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Procedia Technology 3 (2012) 69 – 79

Procedia Technology

The 2012 Iberoamerican Conference on Electronics Engineering and Computer Science

Wireless Sensor Networks and Fusion Information Methods for Forest Fire Detection☆

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Abstract

Research in wireless sensor networks (WSNs) has experienced a significant growth in recent years. One topic of special interest is the use of WSNs in the detection of forest fires. In this paper, we propose two algorithms for forest fire detection. The proposed algorithms are based on information fusion techniques. The first algorithm uses a threshold method and nodes equipped with temperature, humidity and light sensors. The second algorithm uses the Dempster-Shafer theory and assumes that the nodes use temperature and humidity sensors. Evaluation results show that both methods are able to efficiently detect fires in their initial stages.

Keywords: manets, wireless sensor networks, information fusion, forest fire detection

1. Introduction

Mobile ad hoc networks (MANETs) are complex distributed systems comprised of wireless devices [1]. In a MANET, no infrastructure is required to enable information exchange among the nodes, since they are able to self-organize using diverse network topologies and multi-hop communication techniques. Wireless sensor networks (WSNs) are a special case of MANETs. In a WSN, the nodes that conform the network are low power devices equipped with one or more sensors, a processor, memory, a power supply, a radio, and an actuator [2]. The nodes or *motes* of a WSN are able to sense the environment conditions, such as temperature, humidity, barometric pressure, biological or chemical conditions, among others. Wireless sensor networks can be used in many applications. Examples of WSNs applications are military target tracking and surveillance; animals, humans and vehicles tracking; environmental and health monitoring; and disaster recovery.

Due to their memory and processing limitations, the nodes of a WSN are equipped with a radio to transfer wirelessly the important and partially processed data to a base station. The base station receives

☆This work was partially supported by the Dirección General de Educación Superior Tecnológica (DGEST), project no. 4322.11-P.
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2212-0173 © 2012 Published by Elsevier Ltd.
doi:10.1016/j.protcy.2012.03.008

the information from the nodes, process them and take the appropriate actions; for instance, inform a user that an event of interest has taken place. Commonly the main power source in a sensor node is a battery. However, a secondary power supply can be used, such as solar panels.

Among the WSNs applications, forest fire detection can be very helpful in avoiding human and material losses. For instance, in the state of California (USA) only, almost 5,000 forest fires were registered in 2010. In the same state, in the last five years the average of fire occurrences was 6,873, with an estimated annual loss of $ 292,962,667 US dlls [3].

Since forest fire detection has been a main concern in many countries, diverse techniques have been devised to monitor forest fires. One of the most traditional methods is the use lookout towers located at high points. Unfortunately, this method has limitations due to the unreliability of human observations. For this reason, some techniques based on the use of technology have been proposed, as the Automatic Video Surveillance System [4] or the use of satellite images [5]. However, the low spatial and temporal resolution of the satellite images may cause a delay in the fire detection process.

Recently, some proposals have been published that consider the use of WSNs to monitor and detect forest fires [6]. The use of multiple sensor sources, and the deployment of the sensor nodes in areas not visible to the satellite, increase the probability of a more accurate and early fire detection.

WSNs event detection applications are in essence fusion information processes [7]. Fusion information can be defined as "the use of the theory, techniques and tools created and applied to exploit the synergy in the information acquired from multiple sources (sensor, databases, information gathered by humans, etc.), in such a way that the resulting decision or action is in some sense better (qualitatively or quantitatively, in terms of accuracy, robustness, etc.) than would be possible if any of these sources were used individually without such synergy exploitation" [8].

In this paper, two algorithms for forest fire detection are proposed and evaluated. Both algorithms are based on information fusion techniques. The first algorithm uses a threshold method and nodes equipped with temperature, humidity and light sensors. The second algorithm uses the Dempster-Shafer theory and assumes that the nodes use temperature and humidity sensors. Evaluation results show that both methods are able to efficiently detect fires in their initial stages.

The rest of this document is organized as follows. The related work is presented in Section 2. In Section 3, we introduce the proposed algorithm based on a threshold method, and its evaluation. In Section 4, we discuss the proposed algorithm based on the Dempster-Shafer theory, along with the results of the evaluation of the proposed algorithm. Finally, in Section 5 the conclusions and future work are presented.

