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Wireless sensor network for forest fire detection

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Abstract

Some methods for fire detection include monitoring from watch towers and the use of satellite images [1] [2]. Unfortunately, these are not efficient due to several reasons, such as high infrastructure costs (sophisticated equipment), the fact that they require a large number of trained personnel and that they make real-time monitoring difficult, since when the phenomenon is detected, its speed of propagation has produced uncontrollable levels of damage. This paper proposes a method for detecting forest fires, using a network of wireless sensors and information fusion methods.

Keywords: Data analysis; Wireless sensor network; Forest fire detection.

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1. Introduction

A wireless sensor network (WSN) is a distributed system composed of nodes with the ability to obtain information on environmental conditions and transmit it wirelessly to a base station for processing [3]. On the other hand, information fusion techniques allow to improve the quality of the response to an event of interest, by combining the different data sources (sensors, database, etc.) [4][5]. In this paper, a forest fire detection system is proposed in its initial stage, using a wireless sensor network and information fusion methods. The main contribution of this work is

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the implementation of a low-computational complexity algorithm, with the ability to detect a fire event using only the information from two sensors: temperature and humidity.

2. Proposed detection model

As part of the development of the fire detection system, the first step was to know the characteristics of the environment under normal (non-fire) and fire conditions [6]. In order to develop a robust proposal, information on temperature and relative humidity under normal conditions was collected during the summer (the stage of the year most prone to forest fires) in a forest area of the city of Bogotá, in Colombia. The information analysis yielded the following observations [7][8][9]:

1. Under normal conditions, the temperature and humidity values show a cyclical behavior during the different stages of the day.
2. Under normal conditions and fire conditions, the temperature and humidity values maintain an inverse relationship between their magnitudes; that is, when the temperature increases, the humidity decreases and vice versa.
3. Under normal conditions, temperature and humidity values vary very slowly during the different stages of the day. On the other hand, under fire conditions, the rate of variation is higher and manifests itself in much less time.
4. When a sensor node is exposed to the effects of the sun's rays, the temperature shows a rate of change similar to that produced by a fire.

Considering these observations, different techniques were investigated in order to characterize the behavior of a forest fire. In an initial proposal, a function was constructed to relate the behavior of temperature and humidity in a fire, which was named the base function. Later, this function was used to compare the values obtained by the sensors when an event that could be a fire was recorded. Through the use of interpolation techniques and the use of Dempster-Shafer's theory of evidence, it was determined whether the event was a fire or not [10]. However, although a good detection rate was obtained, the method was not robust if the environmental conditions varied greatly from those used to create the base function.

In this paper, the construction of the base function using regression analysis is proposed. Regression analysis offers among its advantages the representation of the data through the adjustment of a mathematical function (straight line, polynomial function, exponential function, etc.), besides it facilitates the estimation of unknown values [11][12][13].

Considering that the values of temperature and relative humidity maintain an inverse relationship in a fire, it was decided to build two base functions, which represent their behavior in the fire, in an independent way. From the analysis of the parameters under study, it was found that the most relevant characteristic of the fire is the reason for the change in temperature and humidity values with respect to time. For this reason, when using regression analysis to construct the base functions, time is considered as the independent variable, and temperature and humidity as dependent variables. These functions are now called T(t) and H(t), respectively, and constitute the base model [14].

For the construction of the base model, it is proposed that temperature and humidity measurements be used in fire experiments, considering some time of the year and a specific time slot. For example, base models can be built for summer, and at different stages of the day (morning and afternoon), which, according to the analysis of historical data, were those that showed the highest incidence of events. The following section will show an example of the construction of the base model [8].

However, the relationship between the variables does not always manifest itself in a linear way. For these cases, there are alternatives such as second order functions or parabolas, third order or cubic functions, and so on. A more general way of representing higher order non-linear functions is shown in Eq. 1:

$$\mathrm{y} = \beta_0 + \beta_1 \mathrm{x} + \beta_2 \mathrm{x}^2 + \ldots + \beta_\mathrm{n} \mathrm{x}^\mathrm{n} \tag{1}$$

The objective of the base model is to have a reference that provides greater precision when representing the existing environmental conditions in a fire. This allows the possibility of not depending on fixed magnitudes or thresholds, but rather on the reason for change that occurs when the fire phenomenon affects the environment [6]. In other words, according to our observations during a forest fire, the values of temperature and humidity always behave in the same way: upwards for the case of temperature and downwards for the case of relative humidity, with a similar rate of change or slope, as can be seen in Figure 1. Having a model that represents this behavior (independently from the magnitudes) allows to compare the data received by the sensor nodes to confirm or discard whether the observed variation corresponds to a fire. For this purpose, the following architecture is proposed, which is composed of three modules: wireless sensor network, middleware and fire detection system.

