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FAST AND ACCURATE RESIDENTIAL FIRE DETECTION USING WIRELESS SENSOR NETWORKS

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Abstract

Prompt and accurate residential fire detection is important for on-time fire extinguishing and consequently reducing damages and life losses. To detect fire sensors are needed to measure the environmental parameters and algorithms are required to decide about occurrence of fire. Recently, wireless sensor networks (WSNs) have been used for environmental monitoring and real-time event detection because of their low implementation costs and their capability of distributed sensing and processing. Although there are several works on fire detection using WSNs, they have rarely paid sufficient attention to investigate the optimal sensor sets and usage of suitable artificial intelligence (AI) methods. Therefore, by aiming at residential fire detection, this paper investigates proper sensor sets and proposes AI-based techniques for fire detection in WSNs. The proposed methods are evaluated in terms of detection accuracy rate and computational complexity.

Key words: artificial intelligence, residential fire detection, Wireless Sensor Networks (WSN)

1. Introduction

Fires may happen in various places; examples include residential places, forests or public spaces. Since it can have catastrophic outcomes, any practice facilitating fast and accurate fire detection and extinguishment is definitely valued. In this regard, the aim of this paper is to show the environmental saving effect of the wireless sensor networks (WSNs) and their capabilities for environmental monitoring. Therefore, applicability of WSNs for residential fire detection is investigated, and then the proposed approach can be extended to other types of fires or further catastrophy detections. Additionally, this paper brings the two fields of environmental monitoring and the wireless sensor networks (WSN) together and allows them learn from each other's experience and expertise by integrating the existing knowledge of researchers in environmental monitoring field to WSN project (which is a newer concept).

By looking back to the basic notions of fire alarms using electronic devices, it can be seen that use of smoke sensor is the preliminary tool for detecting fires. Smoke sensors are generally either responsive to air ionization or obscuration (Brain, 2000). The problem with such simple detectors is that they are prone to false alarms because they assume that only fires and nothing else may produce smoke. However, lighting a cigarette or toasting a bread may also generate smoke and consequently cause false alarm (Milke, 1999; Gottuk et al., 2002). Generally, to reduce false alarms and perform fire detection accurately, two classes of approaches are used. The first class uses one type of sensor and conducts the fire detection using a complex algorithm (e.g., Thuillard, 2000). In contrast, the second class uses multiple sensors and performs the detection by a simple mathematical operation (e.g. Gottuk et al., 2002). Some researchers have also attempted to unite both classes by combining a couple of sensors along with a roughly complex algorithm (for instance using artificial intelligence techniques instead of simple arithmetic operations) to augment detection rate (Cestari et al., 2005). In recent studies, wireless sensor networks (WSNs) have also been proposed for fire detection (Bagheri, 2007; Bernardo et al., 2007; Marin-Perianu and Havinga, 2008; Pripužic et al.,

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2008; Tan et al., 2007; Yu et al., 2005; Yang et al., 2006; Zhiping et al., 2006). In this type of research, fire detection in residential areas as well as forests and mines are considered.

Nevertheless, in spite of many achievements in the area of classical fire detection in terms of selecting optimal sensors and algorithms, these achievements have often not made their own ways into the WSNs field. The extensive knowledge of the traditional fire detection and environmental monitoring communities is crucial for the WSN community to devise precise fire detection algorithms. Data processing and reasoning expertise of the environmental scientists is a valuable help for the WSN researchers to have a better understanding of the environment and its phenomena. On the other hand, sensing, communication, collaboration and reasoning capabilities of wireless sensor nodes pervasively deployed over large areas can speed up the process of fire detection and guarantee the detection accuracy and consequently save the environment.

In this paper, we use the optimal sensor set recommended in (Cestari et al., 2005) and propose fire detection algorithms using AI approaches (because of their learning capability to deal with dynamic nature of network and observed phenomena, reasonable accuracy and computational cost). We explicitly investigate applicability of the Feed Forward Neural Networks (FFNN), Support Vector Machines (SVM) and Naïve Bayes methods in terms of detection accuracy and computational complexity

The rest of this paper is structured as follows. Section 2 concisely reviews previous contributions to fire detection using WSN. In Section 3, a brief introduction to WSNs is presented. In Section 4, our proposed fire detection techniques are introduced. Section 5 reports the experimental results. Finally, some conclusions and lessons learned are given in Section 6.

