International Journal on Electrical Engineering and Informatics - Volume 12, Number 1, March 2020

Efficient Forest Fire Detection System Based on Data Fusion Applied in Wireless Sensor Networks

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Abstract: In this paper we propose an intelligent hybrid model for reliable and fast fire detection applied in Wireless Sensor Network platform. This model discusses a data fusion strategy hybridized with an intelligent information routing system based on a clustering method of sensor nodes located in the vicinity of the event. The transfer of the alert message to the base station is performed through the elected sensor nodes CH and IN. The alert message is transferred to notify BS in two successive levels of danger; first, the detection of the appearance of fire; second, the danger spread. The data fusion side is proposed in a hierarchical manner; the first step makes it possible to affirm the first appearance of fire detected by a first sensor node through a reasoning performed by the KNN classifier. The second is conditioned by the previous step, it allows in the positive case to perform an overall heterogeneous data fusion for a defined area where, in its first-level processing, data sorting operation are carried out using the K-means clustering. This processing allows ignoring unnecessary and incorrect data that influences the reliability of the detection. The magnitude of the event propagation is estimated in the second level using the Fuzzy Inference System in the final fusion center. This model shows, through its simulation experiments, a robustness of performance in terms of reliability of detection, rapidity of triggering of the alert, elimination of useless and redundant information, and will also guarantee an efficient energy consumption of the network which will lead to a remarkable extension of its lifetime.

Keywords: Wireless Sensor Networks, Data fusion, Event detection, KNN classifier, K-means clustering, Fuzzy Inference System.

1. Introduction

The advanced technological development of low power microelectronic circuits has contributed to the miniaturization of the design of wireless sensor nodes that become inexpensive, more powerful with low power consumption [1]. These sensors comprising a wireless sensor network (WSN) system [2] which, in its turn, is increasingly required in various critical applications. Without such a technology, the application of environmental monitoring against fires where human presence for surveillance of a large geographical area is very difficult and ineffective. Thanks to the application of the wireless sensor network system in the forest, monitoring of this environment will be more controlled, more reliable, more convenient, and less expensive. The wireless sensors deployed in this area has the ability to measure, process, detect, collaborate and communicate these physical measurements of this monitored area and forward them until reaching the base station [3], [4], [5].

However, several constraints influence the quality of service (QoS) of the WSN system, especially in the energy side where the life of a sensor node is generally affected by the global communication topology, and also by the quality of information measured, processed, and transmitted to the base station.

To overcome the various errors that may adversely affect the WSN system, and to increase the reliability of the information, and to reduce the redundant transmission of information, multi-sensor data fusion has been solicited in this case, contributing to solve these problems and improve the performance of the system [1],[2],[3]. This processing of data fusion has an

Received: February 18th, 2018. Accepted: Februari 28th, 2020
DOI: 10.15676/ijeei.2020.12.1.1

important and necessary effect, which cannot be replaced.

But it is also necessary to consider, in the monitored fields, an effective technique of routing information to the base station. This highly recommended routing technique will play a very important role in optimizing the energy consumption of the WSN and positively affects its lifetime through the life of its nodes, taking into consideration that the node has a limited energy source, which is likely to be consumed more by its transmission / reception module. The energy consumed based on a transmission of *k* bits data, from one node to another, depends also on the distance that separates these two nodes, and knowing that the base station is further from the zone (in various cases); thus, if the transmission of the measured data from the sensor nodes is done directly to the base station, the network will lose its energy resources quickly, die, and become ineffective.

In such a WSN system applied for environmental monitoring, there is a master node deployed in a limited area with the other sensor nodes intended to aggregate samples transmitted by these sensors and will, therefore, be responsible for processing and merging of these collected data. This will reduce the overall network traffic, minimize network energy consumption while increasing the reliability of the information transmitted, and in general all this information combined in the master nodes will be forwarded to the Sink through a predefined routing protocol. This Sink can function in some applications as a gateway that will allow the interfacing of information between the sensor network and the user (the control station) or it can be inside the final base station and thus representing its location.

So, this paper presents an intelligent approach based on multi-sensor data fusion, applied in wireless sensor network system for making fast and reliable fire detection alert in the first level of danger, and alerting whether it is a state spread of fire in the second level. This model has the particularity of interacting the network with the appearance of the danger while ensuring an intelligent and optimal exploitation of its sensors in a well-defined danger area; this approach consists of hybridization that is based on a method of data fusion and decision making with an intelligent information routing technique that efficiently allows the routing of data to the base station with a wise energy consumption. The proposed system will improve the quality of service in the reliability side of alerts transmitted to the base station, in the rapidity of detection of the danger, and also, in the efficiency of energy consumption in this network system that will lead to a maximization of its lifetime platform.

2. Related Work: Multi-sensor data fusion applied for event detection

Many researches on multi-sensor data fusion applied for event detection have been recently studied:

A two-level multi-sensor data fusion system was developed by E. Zervas et al. [6]. This mechanism consists in a first stage of a sequential test of the cumulative sums (CUSUM), allowing early detection of fires. The Dempster-Shafer algorithm was applied in the second stage of fusion, in order to reason about the fire probability.

The authors Ç. Elmas and Y. Sonmez, presented in [7] a designed data fusion system based on multi-sensors for reliable and fast forest detection and estimating the fire spread speed. The proposed system integrates for its processing operations some common data fusion algorithms, talking about Naïve Bays classifier, Artificial Neural network, image processing and Fuzzy Switching, the proposed approach shows through its experiment results that it can provide an effective strategy to cope this event.

In [8], Wen-Tsai Sung applied in a wireless sensor network system, the back propagation network technology (BPN) for the classification and fusion of multi-sensor data. The technique used, allows also the error correction with learning.

An approach of data fusion and decision making has been presented by Khanna & Cheema in [9]. This model uses the type II fuzzy logic algorithm, in order to estimate the probability and the direction of detected event. The multi-sensor network can be divided by several clusters, each of which is formed by member nodes with their own CH. the latter receives the data measured by the nodes of its cluster.