2. Related Work

One of the first proposals of the use of wireless communication for fire detection was the *SIGMASPACE* system, that used smoke detectors [9]. In [10], Chen *et al.* proposed a method based on data fusion. The algorithm used temperature, smoke density and CO density values, and neural networks and fuzzy inference to determine if a fire has occurred. However, none of these proposals are based on the use of WSN technology.

Doolin and Sitar described in [11] a system to monitor forest fires, based on the use of WSNs. The nodes of the system were able to sense temperature, humidity and barometric pressure, and were equipped with GPS units. However, the authors did not describe any method to detect fires.

Yu *et al.* proposed in [12] a paradigm for forest fires detection that use a WSN. It considered that the motes included temperature, relative humidity, smoke and wind speed sensors. The nodes of the WSN are organized in clusters, and assign a node as a cluster leader. Processing the data sensed by the nodes, the cluster leader calculates a weather index using a neural network. This index is sent by each cluster leader to the manager node, which determine if there is a risk of a fire.

FireWxNet was proposed by Hartung *et al.* in [13], a multi-tiered portable wireless system for monitoring weather conditions in rugged wildland fire environments. The motes of the WSN sensed temperature, relative humidity, and wind speed and direction. *FireWxNet* was designed to provide a better comprehension of the weather conditions related with the presence of fire, and did not considered its detection.

Sha *et al.* proposed the *FireNet* architecture in [14], to support fire rescue operations. In their proposal, each firefighter in the sensor field carries a sensor node, which can sense parameters of interest. The sensor board records all the information expected by the incident commander and the fire department, that is used for real-time decisions and post-event analysis.

The *Forest-Fires Surveillance System* (*FFSS*) was proposed by Son *et al.* in [15], which consisted of a WSN, a middleware and a web application. The nodes of the WSN measure temperature and humidity, and detect smoke. The middleware program and the web application analyze the collected data. An index, defined by the South Korea government, was used to trigger an alarm notification indicating that a fire may occur.

In [16], Bernardo *et al.* proposed an application based on scattered wireless sensor networks composed by several isolated WSNs. The main goals of the application were: energy efficiency, to improve mote lifetime; low delay, to detect and store information about danger spots and fires in progress; and resilience to mote loss. The WSNs measured temperature, light and relative humidity. However, the proposal does not explain the way these values are used to determine the potential existence of a fire.

A WSN was used by Vescoukis *et al.* in [17]. Their nodes were equipped with temperature sensors. The method to detect a fire was simple: if the sensed temperature was greater than 55°, than an alarm was emitted.

Zervas *et al.* proposed in [18] the *Sensor and Computing Infraestructure for Environmental Risks* (*SCIER*) project, to detect fires in their early stages. It used a WSN with temperature sensors and the *Maximum Likelihood* criterion, to decide if there is a chance that a fire occurs.

Hu *et al.* introduced a system conformed of a WSN and a routing protocol in [19]. They conducted a series of experiments to prove the feasibility of the proposed protocol. Zhang and Wang proposed an automatic fire alarm system based on WSNs in [20]. The proposal described only the network architecture and the communication protocol.

Hafeeda and Bagheri introduced in [21] the design and evaluation of a WSN for forest fires modeling and early detection. They described the Fire Weather Index system [22] and showed how to use it to detect fires. They recorded real data and analyzed the behavior of fires, relating temperature and humidity. Moreover, they modeled the forest fire detection problem as a node k-coverage problem ($k \geq 1$) in wireless sensor networks and proposed an approximation method to solve it.

Finally, in [23], da Penha *et al.* proposed and evaluated two algorithms for forest fire detection, based on information fusion techniques. They used a WSN to sense light and temperature values. The proposed algorithms were based in the threshold and Dampster-Shafer methods. It is important to mention that our work was mainly motivated by the results provided by da Penha *et al.* in [23].

3. Algorithm Based on the Threshold Method

In order to devise an algorithm to detect forest fires using a WSN, it was important to understand the prevailing environmental conditions when a fire occurs. To achieve this, we collected measurements of temperature, light and relative humidity during the months of July and August, since these are the months with the highest incidence of fires in the north region of the state of Baja California, México, and the south region of the state of California, USA. We used temperature, light and relative humidity sensors since they are available in many WSN platforms. We wanted to devise a proposal based on the use of economic and highly available sensors. The use of more sensor will add reliability to the detection process, but will increase the energy consumption and the deployment costs. Thus, our goal was to make a compromise between efficiency and cost.