2. Literature review

Since this study is focused on fire-detection in residential area from a WSN perspective, the focus of the literature review is on the WSN-based fire detection techniques and not on the classical fire detection approaches. For a complete literature survey on fire detection from classical perspective, the reader can refer to our technical report (Bahrepour et al., 2008).

Existing WSN-based fire detection techniques are either threshold-based (Lorincz et al., 2006; Liang and Wang, 2005; Segal et al., 2000; Vu et al., 2007; Werner-Allen et al., 2006) or pattern-matching based (Jin and Nittel, 2006; Li et al., 2002; Marin-Perianu and Havinga, 2008; Zoumboulakis and Roussos, 2007).

Threshold based techniques define a threshold value for their sensor readings and when the sensor value is larger or smaller than the pre-defined threshold value, an alarm is generated. To avoid fixed and assumption-based thresholds values, Liang and Wang (2005) presents an automatic-selected threshold value approach, in which the threshold value is dynamically calculated by a sliding window technique. In case of having more than one feature, Vu et al. (2007) propose evaluating various sensor values separately by considering them as an ‘atom’ or distinct value. For example, if fire is detected using both smoke and temperature sensors, an alarm will be generated when temperature exceeds 30^{o}C and smoke exceeds 100 mg/L. Lim et al. (2007) introduce generic fire detection and rescue support system, which they claim to be applicable for any other disaster recovery.

In the pattern-matching studies, techniques such as contour maps (Xue et al., 2006), sensor-reading maps (Jin and Nittel, 2006), and distributed fuzzy logic (Marin-Perianu and Havinga, 2008), are proposed. Map-based studies define an acceptable range for sensor values, which exceeding from it generates an alarm indicating a fire event.

WSN based fire detection techniques have not only been proposed for residential fires but also for forest and mine areas (Bagheri, 2007; Pripužic et al., 2008; Tan et al., 2007; Vescoukis et al., 2007; Yu et al., 2005; Zhiping et al., 2006; Zervas et al., 2007). The most significant difference between detecting residential fire and fire happening in other locations is the optimal set of sensors to be used, while detection schemes remain almost intact.

3. Introduction to Wireless Sensor Networks

Wireless sensor networks (WSNs) were emerged by developments in processing technologies and wireless communications. These developments have facilitated production of small-size, low-cost sensor nodes with sensing, computation and short-range wireless communication capabilities. WSNs consist of a collection of nodes organized as cooperative networks (Hill et al., 2000). Each sensor node contains one or more processors (CPU or DSP), may also contain multiple kinds of memories (program, data or flash memory), have a transmitter, a power sources (usually a battery) and accommodates various sensors (Stankovic, 2008). WSNs can provide not only fine-grained real-time data of their sensor readings but also detect time-critical events. This means, in circumstances like fires, they can generate alarm signal to make a notification of the current event. These capabilities make a wide variety of applications for WSNs; examples include environmental and habitat monitoring, object and inventory tracking, health and medical monitoring, battlefield observation, industrial safety and control. Fig. 1 illustrates a sensor node.

4. WSN-based Fire Detection

Use of temperature sensor to detect fire is a common practice in the WSN community. Although temperature sensors are probably the simplest and the most obvious sensors for fire detection, studying various sources in the classical fire detection field reveals that all researchers agree on the fact that it alone is not a suitable indicator for fire, and gas concentration sensors result in a better fire detection and discriminating fire and noise sources (Milke, 1999; Cestari et al., 2005).

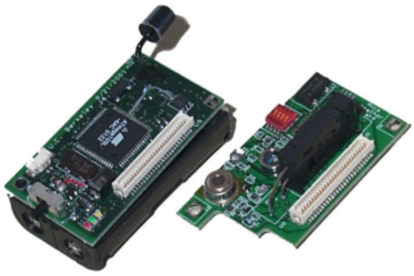


Fig. 1. A sensor node (Mainwaring et al., 2002)

In our approach, we adapt the optimal sensor set from (Cestari et al., 2005) and use temperature, ionization, photoelectric, and CO sensors. We assume that every sensor node in the WSN deployed in a building has all the required sensors. In this case, communication overhead between neighboring nodes is avoided and each sensor node can detect fire locally by itself. Local decision making also saves the energy of sensor nodes since data transmission is very energy consuming.