Another work proposed for predicting the forest fire was discussed by M. Saoudi et al, in [10]. This method is also applied using WSN, and performed based on Data Mining technique. The measured data provided by sensors are combined by integrating the Artificial Neural Network. This system shows good results in decision making, rapid reaction, and providing efficient energy consumption.

In [11] Arikumare et al. proposed a data fusion model for event (fire) detection. By reducing the transmission of the packets generated by the sensors, which are transmitted to the base station (BS) via the head node (CH), this mechanism has been able to reduce the redundant data. In a first place, the first two levels of the fuzzy inference system (FIS) are performed within the sensor node to decide, through its confidence factor, to transfer (or not) the measurements to CH where the last FIS level is performed.

And after a global reading and analysis of these bibliographic researches, and others, we have tried to design a hybrid model of rapid fire detection based on a platform of wireless sensor networks. This system is able to improve QoS quality of service of the network on two major aspects; on the one hand, in its energy consumption which will affect its lifetime through a proposed technique of intelligent clustering and data routing in the event of fire occurrence, this technique will partially exploit the network in the side of its data communication; on the other, this system guarantees a systematic performance improvement in terms of reliability of information, decision-making and early alerting in the case of event of danger. This alert is subdivided into two successive levels embodying two states of danger: the detection of fire appearance, and the fire spread state. These alert messages allow notifying and describing this zone under surveillance in efficient manner for the emergency authorities.

3. Proposed Approach

A. System Generalized Architecture

The proposed approach presents a reliable method of rapid fire detection and fire spread estimation based on the processing of multi-sensor data fusion and decision-making. This system allows also realizing an optimal energy management of the WSN to extend its life through an integrated intelligent data routing technique, this latter is conditioned by the appearance of the event.

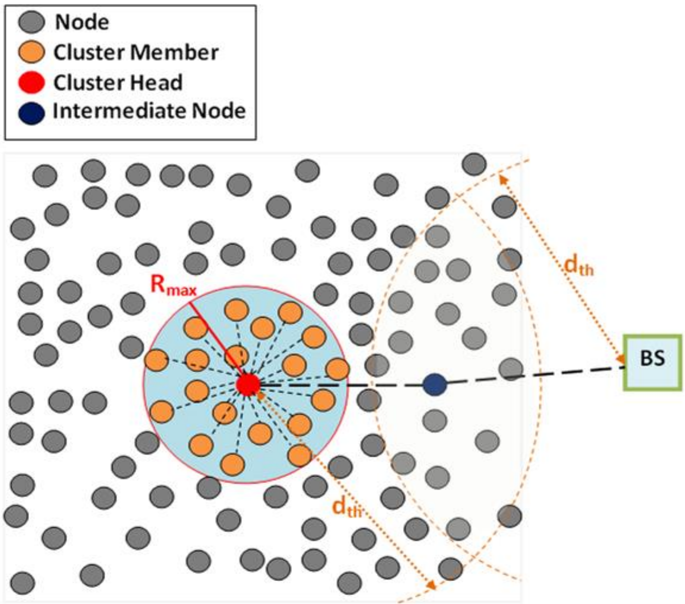

Figure 1. WSN architecture exploited in the proposed model.

So, this system makes it possible to decide before transmitting to the base station only the useful information, in case of a detected danger, two levels of possible alerts (see Figure 1):
The first alert illustrates the state of a presence of fire event based on a reasoning that takes into account the internal decision of the first sensor node with the confirmation based on the dominance of decisions of its four neighboring nodes, thus, this reasoning is carried out on the basis of the first detector node S_1 which aggregates the other decisions provided from these four neighbors. In the case of an affirmative collaborative decision, S_1 node sends a warning message of a primary level to the base station through an intermediate node named IN. This latter is elected statistically based on two criteria; first, on the distances that separate the IN from the BS and S_1, these distances must be less than a threshold distance denoted d_{th}; The second criterion evaluates the sensor by examining its residual energy which must be higher among others. Therefore, the sensor which approves to have at once these two criteria will be directly elected, for this round, as an intermediate node.