The measurements were taken without the occurrence of fires. Besides, we measured the environmental conditions when we artificially generated some fires. The experiments were conducted in order to simulate the existing conditions in the early stages of a fire. The sensor nodes were placed on the top of trees of the grounds of the university campus. To simulate the fires, we used torches. The nodes were exposed to the torch flames for periods of ten minutes.

To develop the application to collect the sensed data and send them to a base station, we used the *nesC* programming language [24] (version 1.2.4) and the *TinyOS* operating system [25] (version 2.1). We used

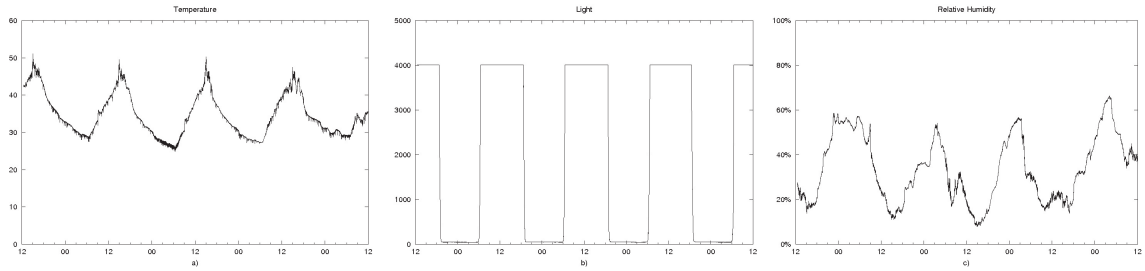

Figure 1. Measurements of: a) Temperature, b) Light, and c) Relative Humidity

IRIS motes with *MTS420/400C* sensor boards. The *IRIS* base station had an *ATmega1281* processor and a *mib520* programming base.

We found that in normal conditions, the temperature, light and relative humidity values show a cyclical behavior, as we can observe in Fig. 1. The temperature and relative humidity values maintain an inversely proportional relationship among them. That is, when the temperature increases, the relative humidity decreases. The light intensity shows a stable and high level during the day, and a stable and very low level during the night. The light values show a sudden change during transition period of day to night, and *vice versa*.

When a fire occurs, the temperature shows a rapid increment, whereas the relative humidity decreases fast. Besides a fire, the exposition of the mote to a direct sunshine is the event that causes a drastic change on these values. The light intensity does not show a significant change in the presence of a fire, unlike the results reported by da Penha *et al.* in [23]. If a bigger source of fire is used to conduct the experiments, perhaps the sensed light values may show an important increment. However, since we want to detect the fire in its early stage, we used a small torch.

Using these observations, we defined two algorithms to detect forest fires. The first algorithm uses a fusion information method known as the threshold method [7]. The algorithm is based on the state machine shown in Fig. 2, which defines five states. The transition from one state to another is generated when a relevant change in the values of temperature, light or relative humidity is detected, indicating the probable existence of a fire.

The initial state is the State0 and represents the normal (i.e. no fire) environmental conditions. The states State1 and State2 are transitional states, since they indicate the probable occurrence of a night fire or a day fire, respectively. The State3 may represent the sunrise, whereas the State4 may indicate that the mote was exposed to direct sunshine. Finally, the State4 represents the presence of a fire.

In normal conditions, the state machine is in State0. Even though the values of the temperature, light and relative humidity are collected, in the State0 only the temperature value is evaluated. Every time the temperature is registered, the ratio between the average of the values of a sliding window of size W_T and the new temperature value, is calculated. The sliding window contains the most recent W_T temperature values recorded. If this ratio is greater than `tr_threshold`, it means a large change in the temperature value and a that possibly a fire has been detected. To determine if it is night fire, the rate of change of the light is evaluated, in a similar way as we did with the temperature. Therefore, if the ratio between the average of the values of the sliding window of size W_L and the most recent light value is greater than `tl_threshold`, the machine changes to the State1. Otherwise, it changes to the State2. It is important to note that while in State0, in `temp_s0` we store the last stable temperature value; that is, the value before the machine moved from State0.

