FOREST FIRE DETECTION SYSTEM BASED ON WSN WITH ANN APPROACH

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ABSTRACT: A forest fire is a serious risk to forest assets and human life. In this paper, we propose a forest fire detection framework that has an artificial neural network calculation actualized in a wireless sensor network (WSN). The proposed detection framework mitigates the risk of forest fires by furnish precise fire caution with low upkeep cost. The exactness is expanded by the novel multi criteria detection, alluded to as an alert choice relies upon various qualities of a forest fire. The multi-criteria detection is executed by the artificial neural network calculation. In the interim, we have built up a model of the proposed framework comprising of the sun oriented player module, the fire detection module and the UI module.

Keywords: Wireless Network, Forest, Fire detection, Artificial Neural Network

INTRODUCTION

In this paper, we propose a forest fire detection framework that incorporates an artificial neural network calculation actualized in a WSN. In general, the fundamental commitments of this paper are as per the following:

•The multi criteria detection relies upon various characteristics of a forest fire and is acquainted into WSNs with increment the exactness of distinguishing a forest fire.

•An artificial neural network calculation is utilized to meld detecting information that compares to various properties of a forest fire into a caution choice.

•We present the rule of the proposed framework and a model containing TelosB sensor hubs and a sunlight based battery to control the WSN

LITERATURE REVIEW

Wireless sensor networks (WSNs) have been thefocus of research over the past few years because of their potential in environmental monitoring, target tracking, and object detection [I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci,2002]. WSNs have also been studied in the context of detectingforest fires, which threaten forest resources and human life.WSNs are not costly and can detect forest fires in real time, un like current detection methods based on human observationand unlike spot weather forecasts or even satellite monitoring.WSNs can also provide information about environmental conditions within the forest, which is useful for predicting forest fires [B. Son, Y. Her, and J. Kim,2006]. Moreover, forest fire detection and prediction is associated with specific location information provided by individual sensor nodes.

Although some practical experiments have been conductedusing WSNs to collect sensed data from a forest fire [D. Doolin and N. Sitar, 2005]-[M. Hefeeda and M. Bagheri, 2007],there are still some challenges to using WSNs for this purpose. A fire detector may sound an alarm based on a simple threshold, which gives rise to false alarms even though the sensingunit of the fire detector may be highly sensitive. False alarms occur for two main reasons:

•A photoelectric smoke sensing unit is sensitive to white aerosol particles from a smoldering fire but also to dust [G. Pfister, 1997].

•Environmental conditions in the forest often severely disturbthe normal behavior of the sensing unit. Sunlight and artificial light are primary sources of interference with the flame sensing unit.

Limited power supply to sensor nodes makes it difficult todetect fires over a long period of time. The potential energysources for sensor nodes can be classified according to whether they store energy within the sensor nodes (e.g., in a battery),distribute power to the sensor node through a wire, or scavengeavailable ambient power (e.g, using a solar battery on the sensor node). Considering the volume of the sensor node, mannerof deployment, and forest conditions, the solar battery is one ofthe most promising sources of energy for detecting forest fires over a long period of time. However, existing works on solarbatteries for sensor nodes, e.g., [M. Minami, 2005]-[J. Taneja, J. Jeong, and D. Culler, 2008], overlook the problemof intermittent sunlight in the forest.

PROPOSED FOREST FIRE DETECTION METHOD

In our proposed framework, detection is made more precise by utilizing numerous criteria, which implies the promotion depends on different criteria of the forest fire. Multi criteria detection is actualized by the artificial neural network calculation. In view of the artificial neural network, the proposed framework has low overhead and makes them learn capacities.

Multi-Criteria Detection

In a framework that relies upon one quality of a forest fire to raise alerts, there is a high likelihood of false cautions in view of natural framework disadvantages or outer aggravations. To conquer such disadvantages and counter outside unsettling influences, the framework must consider the numerous qualities of a forest fire. This is alluded to as multi-criteria detection (Definition 1). With multi-criteria detection, numerous qualities of a forest fire are detected by various kinds of detecting unit. In this way, a detecting unit that has been meddled with can't raise a false alert. Together, different detecting units affirm an alert. Multi-criteria detection builds the exactness of identifying a forest fire.

Artificial Neural Network Algorithm

We utilize the multilayer back proliferation artificial neural network for multi-criteria detection. In spite of the fact that information combination in WSNs has been shrouded in a great part of the point has not been considered with regards to forest fires. A multi-layer back spread artificial neural network is broadly used to imitate the nonlinear connection between its info and yield. Be that as it may, calculation in this sort of network isn't mind boggling in light of the fact that the network is a mix of neurons managing basic capacities. Besides, multilayer back engendering artificial neural network is fit for self-realizing, which implies it can prepare itself to develop relations between the sources of info and wanted targets.