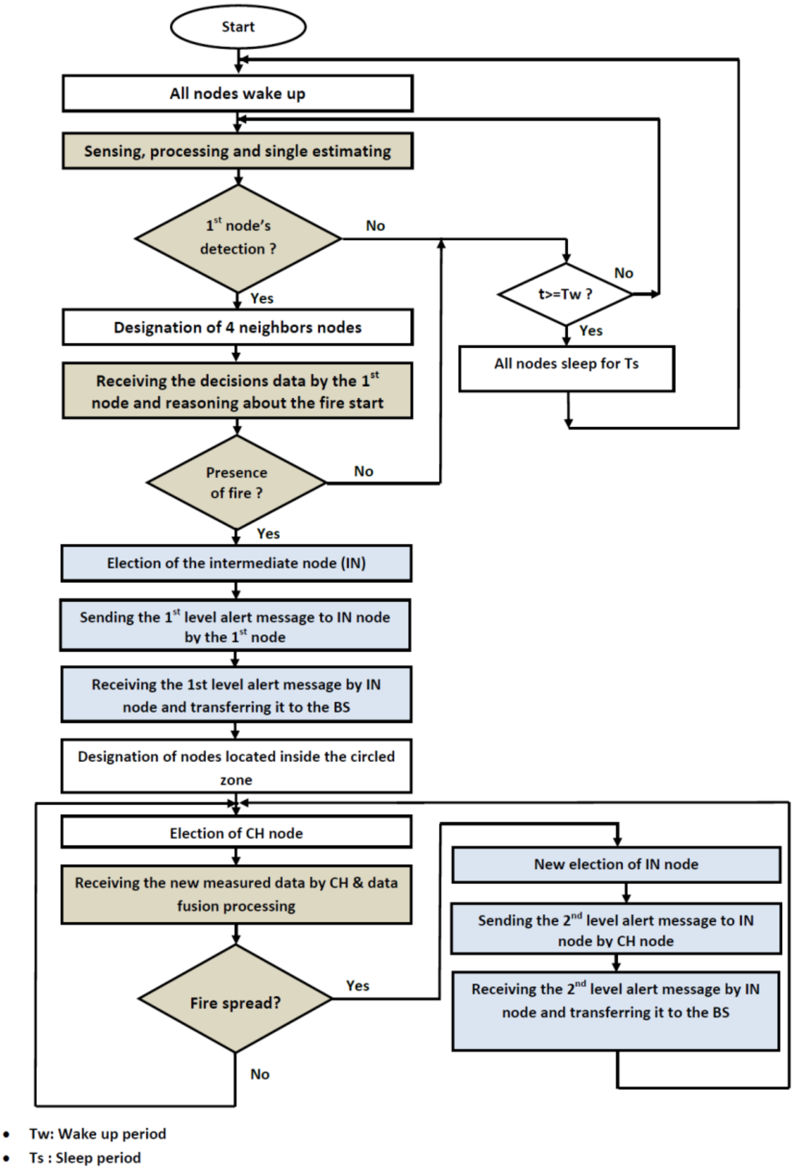

Figure 2. Flowchart of the proposed approach.

And since there will be a strong possibility that the fire will spread, it will be necessary, later, to determine continuously and quickly the extent of this event in propagation; the system designates a zone of analysis in the form of a fictitious disk with the radius R_{max} (fixed by user) and the center which is represented by the node S_1 (see an example in Figure 1). This zone of analysis is created in order to examine it locally of a possible propagation of fire through its intra-disk sensors, then all the sensors included in this zone become the members of the analysis cluster, with an elected cluster head denoted CH. The election of CH relies statistically only on its residual energy which must be higher compared to the other members, this CH node is recruited in order to aggregate all the data measured intra-cluster by the members, and execute the processes of information sorting, data fusion and fire danger estimation. In the positive case, a new alert message of the second level of danger considered to be sent to the BS through the IN which will be elected again in the same way as in the previous level.

This intelligent system allows itself, then, to exploit only one slice of the platform of the network in case of an occurrence of event (see Figure 1). And in the case of normal or non presence of the fire, the sensor nodes are able to switch periodically between two states: the sleeping state where the battery consumption is minimal and the waking-up state where the nodes establish an update of the measurements, and detect whether a possible danger appears in other locations. This will contribute to the optimization of the network energy consumption.

B. Network Model

The present model allows an efficient exploitation on the data communication side within the WSN deployed in the forest. This wireless data communication is established only on a part of its platform based on location of the fire detection. This approach also allows to route only useful information (alert messages and locations) to the base station, for that, some assumptions are taken into consideration:

- The sensor nodes are deployed in a random way, the distances between the nodes can be estimated based on the powers of the received signals.
- The platform of the sensor network is static once installed.
- All nodes have three types of physical sensors whose technical characteristics and their processing performances are similar.
- All nodes are capable of performing data fusion processing, and also being a cluster member (CM) or a cluster head (CH) or an intermediate sensor (IN).
- The BS is located outside the monitored area, its position is still static, and it has an infinite energy.

- Based Energy Model

This part discusses the calculation of energy consumption at the base of a node; this calculation-based is similar to that of the LEACH model discussed in [12].

Then, based on the first-order model [12], the energy consumed after transmitting a message of *m* bits over a distance of *d* is as follows:

$$E_{Tx}(m,d) = m \times E_{elec} + \varepsilon_{efs} \times m \times d^2 \quad (d \le d_{th}) \tag{1}$$

$$E_{Tx}(m,d) = m \times E_{elec} + \varepsilon_{amp} \times m \times d^4 \quad (d > d_{th}) \tag{2}$$

While energy cost for the reception of such a message is:

$$E_{Rx}(m,d) = m \times E_{elec} \tag{3}$$

The E_{elec} parameter in the equation illustrates the energy cost in electronic transmission and reception blocks. Thus, the energy consumed by amplification of the signal can be considered, by one of the two parameters ε_{efs} and ε_{amp}, the switching between these two parameters depends to a comparison result between threshold d_{th} and the distance d, the latter which separates a transmitter node of another receiver.

C. Data Fusion and Decision-Making Steps
C.1. Phase 1: Detection of Fire Occurrence
C.1.1. Single Node Decision

let n = 100 sensors deployed randomly in a matrix area of (100X100) m^2, and as already notified, each node can measure three different physical quantities: Temperature, Humidity, and Smoke, the three measured data are collected and processed by a classifier called K-Nearest-Neighbors (KNN) (see Figure 3) in order to estimate the appearance of the event based on single sensor, an estimate that clarifies the state of the capturing field of this node.

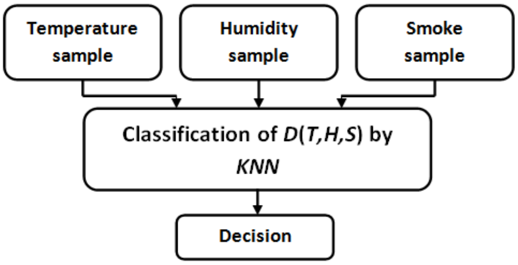

Figure 3. Single node decision process.

The estimation based on KNN technique [13],[14] ,elaborated by a single node Si, is based on a classification of the object named D_i (with $i = 1,2,3...n$) it is also called a "Target", which is composed of three coordinates composing a three-dimensional space, denoted: T_i, H_i and S_i representing these three measured samples. In addition, two 3D clusters are used in this application, denoted: (None-Fire) and (Fire) clusters (see Figure 4), which are considered, in this case, as a database through which the KNN estimator can refer to decide, they contain a variable samples of the three physical quantities in both the hypothesis (Fire) and (Non Fire), thus, the KNN classifies ,through its processing, the $D_i(T_i,H_i,S_i)$ in one of these two clusters. It should be noted that the interval ranges of these clusters have to be well defined taking into account the favorable conditions for generating the fire in different experiment cases; also, these intervals can differ slightly considering the climatic conditions of the zone which may vary from one place to another.

