensor networks are highly dynamic in nature with holds multiple constrains in hostile environment. Hence the occurrence of the change in the environmental parameter has to be appropriately identified with high confidence rate. The composite event detection model was initiated with an idea of reducing the rate of the false alarm. In different perspective the fault alarm rate reduction was analyzed. Since the inherent characteristics of sensor node would lead to an intermittent fault. This occurrence should not mislead the event confirmation. The confidence parameter is updated by analyzing the one way variance that exists between the sensor node and across the sensor nodes in the detection window with the time frame. Based on that, a hypothesis is tested and according to that result the algorithm reect in the condence parameter. The fuzzy decision unit analyses the fire occurrence by using the reading of temperate and smoke parameter value in terms of spatial and temporal properties of sensor fields are analyzed. This shows that there was a drastic change in controlling the false alarm rate. In addition to that the confidence factor has supported a lot to further scale back the fake alert. The proposed algorithm is implemented in MATLAB. The simulation and test bed results show that the inclusion of Confident Factor of Sensor Node is found to yield better results compared to the earlier works.

References

[1] Callaway E.H., Wireless sensor networks: architectures and protocols, Auerbach Publications, New York, USA (2004).
[2] C. Buratti, A. Conti, D. Dardari, and R. Verdone, An Overview on Wireless Sensor Networks Technology and Evolution, Sensors, 6869–6896 (2009).
[3] J.N. Al-Karaki, and A.E. Kamal, Routing techniques in wireless sensor networks: A survey, IEEE Transactions on Wireless Communication, **11**, 6–28. (2004).
[4] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, Wireless sensor networks: a survey, Computer Networks, 393–422 (2002).
[5] N. Meratnia, B.J.V.D. Zwaag, H.W.V. Dijk, D.J.A. Bijwaard, and P.J.M. Havinga, Sensor Networks in the Low Lands, Sensors, 8504–8525 (2010).
[6] N. Xu, A Survey of Sensor Network Applications, IEEE Communications Magazines, (2002).
[7] Waltenegus Dargie, and Christian Poellabauer, Fundamentals of Wireless Sensor Networks: Theory and Practice, ISBN: 978-0-470-99765-9, John Wiley & Sons (2010).
[8] S. Li, S.H. Son, and J.A. Stankovic, Event Detection Services Using Data Service Middleware in Distributed Sensor Networks, Proceedings of the 2nd International Workshop on Information Processing in Sensor Networks, 502–517 (2003).
[9] http://nationalarchives.nic.in/writereaddata/html_en_files/html/22.GuidelinesforPreventiondetectionandControl.pdf
[10] Kazem Sohraby, Daniel Minoli, and Tajeb Znzati, Wireless Sensor Networks: Technology, Protocols, and Applications, ISBN: 978-0-471-74300-2, John Wiley & Sons (2007).
[11] L.A. Zadeh, The concept of linguistic variable and its application to approximate reasoning, Inform Sci. **8**, 199–245 (1975).
[12] Mengxia Zhu, Song Ding, Richard R. Brooks, Qishi Wu, Nageswara S.V. Rao, and S. Sitharama Iyengar, Fusion of Threshold Rules for Target Detection in Sensor Networks, ACM Transactions on Sensor Networks, **6**, (2010).
[13] G. Werner-Allen, K. Lorincz, M. Ruiz, O. Marcillo, J. Johnson, J. Lees, and M. Welsh, Deploying a wireless sensor network on an active volcano, IEEE Internet Computing, **10**, 1825 (2006).
[14] M. Bahrepour, N. Meratnia, and P.J. M. Havinga, Automatic Fire Detection: A Survey from Wireless Sensor Network Perspective (2008).
[15] L. Gu, D. Jia, P. Vicaire, T. Yan, L. Luo, A. Tirumala, Q. Cao, T. He, J. A. Stankovic, T. Abdelzaher, and B.H. Krogh,