If the machine is in State1, we calculate the ratio of the average of the values of the sliding window of size W_H and the most recent value of the relative humidity. If this ratio is less than `th_threshold`, the machine moves to State3; otherwise, it goes back to State0. While the machine is in State3, the ratios are still computed, and if they are greater (or smaller, in the case of humidity) than their respective thresholds (i.e., the temperature is still increasing while the relative humidity is decreasing), the machine moves to State5 and an alarm is triggered, indicating the probable occurrence of a night fire.

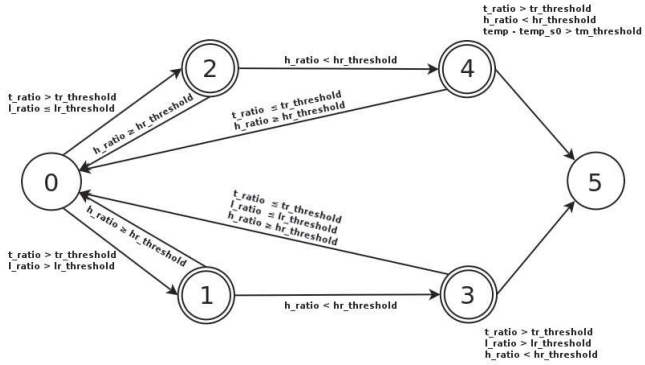

Figure 2. State machine to detect forest fires

In contrast, if the machine moved from State0 to State1, there is a chance that a fire has been generated, that the mote is exposed to direct sunlight, or that it is a normal temperature increment. To identify the event, we calculate the ratio of the average of the values of the sliding window of size W_H and the most recent value of the relative humidity. If the ratio is less than `th_threshold`, the machine moves to State4; otherwise, it goes back to State0. In State4, if the temperature and humidity ratios maintain their relationships, we calculate the difference of the current temperature value and `temp_s0`. If the difference is greater than `th_threshold`, the machine changes to State5, which means that perhaps a day fire has occurred.

3.1. Evaluation

As mentioned previously, we collected measurements of temperature, light and relative humidity during the months of July and August. Also, to evaluate the proposed algorithm, we artificially generated several fires during the same period of time. We measured the environmental conditions every seven seconds. To save energy, the sensed data were sent to the base station every 28 seconds. The experiments were conducted at different times of the day throughout the experimental period.

We define empirically the parameters used in the algorithm, as a result of the analysis of the collected data. The values of the size of the sliding windows W_T, W_L y W_H varied from 5 to 35, with increments of 5. We evaluated the performance of the algorithm using these values. We concluded that the best performance was obtained using a sliding window size greater than or equal to 15, and the following threshold values: `tr_threshold` = 1.01, `tl_threshold` = 1.1, `th_threshold` = 1, and `tm_threshold`=3°C.

To evaluate the performance of the proposed algorithm we used the following metrics: *false positives* and *false negatives*. A false positive indicates erroneously that a fire has occurred, whereas a false negative fails in identifying when a fire is really occurring.

Table 1 shows the obtained results. We can observe that using appropriate values of the algorithm parameters, it is able to detect all the existing fires. On the other hand, the number of false positives can be reduced or eliminated if the motes are covered with a shell, to protect them from direct sunlight exposure.

4. Algorithm Based on the Dempster-Shafer Method

From the results obtained from the evaluation of our first algorithm, it could be concluded that the light values were not relevant to detect a fire. They were useful to detect easily a night fire. However, we guessed that a night fire can be detected using only temperature and relative humidity sensors. Furthermore, if we use only these sensor, we can save energy consumption.

The second proposed algorithm is based on the Dempster-Shafer theory, and uses temperature and relative humidity sensors. The Dempster-Shafer theory, also known as the theory of belief functions, is a generalization of the Bayesian theory of subjective probability. It is based in the work published by A. P. Dempster on upper and lower probabilities [26], which was later extended and refined by G. Shafer as a

Window Size	Number of Experiments	Fires Detected	False Positives	False Negatives
5	6	4	1	2
10	6	4	2	2
15	6	6	3	0
20	6	6	3	0
25	6	6	3	0
30	6	6	2	0
35	6	6	2	0

Table 1. Evaluation results of the threshold method

Mathematical Theory of Evidence [27]. Shafer rebuilt the mathematical theory around the Dempster concept and introduced degrees of belief instead of lower probabilities [28].