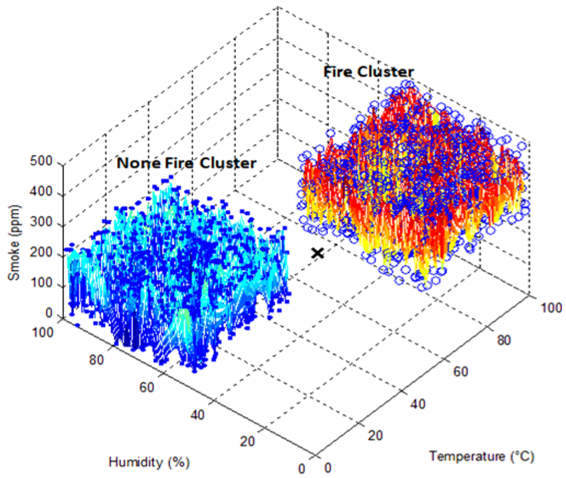

Figure 4. An example of a projection of D target over two database clusters (Fire and None Fire Clusters).

This classification is based on the measure of similarity between the D_i target, to be classified, and the objects of the clusters in order to define the K nearest neighbors, the data D_i is assigned to the cluster having a predominance number of K neighbors. (We choose $K = 5$ in this application). The measure of similarity or what is also called distance is defined in general by applying the distance of Minkowski [15].

In sum, this single estimate is given at the end by the following reasoning: when Di is assigned to the 'Fire' cluster then the binary decision denoted d_i (with $i= 1,2,3..n$), provided by the node S_i , is '1', otherwise it remains to '0'.

C.1.2. Local Collaborative Affirmation:

At the appearance of the fire, estimated by a first S_i node, there is a non-negligible probability that this sensor can provide erroneous measurements caused by an eventual failure inside it. These errors can negatively influence the reliability of this alert. And in order to provide accurate information and increase the credibility of alert, it is necessary to add additional information in the form of single binary decisions performed by the nearest neighboring nodes (as shown in Figure 5), the collaborative affirmation (4) will be reasoned based on the result of the predominance of '1' or '0' on the five binary data which is described below:

Let S_1 be the first sensor that detects the fire, this node is surrounded by four neighboring nodes [16]: S_2, S_3, S_4 and S_5 (see Figure 5), the operation of the primary collective estimate is described as follows:

$$S_d = \sum_{x=1}^{5} d_x \quad (4)$$

$$D_p = \begin{cases} 0, & S_d < Th \\ 1, & S_d \geq Th \end{cases} \quad (5)$$

Where S_d is the sum of the independent binary decisions d_x coming from five nodes, D_p represents the primary collective estimate whose resulting value is based on the comparison of the sum S_d of the decisions, with the threshold denoted Th, which is set by user (Th = 3 is considered to be used in this work).

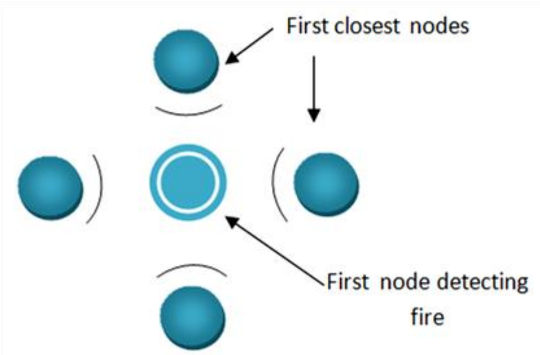

Figure 5. A first node detecting fire and its four neighboring nodes.

In brief, the estimate D_p, affirm collaboratively, at this stage, whether it is a fire event state; that will allow the system to alert quickly and reliably if there is a danger of fire since its first appearance.

C.2. Phase 2: Clustering, Sorting, and Fusing Data

C.2.1. Selecting Nodes Closest to Event:

After confirming the beginning of the fire in the localized area, it is very probable that the fire enters its phase of propagation. Therefore, this method tends to distinguish the node sensors, nearest to the fire event, among the n sensors deployed and the area before making a data fusion. To do this, the system define a processing zone disk whose center is represented by the first sensor S_1 and a user-defined maximum radius noted R_{max} , as illustrated in Figure 1. This surface disk remains at the base a small area on which all the measured data collected by sensors included in this disk are aggregated and processed through an elected CH node [17] in order to rapidly and reliably alert in case of a positive decision before this fire propagated over the entire area.

So, there is an aggregated sample vectors of the three measured parameters: Temperature and Humidity and Smoke, denoted respectively $\{Tex_j\}$,$\{Hex_j\}$,$\{Sex_j\}$,(with j=1,2,..z), these data vectors are not yet pre-processed for a central fusion since there may be erroneous data transmitted by faulty sensors. Besides, some redundant data can be provided by sensors that are still far from the event. All these kind of data can influence negatively on the performances of estimation and the sensitivity of the system. To overcome these different constraints, a processing operation for the extracted raw data is performed. This step is very crucial before forwarding to the central data fusion; the explanation of this global data fusion process will be detailed in the following section.

C.2.2. Overall Data Fusion Steps

This section discusses a global data fusion approach realized within the CH node, (which combines two successive levels of processing). This step allows a process based on a set of raw measurements inside an analysis disk surface already defined since the hypothesis of the beginning of the fire is assumed to be confirmed. The proposed approach allows collecting and processing all these heterogeneous physical quantities measurements to analyze them, distinguish the correct and useful measures and finally merge them with the aim of reasoning and estimating the final output. And since the system is applied to the environment, it has the advantage to treat about the fire spread danger, taking into consideration that atmospheric events can be complex, less precise or vague in nature. Then, in this approach, the method aims to perform a reliable global estimate while maintaining a good flexibility to the various constraints that can be confronted with the atmospheric events and also with different errors that may affect the estimation reliability.