To be suitable for resource-constrained wireless sensor nodes, fire detection algorithms need to be computationally inexpensive yet accurate. For this reason, we propose to use Feed Forward Neural Network, Naïve Bayes classifier, and Support Vector Machines (SVM). Subsections 4.1-4.3 provide information about these classifiers and the reasons why they are useful for WSN.

4.1. Feed Forward Neural Network (FFNN)

The artificial neural network (ANN) is a mathematical model or computational model based on biological neural networks. It is composed of an interconnected group of artificial neurons and processes information using a connectionist approach for computation (Wikipedia). Feed forward neural network (FFNN) is a sort of the neural networks, in which each layer is fed by its behind layer (Mehrotra et al., 1996). FFNN consists of one input layer, one or more hidden layers and one output layer.

The challenge of such networks is finding the appropriate weights for these networks. The process of finding these weights is called 'learning' or 'training' the network. The training job may be very complicated and time consuming but it is usually performed once. If the training phase is conducted offline, then programming the FFNN into sensor node is then simple. FFNN can be programmed into sensor nodes as a set of business rules (if-then-else rules). By applying the aforementioned approach, an arbitrary network can be formulated as Eq. (1). By doing so, FFNN is turned into an explicit mathematic formula to be easily programmed into sensor nodes.

$$Output = \left[W_{3,1} \times \sum_{j=1}^{3} (W_{1,j} \times I_j)\right] + \left[W_{3,2} \times \sum_{j=1}^{3} (W_{2,j} \times I_j)\right] \quad (1)$$

4.1.1. FFNN Computation Complexity

Training phase is the most time and resource consuming part to make FFNN ready for classification task. However, as we consider that FFNN is trained once (in a computer) and then is programmed into the sensor nodes, we ignore the complexity of training phase.

The computation complexity of an FFNN with m neurons in its input layer (number of features), n neurons in hidden layer, and p neurons in output layer is shown in Eq. (2):

$$O_{FFNN} = O(m \times n \times p) \quad (2)$$

In this calculation the multiplication operator is considered as the key for computation complexity calculation. In Eq. (2), $p = 1$, for fire detection because fire detection can be conducted by only one output layer (e.g., -1 for nuisances, 0 for none-flaming fires and 1 for flaming fires).

4.2. Naïve Bayes classifiers

A Naïve Bayes classifier uses Bayesian statistics and Bayes' theorem to find the probability of each instance belonging to a specific class. It is called Naïve because of emphasizing on independency of the assumptions. To find the probability of belongingness of each instant to a specific class, Eq. (3) can be used which expresses the probability of an example $E = (x_1, x_2, ..., x_n)$ belonging to class c (Zhang, 2004).

$$p(c \mid E) = \frac{p(E \mid c)p(c)}{p(E)} \quad (3)$$

Similarly to FFNN, Naïve Bayes is algorithmically simple and computationally light to be programmed into sensor nodes. The most time and resource consuming part is computation of $p(E \mid c)$. This probability calculation is important to make the classifier more accurate. In basic literatures of pattern recognition or machine learning, it is proposed that this probability can be estimated by some standard data distribution such as Gaussian or Poisson (Alpaydin, 2004). To do a more accurate probability calculation, a histogram approach can be used. The histogram partitions data into several intervals and counts the data frequency within each interval. Frequency of repetition in each interval can show the probability of each instance belonging to that interval. The data frequency for each interval is obtained by dividing the total instances on each interval by total instance in the respective class (that is also called normalization).

4.2.1. Naïve Bayes computation complexity

We assume that training phase of the Naïve Bayes classifier is made once offline and then the probability table is programmed into the sensor nodes. In this case computation complexity is calculated for seeking the table only. Therefore, the computation cost of Naïve Bayes is based on the Eq. (4), where m is number of features, i is number of classes, and j is number of intervals.

$$O_{NaiveBayes} = O(m \times i \times j) \qquad (4)$$

4.3. Support Vector Machine (SVM)

Support vector machine (SVM)-based techniques are from the family of classification-based approaches. The main idea of these techniques is to separate the data belonging to different classes by fitting a hyperplane that produces a maximal margin. The basic notion of SVM is to separate two classes of data with only one line (or a hyperplane). Since this hyperplane may not be possible to find, data are mapped into higher dimensions. This process of mapping into higher dimension is iteratively performed till in a certain dimension this hyperplane can be found. Fig. 2 (a) demonstrates an example of 2D data that are not linearly separateable. However, the same data in 3D space can be separated by a hyperplane (Fig. 2 (b)).