The main advantage of the D-S theory is that is able to handle uncertainty; that is, it does not need the knowledge of the complete probabilistic model. In contrast, Bayesian inference requires *a priori* knowledge and does not allow allocating probability to ignorance or uncertainty.

In the D-S theory, all the mutually exclusive propositions about a problem domain are enumerated in the *frame of discernment* Θ. The function $m: 2^{\Theta} \rightarrow [0, 1]$ is called a *basic probability assignment* whenever

$$m(\phi) = 0, \tag{1}$$

and

$$\sum_{A \subset \Theta} m(A) = 1. \tag{2}$$

The mass value of A ($m(A)$) is also called the *basic probability number* of A, and it is understood to be the measure of the belief that is committed exactly to A [27].

The *belief function* is a belief measure, and represents the weight of evidence supporting proposition A. It maps each hypothesis A to a value $Bel(A)$ between 0 and 1, defined as

$$Bel(A) = \sum_{B \subseteq A} m(B). \tag{3}$$

The *plausibility function* is the weight of evidence that does not refute proposition A. It maps each hypothesis A to a value $Pl(A)$ between 0 and 1, defined as

$$Pl(A) = 1 - (\neg A). \tag{4}$$

The functions $Bel(A)$ and $Pl(A)$ represent upper and lower belief bounds. The interval $[Bel(a), Pl(a)]$ represents the *confidence interval*. Fig. 3 shows the relationship between the $Bel(A)$ and $Pl(A)$ values. A one-to-one correspondence exists between basic probability numbers, belief, and plausibility. Shafer showed that any of the three functions is sufficient for deriving the other two.

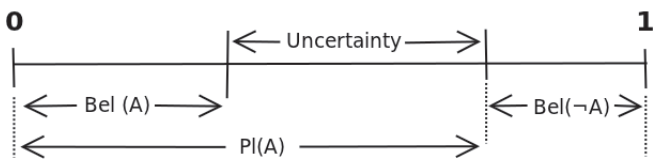

Figure 3. The confidence interval for proposition A

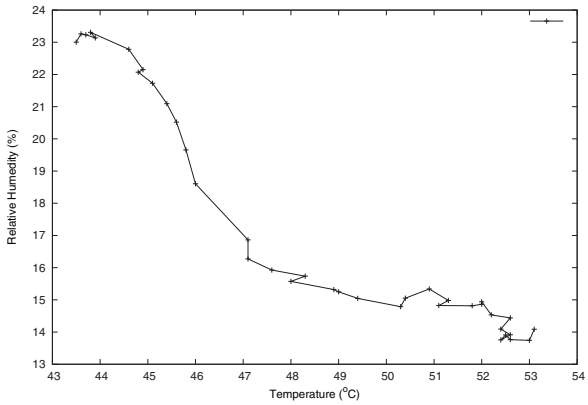

Figure 4. Temperature and relative humidity values in a fire

To combine independent sources of evidence (e.g. data from different sensors) into a total amount of evidence, the Dempster's rule of combination is used. For instance, if we want to combine evidences from sources m^1 and m^2, the orthogonal sum of m^1 and m^2 is calculated as

$$(m^1 \oplus m^2)(C) = m^{1,2}(C) = \frac{\sum_{A \cap B = C} m^1(A)m^2(B)}{1 - \sum_{A \cap B = \emptyset} m^1(A)m^2(B)}, \tag{5}$$

where $A, B, C \subseteq \Theta$.

In our proposal, the frame of discernment contains two propositions,

$$\theta = \{fire, no\_fire\}. \tag{6}$$

The *power set* of Θ, denoted as 2^Θ, consists of all possible hypotheses or *focal elements*,

$$2^\Theta = \{\{fire\}, \{no\_fire\}, \{unkown\}\}. \tag{7}$$

If we denote $f = \{fire\}$, $n = \{no\_fire\}$ and $u = \{unkown\}$, to calculate $m(f)$ using Eq. 5, we have

$$m^{1,2}(f) = \frac{m^1(\{f\})m^2(\{f\}) + m^1(\{f\})m^2(\{u\}) + m^1(\{u\})m^2(\{f\})}{1 - m^1(\{f\})m^2(\{n\}) - m^1(\{n\})m^2(\{f\})}, \tag{8}$$

where m^1 and m^2 are independent sources of evidence.