So, in this part, two known algorithms are applied, the first one is a classifier named K-means [18],[19], applied separately in the first fusion level, for each category of measurements, while in the second phase the fuzzy inference system [20],[21] (This step is inspired by the model discussed in [20], is used in the fusion center that is also called the second fusion level, in order to perform an overall reasoning, to evaluate and to estimate the extent and severity level of the event danger in its propagation. The overall process is illustrated in Figure 6.

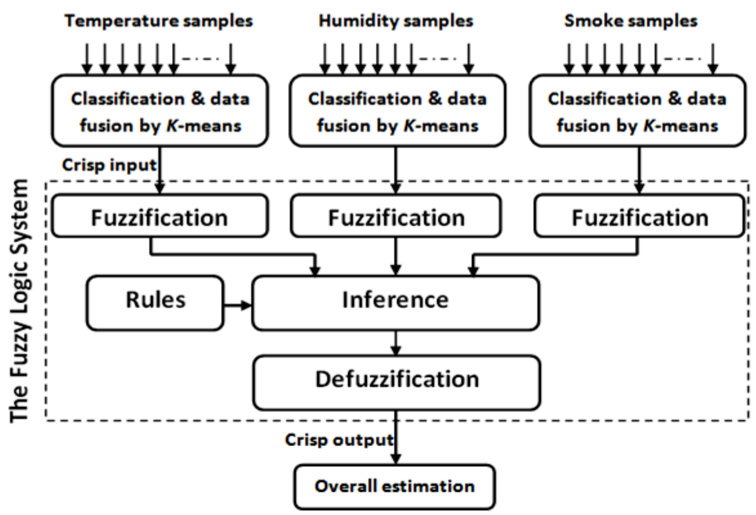

Figure 6. Overall data fusion structure relative to the collected measurements in the disk area.

C.2.3. Sorting, and Fusing Homogeneous Data

K-means is one of the best known partitioning methods used first by James MacQueen in 1967 [18],[19], whose objective is to extract the *K* clusters data which are aggregated by a better partition where each cluster is represented by a centroid closer to its objects. It, therefore, allows to minimize the intra-cluster variance and to maximize the variance of the inter-cluster.

In the first level processing, the application of this clustering method by K-means is used for data sorting which is based on the samples measured by CM nodes within the processing disk and aggregated by CH node [20], [22], to do so, the unnecessary data will be discarded after selecting the correct samples for each category (see Figure 7).

- In the case of non-propagation of fire, the choice will be in favor of the subset having a dominance of objects (data) among others.

- In the case of the existence of fire propagation, the fire cluster which constitutes, at least, five collected data will be in priority selected as a sorted correct data (see Figure 7).

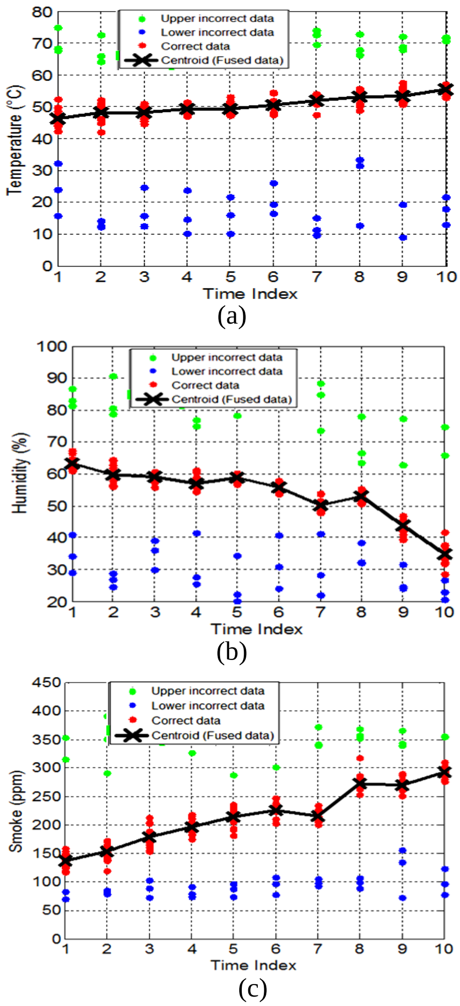

Figure 7. A data clustering performed by K-means, and extracting the centroid of the sorted subset (A simulation over 21 nodes of which: 6 in failure state or still far from the fire zone and 15 detect the fire. *K*=3).

This operation is carried out independently for each category of measurements, the centroids resulting from Temperature, Humidity and Smoke, denoted XG_T, XG_H and XG_S represent the independent outputs of a homogeneous data fusion resulted from the first level, (As shown in Figure 7).

The performance of this treatment is evaluated using ROC curve, which is illustrated and discussed in the section of the simulation results.

C.2.4. Central Fusion of Heterogeneous Data

In the second level of treatment, the state of the zone is reasoned and evaluated based on the three centroids that are extracted from the primary level and used after as inputs for this final processing. The use of the fuzzy inference system (FIS) is strongly recommended for such reasoning. It is a very useful method for such a system with a real or natural input, which may be too complex and imprecise for treatment [20]. Its principle is to be able to estimate output parameters while providing the system with a set of rules formulated in natural language.

The structure of the fuzzy logic system is divided into three essential phases [20]. The first phase called fuzzification, which allows transforming the data input into a linguistic variable, in other words, this phase translates a quantitative data input into a qualitative linguistic variable through a function defined called: membership function, which is used to associate numerical data with each linguistic variable. Note that the number of these functions may vary according to the desired resolution and can be different from one application to another. In this work, there is three fuzzification phases designed to transform the three numerical values (input fuzzy variables) of Temperature, Humidity and Smoke centroids (called previously XG_T XG_H and XG_S), into qualitative linguistic variable associated by one of these three membership functions named respectively, LOW, MEDIUM and HIGH, these membership functions are defined by user for the three input variable categories (as shown in Figure 8, Figure 9 and Figure 10). As for the output variable, which is the estimate of danger in propagation, the defined membership functions are VERY LOW, LOW, MEDIUM, HIGH and VERY HIGH (see Figure 11). At the output of fuzzification process, linguistic variables for the three categories are extracted to be used in the second step.