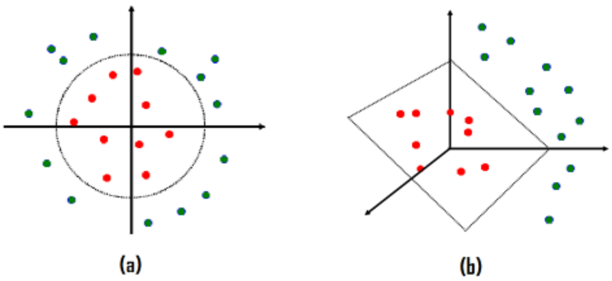


Fig. 2. (a) sample data in 2D dimension; (b) the same data in 3D dimension

Finding this hyperline offline and using it online to find data belonging to each class is a suitable approach for the WSNs. In this way, SVM classifier can be formulated as a mathematical formula that inputs data and outputs the class of data.

4.3.1. SVM computation complexity

The most complicated part of SVM is mapping the data into a higher dimension and finding the optimal hyperplane. This process belongs to the training part and is only performed once offline. To do the classification, only a comparison with the hyperplane is needed. By ignoring the training costs, Eq. (5) presents the complexity of SVM, where m is number of features, i is number of classes (or data vectors).

$$O_{SVM} = O(m \times i) \qquad (5)$$

4.4. D-FLER

D-FLER is a distributed detection system that combines individual sensor reading with neighboring observations (Marin-Perianu and Havinga, 2008). It inputs temperature and smoke and generate fire/ no-fire signal using its distributed fuzzy engine. Fig. 3 shows D-FLER structure.

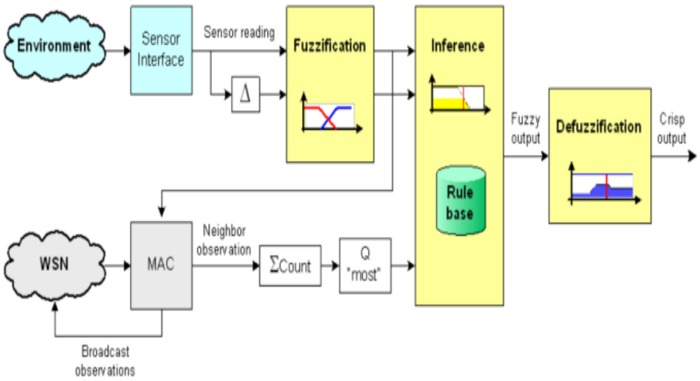


Fig. 3. Structure of D-FLER (Marin-Perianu and Havinga, 2008)

4.4.1. D-FLER computation complexity

Defining the fuzzy rules and membership functions is the most complicated part of the fuzzy inference engine design. Assuming that these are programmed into the sensor nodes, the time complexity of the fuzzy inference engine is calculated based on the Eq. (6), where m is the number of membership functions per input, i is the number of inputs, r is the number of rules, o is the number of outputs (in the particular case of fire detection, o =1).

$$O_{D-FLER} = O(m \times i \times r \times o) \qquad (6)$$

As shown in (Marin-Perianu and Havinga, 2008), the actual execution time can be greatly influenced by the specific defuzzification method chosen, to the extent that the number of outputs o can become the determinant factor.

5. Empirical results

To gauge the performance of the proposed approach, a dataset is obtained and a couple of experiments are conducted. To compare the approaches, both accuracy rates and computational complexities are analyzed. Subsection 5.1 first describes the dataset, while Subsection 5.2 describes the experiment methods and obtained results.

5.1 Dataset

A set of residential fire data was obtained from NIST website (http://smokealarm.nist.gov/). Fires might be flaming or smoldering. Therefore, both kinds of fires are taken into consideration and mixed together. Additionally, some nuisance resources are also mixed to make the detection more realistic. Thus, two smoldering fire datasets (SDC31, SDC40), two flaming fire datasets (SDC10, SDC14) and two nuisance resource dataset (MHN06, MHN16) were merged together. In total, 1400 data instances were prepared that are divided into training and test sets. A calibration is also performed to make all the data in the same units.

Fig. 4 displays scatter plots for each sensory data (or each feature). This picture shows how data of various sensors are in overlap. Consequently, the goal is to classify different types of data (i.e. smoldering fires, flaming fires and nuisances) into their respective class.