In general terms, the proposed model works as follows: 1) The sensor nodes collect environmental measurements periodically; 2) when they detect an increase in temperature, they transmit the information to the base station; 3) the base station sends the data back to the server for storage in a database; 4) the server takes the most recent information from the database and compares the data with respect to a previously defined base model; and 5) according to the degree of similarity between the data and the base model, the system determines whether or not there is a fire in the monitored area. Each of the stages is described in more detail below.

In the wireless sensor network, each node takes a temperature reading using a constant sampling period P. Each reading is stored in a FIFO (First-In, First-Out) structure called WT that uses an n-size slider window. When WT is full, it checks whether the most recent reading Tn+1 has shown a change (increase or decrease), through the following ratio represented by Ω [4]:

$$\Omega = \mathrm{T}_{\mathrm{n}+1}/\mu(\mathrm{W}_{\mathrm{T}}) \tag{2}$$

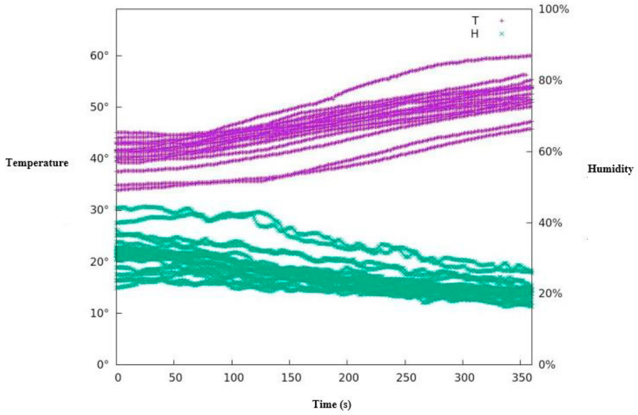

Fig. 1. Temperature and humidity values in a fire.

Where, on the other hand, μ(WT) is the average of the temperature data set stored in WT. The result from Ω will be compared with a temperature threshold called Tthreshold. If, and only if, Ω is higher than Tthreshold, the sensor node takes a reading of humidity H and then transmits a data packet to the base station with the following information: node ID, temperature sample T, humidity sample H and a time stamp t to identify the time when the event was generated. For the first packet transmitted, the value of t will be equal to zero, and for subsequent cases, the value of t will be a function of P. If the temperature threshold is not exceeded, the sensor node must continue reading and evaluating samples. This procedure is described in Algorithm 1.

Algorithm 1 Pre-processing on the sensor node Be T = temperature, P = sampling period, WT = temperature sample buffer, n = size of sliding window, Ω = 0, Tthreshold = temperature threshold, id = sensor node identifier, H = humidity, t = 0, i = 1;

```
while (1) {
T = Read ambient temperature;
if (i⩽ n) {
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        WT [i] = T ;
        i=i+1;
    } else {
        Ω = $T/\mu(WT)$
        while (Ω> Tthreshold ) {
            H = Read ambient humidity;
            Send(id, T , H ,t);
            WT's Oldest T-Strip;
            Store latest T in WT;
            t = t+P ;
            T = Read ambient temperature;
            Ω = $T/\mu(WT)$
        // end of the while cycle
        t = 0;
        i = 1;
    } //end else
} // Wait for the next period
```

When the sensor node transmits a packet to the base station, the information is stored in a database for immediate analysis. The function of the middleware is to establish communication mechanisms between the base station and the server. The middleware assigns an arrival time composed by the date and time of the server for each received packet according to the node identifier and the equivalent to its respective t-value.

Subsequently, the server obtains the most recent information from the database, taking into account that each packet obtained by the sensor nodes is composed of the following data: id, T , H and t. To describe the flow of the fire detection system, A is used as the least recent set of information or information that exceeded a temperature threshold for the first time, and B is used as the most recent information or subsequent information about environmental conditions.