Lightweight detection and classification for wireless sensor networks in realistic environments, Proceedings of the 4th ACM Conference on Embedded Networked Sensor Systems (2005).
[16] S.-J. Yim and Y.-H. Choi, Fault-Tolerant Event Detection Using Two Thresholds in Wireless Sensor Networks, 15th IEEE Pacific Rim International Symposium on Dependable Computing, 331–335 (2009).
[17] Hejun Wu, Jiannong Cao,Xiaopeng Fan Dynamic collaborative in-network event detection in wireless sensor network Telecommun Syst., Springer Science+ Business Media, New York (2015).
[18] Chinh T. Vu, Raheem A. Beyah and Yingshu Li, Composite Event Detection in Wireless Sensor Networks, IEEE, 264–271 (2007).
[19] M. Bahrepour, N. Meratnia, and P.J. M. Havinga, Use of AI Techniques for Residential Fire Detection in Wireless Sensor Networks, in AIAI 2009 Greece, 2009.
[20] D. Li, K.D. Wong, Y.H. Hu, and A.M. Sayeed, Detection, classification, and tracking of targets,Signal Processing Magazine, IEEE, **19**, 17–29 (2002).
[21] W. Xue, Q. Luo, L. Chen, and Y. Liu, Contour map matching for event detection in sensor networks, International Conference on Management of Data, Chicago (2006).
[22] M. Bahrepour, Y. Zhang, N. Meratnia, and P.J. M. Havinga Use of Event Detection Approaches for Outlier Detection in Wireless Sensor Networks, ISSNIP, Australia (2009).
[23] G. Jin and S. Nittel NED: An Efficient Noise-Tolerant Event and Event Boundary Detection Algorithm in Wireless Sensor Networks, 7th International Conference on Mobile Data Management (2006).
[24] B. Krishnamachari and S. Iyengar, Distributed Bayesian algorithms for fault- tolerant event region detection in wireless sensor networks, IEEE Transactions on Computers, **53**, 241–250 (2004).
[25] X. Luo, M. Dong, and Y. Huang On distributed fault-tolerant detection in wireless sensor networks, IEEE Transactions on Computers, **55**, 58–70 (2006).
[26] F. Martincic and L. Schwiebert, Distributed event detection in sensor networks Proceedings of the International Conference on Systems and Networks Communication, 43–48(2006).
[27] W. Xue, Q. Luo, and H. Wu Pattern-based event detection in sensor networks,Distributed and Parallel Databases, **30(1)**, 27–62 (2011).
[28] K. Ali, T. Anwaro, I.H. Naqvi, M.H.J., Composite Event Detection and Identification for WSNs using General Hebbian Algorithm, IEEE ICC Ad-hoc and Sensor Networking Symposium, 6463–6468 (2015).
[29] F. Bouabdallah, N. Bouabdallah R.Boutaba, Towards reliable and efficient reporting in wireless sensor networks, IEEE/ACM Transactions on Mobile computing, **7(8)**, 978–994 (2008).
[30] M.C.Vuran I.F. Akyildiz, spatial correlation based collaborative medium access control in wireless sensor networks, IEEE/ACM Transactions on Networking, **14(2)**, 316–329 (2006).
[31] C. Intanagonwiwat, R. Govindan D. Estrin Directed diffusion: a scalable and robust communication paradigm for sensor networks, ACM MOBICOM, Boston, USA (2000).
[32] A.V.U.P. Kumar, V. Adi Mallikarjuna Reddy, and D. Janakiram, Distributed collaboration for event detection in wireless sensor networks 3rd International Workshop on Middleware for Pervasive and Ad-hoc Computing, Grenoble, France (2005).
[33] K.-P. Shih, S.-S. Wang, H.-C. Chen, and P.-H. Yang, CollECT: Collaborative event detection and tracking in wireless heterogeneous sensor networks, Computer Communications, **31(14)**, 3124–3136 (2008).
[34] Davood Izadi, Jemal H. Abawajy, Sara Ghanavati, and Tutut Herawan A Data Fusion Method in Wireless Sensor Networks, Sensors (Basel), **15(2)**, 2964–2979 (2015).
[35] Krasimira Kapitanovaa, Sang H. Sona,Kyoung-Don Kang Using fuzzy logic for robust event detection in wireless sensor networks Ad Hoc Networks, **10** 709–722, (2012).
[36] Shukui Zhang, Hao Chen, Qiaoming Zhu, and Juncheng Jia A Fuzzy-Decision Based Approach for Composite Event Detection in Wireless Sensor Networks, The Scientific World Journal (2014).
[37] M. Marin-Perianu, P. Havinga D-FLER: a distributed fuzzy logic engine for rule-based wireless sensor networks Proceedings of the 4th International Conference on Ubiquitous Computing Systems (UCS), Springer-Verlag, Berlin, Heidelberg, 86–101 (2007).
[38] http://web.mst.edu/psyworld/tukeysexample.htm.

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