To assign mass values to the data collected from sensors, we analyzed their values when a fire occurred. Fig. 4 shows the relationship between the values of temperature and humidity in one of our fire experiments. We observed that this relationship is very similar in all the experiments we conducted. For this reason, we propose the use of historical data from fires to construct a function or a set of functions to relate temperature and humidity values. A set of functions can be constructed to represent a fire at different seasons of the year, at different times of the day, or under different environmental conditions. To assign mass values to the information collected from sensors when a possible fire has taken place, we propose the use of interpolation methods. A larger mass value is assigned as the behavior of the event (sensed data) is similar to a fire event. The use of interpolation methods allows the implementation of algorithms with low computational complexity, which is important in a system for forest fire detection in real-time.

Fig. 5 shows the pseudo-code of the proposed algorithm. The nodes are periodically sensing the temperature and relative humidity conditions of the environment. Every time a new temperature value is registered, the algorithm calculates the ratio between the average of the values of a sliding window of size W_T and the new temperature value. The sliding window contains the most recent W_T temperature values recorded. If

```
Algorithm_DS() {
   while(1) {
      read temp, hum;  // read temperature and humidity values
      t_ratio = temp / average of Wt;
      if (t_ratio > tr_threshold) {
         m1 = mass from interpolation method 1;
         m2 = mass from interpolation method 2;
         if [ (m1 >= m_threshold) and (m2 >= m_threshold) ]
            report fire;
         else if [ ((m1 >= m_threshold) and (m2 <  m_threshold)) or
                   ((m1 <  m_threshold) and (m2 >= m_threshold)) ]   {
                m12 = mass from Dempster's rule of combination;
                if (m12 >= m_threshold)
                   report fire;
         }  // end else-if
      } // end if
      wait until next period;
   } // end while
}
```

Figure 5. Algorithm based on the Dempster-Shafer theory

this ratio is greater than `tr_threshold`, it means a large change in the temperature value, and as a consequence the mass values of *m1* and *m2* are calculated using the interpolation methods. If both values are greater than or equal to a mass threshold value `m_threshold`, then the algorithm reports that a possible fire has been generated. However, if the mass value assigned by one of the interpolation methods suggest a fire (i.e. it is greater than or equal to `m_threshold`), and the other one is less than `m_threshold`, the algorithm uses the Dempster's rule of combination (Eq. 5) to calculate the value of the new mass *m12*. If this value is greater than or equal to `m_threshold`, then the algorithm reports a possible fire.

4.1. Evaluation

To evaluate the proposed method based on the Dempster-Shafer theory, the same data employed to evaluate the algorithm based on the threshold method were used. After analyzing the relationship of the temperature and humidity values, we observed a very similar behavior in the experiments we conducted. When a fire occurred, as the temperature increased, the relative humidity decreased. According to the data obtained, we consider that the spline interpolation or the Gaussian process are good choices to assign mass values to the information collected from sensors. However, for sake of simplicity, to evaluate our proposed algorithm we used the Lagrange interpolation method and the Newton polynomial interpolation method.

The Lagrange interpolating polynomial is the polynomial $P(x)$ of degree $\leq (n-1)$ that passes through the n points $(x_1, y_1 = f(x_1))$, $(x_2, y_2 = f(x_2)) \ldots (x_n, y_n = f(x_n))$, and is given by

$$P(x) = \sum_{j=1}^{n} P_j(x), \tag{9}$$

where

$$P_j(x) = y_j \prod_{k=1, k\neq j}^{n} \frac{x - x_k}{x_j - x_k}. \tag{10}$$

The Newton polynomial is also known as the Newton's divided differences interpolation polynomial, since the coefficients of the polynomial are calculated using divided differences. In this method, given a

Window Size	Number of Experiments	Fires Detected	False Positives	False Negatives
5	6	5	4	1
10	6	5	5	1
15	6	5	5	1
20	6	5	6	1
25	6	5	6	1
30	6	5	6	1
35	6	6	6	0