The first step is to verify that the analysis time Y, is less than the limit analysis time Θ, this with the objective of analyzing during a balanced time period that allows having the necessary information to make a decision. At the beginning of the analysis Y = 0, result of the differences must be accumulated between tB - tA to update its value, as shown in Equation 3 [6]:

$$Y = Y + (tB - tA) \tag{3}$$

Assuming that once a couple of samples (A and B) are received, their difference in time is called K, so $Y = K$. For each new sample, the procedure is repeated as long as the value of Y is less than Θ (user-defined value). Once Y is calculated and validated as less than Θ, the next step is to calculate the rate of change of the temperature and humidity values of A and B using the slope formula, i.e., mT and mH as shown in Equations 4 and 5 [8].

$$m_T = (T_B - T_A)/(t_B - t_A) \tag{4}$$

$$m_H = (H_B - H_A)/(t_B - t_A) \tag{5}$$

The derivative of the functions representing the base model, i.e. T(t) and H(t), must then be calculated. However, it should be mentioned that T'(t) and H' (t) should obtain a result equivalent to the value of Y, so they are replaced by $T'(Y)$ and $H'(Y)$. The technique of the average quadratic error is then used, using a number of limit evaluations called emax. The root mean square error is used to measure the error between an estimator (base model functions) and an estimate (data from the sensor node). This value is calculated as shown in Equations 6 and 7 [14]:

$$\mathrm{MSE_T} = \mathrm{add}(\mathrm{T_i}(\mathrm{Y})\text{-}\mathrm{m_{T_i}})^2/\mathrm{emax} \tag{6}$$

$$\mathrm{MSE_H} = \mathrm{add}(\mathrm{H_i}(\mathrm{Y})\text{-}\mathrm{m_{H_i}})^2/\mathrm{emax} \tag{7}$$

3. Evaluation

Sensor nodes with IRIS hardware platform were used to carry out the set of fire experiments, with a sensor board model MTS420/400CC [11]. This board has five types of environmental sensors: relative humidity, temperature, barometric pressure, light intensity and accelerometer. In terms of software, Ubuntu Linux version 12.04 was used in the server. The middleware was developed in Java and the database in MySQL. Finally, for the WSN, the TinyOS operating system version 2.1.2 was used.

The methodology used consisted in placing the sensor node on the middle part of a tree trunk, at a height of approximately three meters. The experiments were carried out during the months of April and May 2019. On the other hand, data collection was divided into two stages: 1) Creation of a base model and 2) Controlled fire experiments. Each of them is described below.

Table 1. Parameters used in experiments.

Parameter	**Description**	**Value**
n	WT window size	15
Tthreshold	Temperature threshold Sampling period of the sensor node	1.01
P		6 seconds
Θ	Limit analysis time	360 seconds
emax	Maximum number of evaluations for the SSM	5
α	Threshold used to determine a fire	0.7

1. Base model: In order to have enough information for the development of the base functions T(t) and H(t), in this stage, the sensor node was exposed to firework conditions using a garden torch. The duration of the experiment was 6 minutes using a sampling period of 1 second. 20 experiments were performed in this stage.
2. Controlled fire experiments: A series of experiments were carried out with different sampling periods: 3, 4, 6 and 8 seconds. The objective was to investigate the sampling period with the best performance for the detection of the event. At this stage, 32 experiments were conducted (8 for each type of sampling period). The purpose was to determine the sampling period to be used in the next stage of experiments.

To build the new base model, curve fitting by simple regression analysis was implemented with the help of IBM's SPSS statistical analysis software [15]. With the data collected, the following base model was obtained:

$$T\ (t) = -2.477 \times 10\text{-}7\ t3 + 1.12 \times 10\text{-}4\ t2 + 2.2441 \times 10\text{-}2\ t + 28.8861, \tag{8}$$

$$H\ (t) = 2.26 \times 10\text{-}8\ t3 - 1.7 \times 10\text{-}5\ t2 - 2.7444 \times 10\text{-}2\ t + 17.505 \tag{9}$$

It is worth mentioning that the determination coefficients were 0.87 for the T(t) function and 0.68 for the H(t) function.

Subsequently, 50 fire experiments were carried out, using the parameters shown in Table 1, 30 of them shadow scenarios and with sensor node exposed to fire. The remaining 20 were events without fire and with the sensor node exposed to the sun's rays, without any protection. These values were processed using the base model described by

Equations 8 and 9. The model obtained a 100% detection rate in shadow scenarios. By analyzing the data obtained by a sensor node exposed to the sun's rays, a 100% false positive rate was obtained. However, to avoid this, the sensor node can be covered with special protection to avoid direct exposure to sunlight. To check this, a new set of 50 experiments were carried out with the sensor node exposed to the sun's rays, but covering it with a shield. Using the proposed method under these conditions, a 100% detection rate was obtained.

4. Conclusions

In this study, a forest fire detection system was proposed in its initial stage using a wireless sensor network and information fusion methods. The base model is built using regression analysis. When the system detects temperature and humidity values that could represent a fire, it compares the collected values with the base model to determine whether or not a fire exists. The results of the model evaluation showed a 100% detection rate when the nodes are not directly exposed to the sun's rays. A future research will seek to extend the model considering the energy consumption of the WSN, through the distribution of nodes in clusters and the use of distributed sensing.

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