5.2. Experimental results

Accuracy of different methods can be measured by cross validation. Cross validation divides data into training and testing sets, and then the accuracy of classification on testing set demonstrate the total accuracy of the approach.

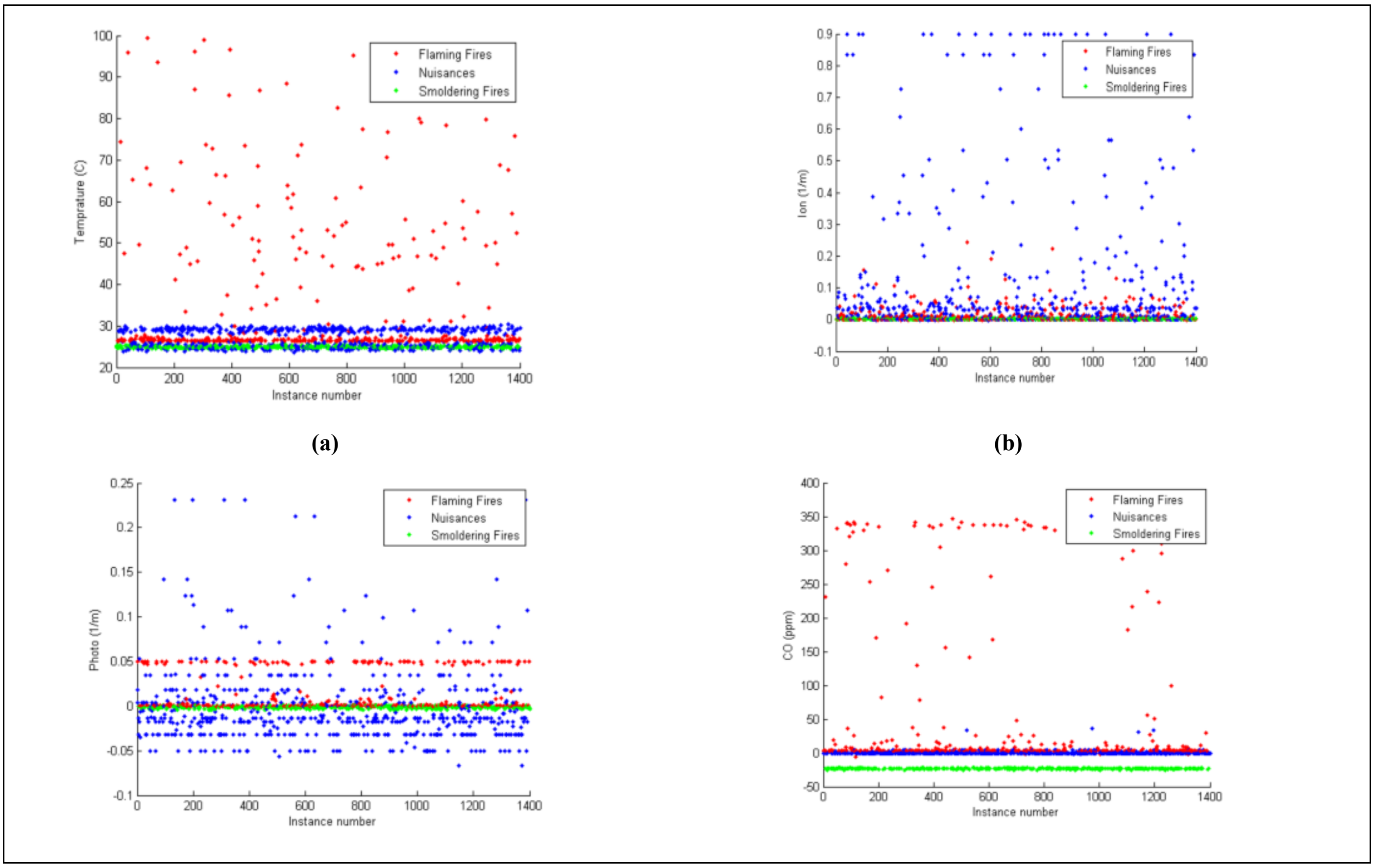
Accordingly, we validate the approaches by 1000 instances training and 400 instances testing data. All data were randomly mixed and given to the classifiers. Each test repeated 10 times and the average accuracy rate by changing the classifiers' parameters is reported in Table 1. Table 1 also provides a general comparison of our methods with the fuzzy logic based D-FLER (Marin-Perianu and Havinga, 2008) technique.