Table 2. Evaluation results of the Dempster-Shafer method

set of $n + 1$ data points $(x_0, y_0), \ldots, (x_n, y_n)$, the interpolation polynomial in the Newton form is a linear combination of Newton basis polynomials,

$$\pi(x) = \sum_{k=0}^{n} a_k n_k(x), \tag{11}$$

with the Newton basis polynomials defined as

$$n_k(x) = \prod_{i=0}^{k-1} (x - x_i), \tag{12}$$

for $j > 0$ and $n_0 \equiv 1$.
The coefficients are defined as

$$a_k = [y_0, \ldots, y_k], \tag{13}$$

where $[y_0, \ldots, y_k]$ are the divided differences.
The Newton polynomial can be written as

$$N(x) = [y_0] + [y_0, y_1](x - x_0) + \cdots + [y_0, \ldots, y_k](x - x_0)(x - x_1)\ldots(x - x_{k-1}). \tag{14}$$

In the proposed algorithm, the nodes are periodically sensing the temperature and relative humidity conditions of the environment. Every time a new temperature value is registered, the algorithm calculates the ratio between the average of the values of a sliding window of size W_T and the new temperature value. We defined empirically the parameters used in the algorithm, as a result of the analysis of the collected data. The values of the size of the sliding window W_T varied from 5 to 35, with increments of 5. Also, we set `tr_threshold` = 1.01 and `m_threshold` = 0.6.

In order to use the Dempster's rule of combination described in Eq. 8, we defined two independent sources of evidence. The first one (m^1) uses the measured values of temperature and humidity, and the Lagrange interpolation method to assign mass values. The second one (m^2) uses the measured values of temperature and humidity, and the Newton polynomial interpolation method to assign mass values. To assign the mass values, we employ the most recent temperature value to calculate the expected humidity value using the interpolation method. Then, we compare it with the sensed humidity value. If the sensed value is less than or equal to the calculated value, the algorithm assigns to the $\{fire\}$ hypotheses a mass value greater than or equal to 0.6. Otherwise, it assigns a mass value from 0.59 to 0. The $\{no\_fire\}$ hypotheses is assigned a mass equal to $1 - m(\{no\_fire\})$.

If both methods assign to the $\{fire\}$ hypotheses a mass value $\geq$ `m_threshold`, then the algorithm indicates that a possible fire is occurring. On the other hand, if both methods assign to the $\{fire\}$ hypotheses a mass value $<$ `m_threshold`, the algorithm continues collecting data. However, if one of the methods

assigns a mass value ≥ `m_threshold` and the other one assigns a mass value < `m_threshold`, then Eq. 8 is used to calculate the combined mass (m^{12}).

Table 2 shows the obtained results of the evaluation of the algorithm based on the Dempster-Shafer theory. We can observe that the algorithm was able to detect all the existing fires using a sliding window value of $W_T = 35$. For smaller W_T values, the algorithm failed in detecting a night fire. Furthermore, the algorithm was not able to distinguish a fire from direct sunlight exposition. However, the number of false positives can be reduced if the motes are protected from direct sunlight, as mentioned before.

5. Conclusions and Future Work

In this paper, we proposed two algorithms to detect forest fires based on a information fusion methods. The first algorithm uses a threshold method and nodes equipped with temperature, humidity and light sensors. The second algorithm is based on the Dempster-Shafer theory and assumes that the nodes use temperature and humidity sensors. Evaluation results showed that both methods are able to detect fires in their initial stages. Both algorithms reported false positives when the motes were exposed to direct sunlight. However, if the motes are covered to avoid direct sunlight exposure, the number of false positives may be reduced.

The algorithm based on the threshold method was simpler to implement and showed a good performance. The algorithm based on the Dempster-Shafer theory, that used only two sensors (temperature and relative humidity), and showed difficulties to detect night fires. To improve its performance, the light intensity sensor should be added. Fortunately, this may not represent a significant change in the proposed algorithm, due to the advantage of the Dempste's rule of combination to add a new source of evidence easily.

As future work, we plan to implement the algorithm based on the Dempster-Shafer theory using the spline interpolation and the Gaussian process, and including light intensity sensors. We also plan to develop a new algorithm to detect forest fires based on the use of evolutionary programming.

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