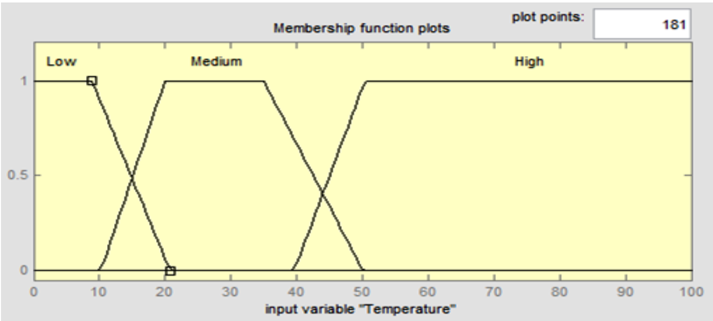

Figure 8. Membership functions for Temperature.

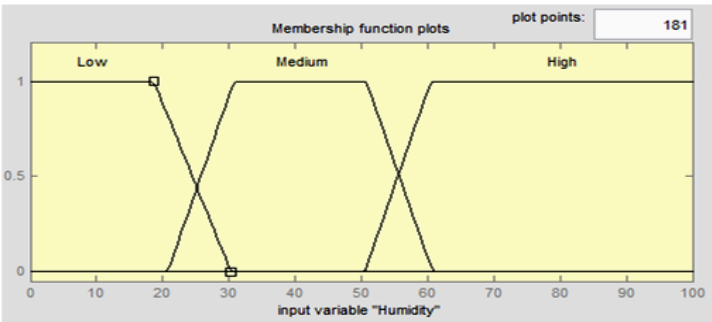

Figure 9. Membership functions for Humidity.

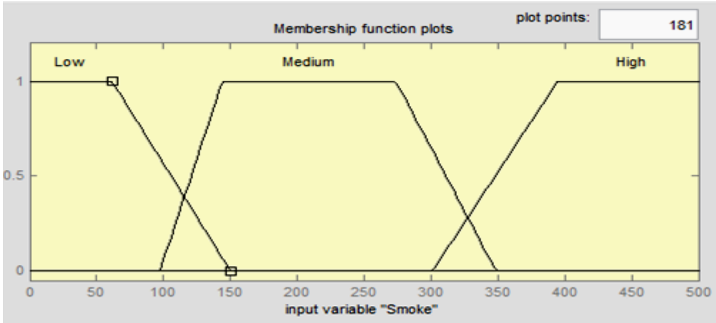

Figure 10. Membership functions for Smoke.

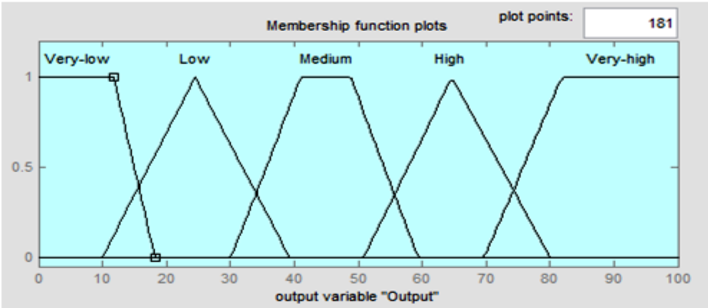

Figure 11. Membership functions for event danger estimation.

Regarding the second phase, it represents the engine of inference on which a set of rules of inferences are performed. (Example of a single defined rule: IF Temperature is HIGH and Humidity is LOW and Smoke is HIGH THEN Fire danger probability is VERY HIGH). And it is through human expertise that a set of knowledge is recorded on the system. This knowledge is exploited to apply these rules of inferences [20], and this phase will generate, at its output, a series of commands in the form of linguistic variables where each command is generated by a rule.

Regarding the definition of the number of rules used in this application, it is based on the number of input variables which is equal to three in this application, each of these input variables is relative to three fuzzy linguistic variables [20], which summarizes that the possible combinations for these input variables are $3^3 = 3x3x3 = 27$ combinations, that therefore, represent the total number of rules used.

Figure 12, Figure 13, and Figure 14 illustrate the FIS output surface of fire spread danger probability based on the three physical parameters. These simulation results are extracted using the Fuzzy Logic ToolBox under MATLAB environment [25].

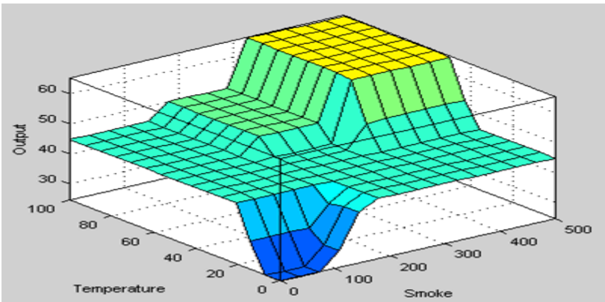

Figure 12. FIS output surface of fire propagation probability with the respect to Temperature and Smoke.

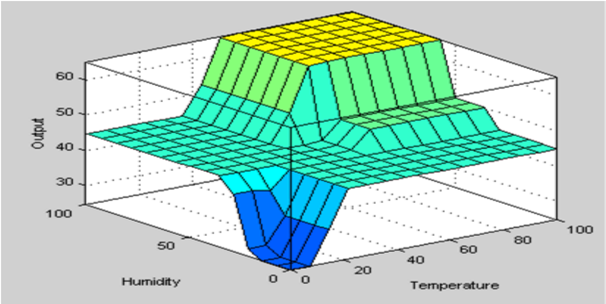

Figure 13. FIS output surface of fire propagation probability with the respect to Humidity and Temperature.