For simulation purposes, Matlab® 7.1 is used. Naïve Bayes code is completely implemented by the authors; however, FFNN and SVM are executed using Matlab toolboxes. Since D-FLER uses the same dataset as ours, we can compare our techniques with it.

From Table 2, it can be seen that D-FLER and FFNN achieve almost same accuracy level. SVM takes the third position and Naïve Bayes is the last.

5.3. Computation Complexity Comparison

To compare these detection approaches, not only the accuracy rate but also computation complexity is important, especially because they need to be implemented on tiny resource-constrained sensor nodes. Table 2, provides a comparison between complexities of different approaches. It can be seen that FFNN and SVM have lower computational complexity (order of two) and Naïve Bayes and D-FLER have higher complexity (order of three).



(a) **(b)**

(c) **(d)**

Fig. 4. Scatter plot of sensory data. (a) temperature; (b) Ion; (c) Photo; (d) CO

Table 1. Comparing the Empirical Results with D-FLER (Marin-Perianu and Havinga, 2008)

Best Result	*Naïve Bayes*	*FFNN*	*SVM*	*D-FLER*
Accuracy Rate	71.58%	98.65%	92.96%	98.67%
Parameters	1000 intervals	100 neurons in hidden layer and 3000 epochs training	Quadratic Kernel	Result is directly obtained from the original work.

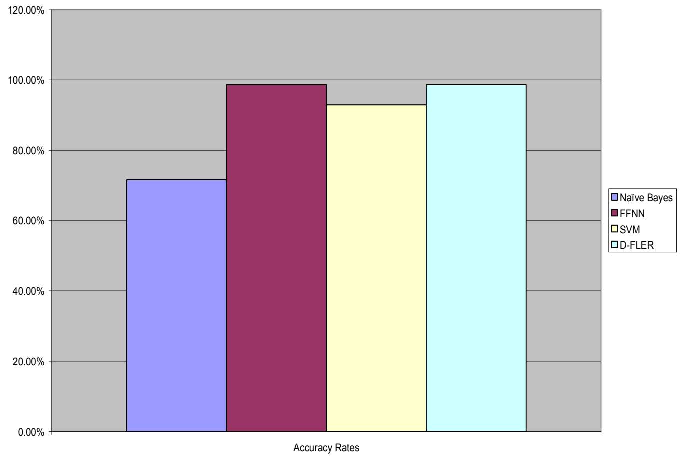


Table 2. Computation Complexity Comparison

	Naïve Bayes	*FFNN*	*SVM*	*D-FLER (Marin-Perianu and Havinga 2008)*
Computation Complexity	$O(i \times j \times m)$	$O(m \times n)^{*}$	$O_{SVM} = O(m \times i)$	$O(m \times i \times r)^{**}$
* p is removed because $p=1$ for fire detection; ** o is removed because $o=1$ for fire detection.				

6. Conclusion

This paper shows the environmental saving effect of the wireless sensor networks and their applicability to detect residential fires accurately and promptly. By bridging the gap between classical fire detection techniques and pervasive sensing and reasoning capabilities of WSNs on the one hand, and making use of artificial intelligence based learning mechanisms on the other, we present in this paper accurate and fast residential fire detection techniques. We explicitly investigate applicability of FFNN, SVM, and Naïve Bayes based techniques running locally on wireless sensor nodes equipped with all necessary sensors along side with the distributed fuzzy logic based technique called D-FLER. The experimental results performed on a real dataset from NIST shows that our local FFNN based technique outperforms SVM and Naïve Bayes and achieves almost similar detection rate as fuzzy logic based D-FLER. In terms of computational complexity, FFNN and SVM are less complex (order two) than Naïve Bayes and D-FLER (order three).

Our local methods are appropriate for applications that do not need distributed decision making and require local processing only, while D-FLER uses a distributed decision making mechanism and is suitable for the scenarios, in which collaborative behavior is desired. We have further extended our local approaches in (Bahrepour et al., 2009) to perform distributed fire detection . The advantage of distributed approaches is definitely their robustness in case of sensor failures and in some cases higher detection accuracy. However the required information exchange may introduce a delay as well as communication overhead. The application requirements and the deployment setup dictates which technique (in terms of being local or distributed) to be used.

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