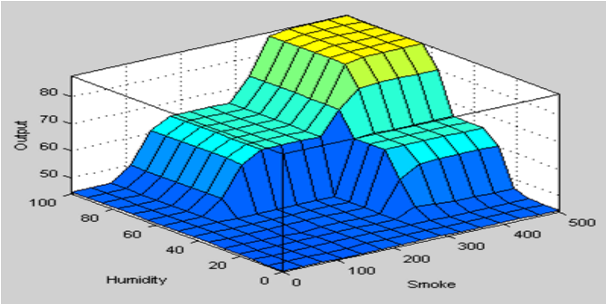

Figure 14. FIS output surface of fire propagation probability with the respect to Humidity and Smoke.

Finally, the last phase called defuzzification that is responsible for merging the commands generated by the inference engine in order to outcome a single command and transform this resulting parameter into a crisp number that represents the output final estimation of the FIS system.

D. Experiment Simulations & Results

D.1. Clustering, Sorting and Fusing Data

The following Figure 15 of the *ROC* curves [23],[24] describes the performance of the proposed method applied by K-mean, after aggregating only data inside the treatment disk compared to the raw data fusion method (performed as a data average). (The treatment of temperature measurements is taken in this example of simulation)

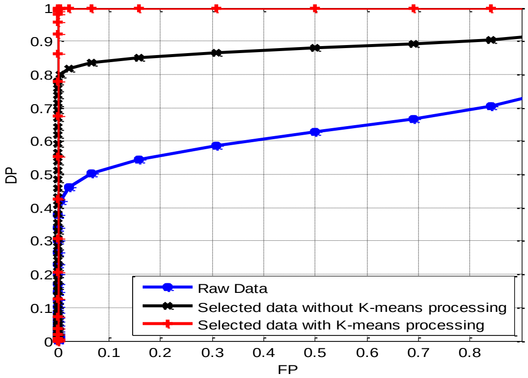

Figure 15. A ROC performance evolution based on the selected data processed by K-means clustering, K=3, with the respect to temperature collected samples.

It is clear that after, clustering data, eliminating erroneous and none meaningful data, and making a homogeneous data fusion (resulting the centroid) by the K-means, the performance of the system has increased significantly by increasing the probability of detection, and on the other hand, it allows decreasing the influence of the probability of false alarm. Consequently, this proposed step proves its importance in increasing the accuracy of the system affected with the inputs data before carrying out the second level data fusion.

D.2. System Output Performance

To evaluate the competence of the system in terms of reliability of fire propagation estimation, sensitivity and speed of alert, we consider a case of fire occurrence affirmed in advance by a collaborative estimate of 5 neighboring sensors. The analysis surface, designated subsequently, comprises 21 sensor nodes deployed randomly (20 CM and a CH) , the propagation is supposed to be in the form of a disk whose center is the first node location, where its surface varies and grows continually over 4 successive levels (*P1, P2, P3, P4*), (as shown in Figure 16). Thus, in each studied present level there are nodes detecting the fire, while the others, outside this level, are supposed far from the event, and at that moment, their measurements interpret a normal situation on their territories until the fire spread reaches them. Each of these four levels includes a limited number of sensors that detect fire, illustrated as follows:

- *P1* Level: 5 nodes/21 detect fire.
- *P2* Level: 10 nodes/21 detect fire.
- *P3* Level: 15 nodes/21 detect fire.
- *P4* Level: 21 nodes/21 detect fire.

We considered that the *P0* level (see Figure 17) reflects a situation of non-propagation of fire after a prior detection of fire occurrence by nodes with number less than five (this number of nodes can be 3 or 4).

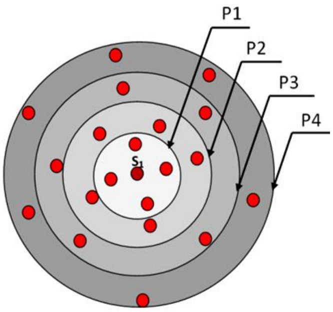

Figure 16. Definition of the four levels of propagation within the analysis surface

Figure 17 illustrates the estimated probability of danger severity using the proposed approach in different levels of propagation. These estimation outputs are compared to the event detection model discussed by P. Manjunatha et al, in [20] which applies the fusion inference system (FIS), fed in inputs by the estimated average of each variable.

Note that this simulation experiment refers to intra-disk aggregated data, it is based on the parameters described in Table 1:

Table 1. Parameters of probability density functions, that resumes the assumed data taken on both hypotheses.

	Assumed data in normal condition		Assumed data in fire condition	
	μ_0	σ_0	μ_F	σ_F
Temperature	27°C	5	55°C	10
Humidity	60%	10	20%	15
Smoke	90ppm	40	400ppm	45

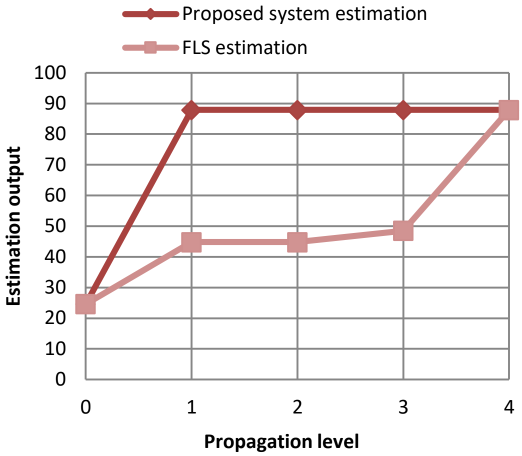

Figure 17. Probability of danger in propagation

The final result is a probability output that estimates the magnitude and severity of this fire propagation on the disk surface, after having previously detected and confirmed the appearance of the fire. And according to Figure 17, the estimate of the propagation of danger using the proposed approach is more efficient in terms of rapidity and reliability of alert, compared to the model discussed by P. Manjunatha et al in [20], whose estimated alert level has become maximal only when the propagation reaches the entire surface of the disk in the level *P4*, contrary to the proposed approach, which estimates the state of danger in propagation from its beginning in the level *P1*. Finally, this proves that the proposed approach demonstrates its robustness for early detection and sensitivity to the danger propagation.

D.3. Energy Consumption Performance

Another simulation experiment is developed. Its objective is to see the impact of energy consumption on the wireless sensor network (defined in this present work), assuming the existence of fire that manifests itself in a region far from the BS with a center location of (100,0), and using the proposed model that is evaluated and compared to the routing protocols LEACH [12] and M-GEAR [26] as shown in Figure 18 and Figure 19. The simulation on MATLAB is executed over 600 rounds; thus, the parameters of this simulation experiment are defined in Table 2:

Table 2. Simulation parameters

Parameter	Value
Network area	100m x 100m
Number of network nodes	100
Initial energy of node	0.1 J
Transmitter Electronics	50 nJ/bit
Receiver Electronics	50 nJ/bit
Sleep Energy	5nJ/bit
Transmit amplifier (εamp)	0.0013 pJ/ bit/m^4
Transmit amplifier (Efs)	10 pJ/ bit/m^2
Number of Rounds	600
Data transmission	4000 bit

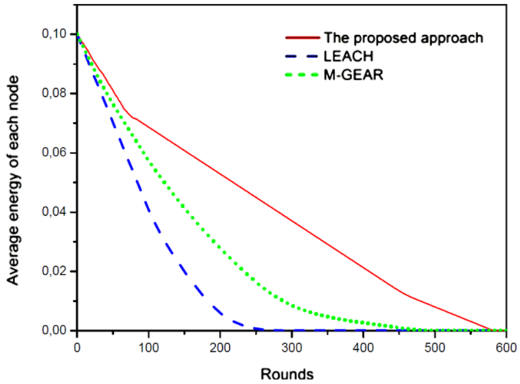

Figure 18. Node average energy during 600 rounds.

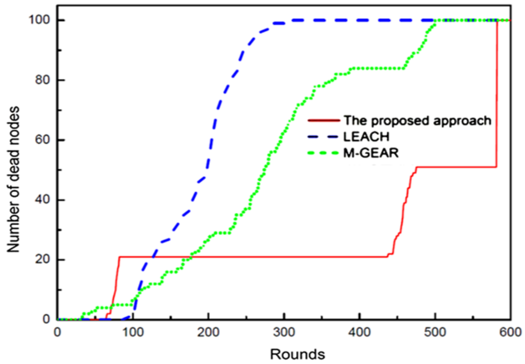

Figure 19. Variation of dead nodes number during 600 rounds.

Figure 18 describes the average energy consumed for each node during 600 rounds using the proposed approach compared to the utilization of the two existing protocols LEACH and M-GEAR. Thus, we can notice that the average energy consumed by using our approach is too low compared to those used by LEACH and M-GEAR. The proposed approach succeeds in maintaining network activity as long as possible. Moreover, in Figure 19 which shows the number of nodes of the network die, during these 600 turns, the result shows well that the network using the proposed approach presents a minimal number of the nodes which die during these turns compared to the use of LEACH and M-GEAR. On the other hand, we can notice that in Figure 19, the curve based on the proposed approach, goes up on three levels of stairs. The first level is reached in the vicinity of 80 rounds, with a number of 21 nodes which are dead, these nodes represent, obviously, the member nodes (intra-cluster), as the sensor nodes, included in this analysis disk, are more exploited and concerned in data communication with respect to the whole platform. In the second level, a number of dead nodes are added. They represent the IN nodes previously elected and returned later to their normal operating state after the death of the analysis cluster nodes. The last level represents the rest of the sensors nodes of the platform. These nodes are the last to die since they were the least exploited by the wireless communication module.

Finally and after this simulation experiment, we can conclude that the proposed hybrid approach is very reliable and efficient in the energy consumption of the network. Hence, this system is able to keep the nodes running longer, as well as extend the network lifetime as long as possible.

4. Conclusion and Future work

In this work, an intelligent data fusion system for a detection of fire has been proposed. This approach guarantees a reliable and fast detection of fire, and also, it allows a smart and effective rooting technique of meaningful data with a wise management of energy consumption. This system is based on aggregation of data of heterogeneous sensors types that are deployed in a restricted and well-defined natural area.

We summarized the characteristics of this adopted mechanism as well as its advantages shown through the simulation results, as follows:

- Early and reliable fire detection based on a minimum of sensors (3 to 5 nodes) leading to a first level alert. This detection is based on an individual decision of the first sensor node with the collaboration of these 4 closest neighbors, the decision making being carried out on the individual node using the KNN classifier.
- The second alert estimates the spread of the fire based on aggregated intra-cluster data performed within an elected CH. The process of fusing these data is established on two major levels:
  - The purpose of the first level is to eliminate erroneous data before reaching the information fusion center. This sorting of information is performed using the intelligent concept of "clustering" near event nodes, with the K-means partitioning method. This process considerably minimizes the false alarm rate and contributes to increase the reliability of the final estimate which will be evaluated in the second level by the final processing center.
  - The second level is based on the fuzzy inference system. The latter has the advantage of handling the ambiguity and the uncertainty occurring in such an environment in order to evaluate a final estimate of the danger and its propagation.
  - The estimate of the propagation of danger using this system is more efficient in terms of robustness for early detection and sensitivity to the event propagation, compared to the standard fuzzy inference system.
- The integrated intelligent information routing method, is more efficient than LEACH and M-GEAR. It ensures, in hybridization with the fusion system, an effective and wisely energy consumption of the network, making it possible to enhance and extend the lifetime of network system.

As a future work, it is planned to establish, as a first goal, a real hardware implementation of the proposed model on a WSN platform. We will be able subsequently to carry out a set of tests submitted under different climatic conditions in order to study the results, modify its parameters, and re-evaluate the performances of this system in this real experience.

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