Making an Alarm Decision

Without loss of generality, we assume that the multilayerback propagation artificial neural network is implemented on $s_j$with l types of sensing units that cover l attributes of the forest fire. Sensing data $o^j_i$of u^j_ion $s_j$corresponds to $r^f_i$of the forest fire.

$$A^0=[a^0_1,\ldots,a^0_l]^T \qquad (1)$$

For clarity, let all o^j_i, $1\leq i \leq l$ comprise a column vectorA^0 (1), where $a^0_i=o^j_i$. Vector A^0 is the input to the multiplelayer artificial neural networks.Specifically, A^0 is the input to the first layer of the multilayer artificial neural network. In the first layer, A^0 is multiplied by weight matrix W^1 with dimension $s^1 \times l$ and bias vector B^1 ,including s^1 neurons in the first layer. The intermediate computation result of the first layer is denoted N^1 and isgiven by:

$$N^1 = W^1A^0 + B^1 \qquad (2)$$

Then, N^1 is sent to transfer function F^1 , which may be alinear or nonlinear. That is, F^1 may be a hard limit function orsigmoid function depending on the specific problem it needs to solve. In general, transfer functions in the multilayer artificialneural network are easy to compute. Transfer function F^1 operates on every element of N^1 . The result of transfer functionF^1 ,denoted A^1 , is the output of the first layer:

$$A^1 = F^1(N^1) = \begin{bmatrix} F^1(n^1_1) \\ \vdots \\ F^1(n^1_{s^1}) \end{bmatrix} \qquad (3)$$

The fusion of sensing data proceeds in the second layer ofthe multilayer artificial neural network. The output A^1 of thefirst layer becomes the input of the second layer. The calculation process of the second layer is similar to that of the first layer except the second layer has its own W^2 ,B^2 , and F^2 . Ingeneral, the calculation of the ith layer is given by:

$$A^i=F^i(W^i A^{i-1} + B^i),\ 1\leq i \leq m-1 \qquad (4)$$

where$m$ is the number of layers in the artificial network.For a decision to be made on whether there is a forest fire ornot, the output of the m th layer, A^m(5), is confined to one element.

$$ad=A^m=F^m(W^m A^{m-1} + B^m) \quad (5)$$

This is done by letting the m th layer contain only one neuron. If the alarm decision is confined to a Boolean value, weneed to choose the transfer function, the output of which is a Boolean value, for them th layer, such as the hard limit function.

Self-Learning Capability

Given sensing data that corresponds to multiple attributes ofa forest fire and given correct alarm decisions, the multilayer back propagation artificial neural network trains itself to buildrelationships between the sensing data and correct alarm decisions. However complex the relationship, it is easy for the multi layer back propagation artificial neural network to fulfill thetask. Essentially, self learning means having the output of the multilayer back propagation artificial neural network approximate the target output by adjusting the weight matrixes and biases. This adjustment is made in order to minimize the mean square error (MSE) between the output and target output. Suppose q inputs are denoted $A0i$, $1\leq i \leq q$. Corresponding toA^0_i, the output is denoted $A^m i$, and the target output is denotedT^m_i. Thus, the MSE for the $i$thiterated adjustment is:

$$MSE(i)=E[(T^m_i-A^m_i)^T(T^m_i-A^m_i)] \quad (6)$$

After self learning, the multilayer back propagation artificial neural network builds up a mathematical relationship between the sensing data and correct alarm decisions. Then, theartificial neural network can make an accurate alarm decision.

IMPLEMENTATION

We have developed a prototype of the forest fire detectionsystem using an artificial neural network in a WSN. The system mainly comprises three parts: the solar battery, fire detection module, and user interface.

Solar Battery

To consistently power the unattended sensor nodes deployedin a forest where only intermittent sunlight is available, we develop a solar battery (Figure. 1). The energy from the solar panelis buffered by the super capacitor. When the energy in the supper capacitor reaches a threshold, the super capacitor starts torecharge the Li-ion battery. Because of the intermittent sun light in the forest, the energy produced by the solar panel isnot enough to recharge the battery. If not buffered in the supercapacitor, this energy is wasted. On the other hand, the charge discharge cycles of the Li-ion battery are limited. It is better to charge a Li-ion battery until it is full;otherwise, the life of the battery decreases.

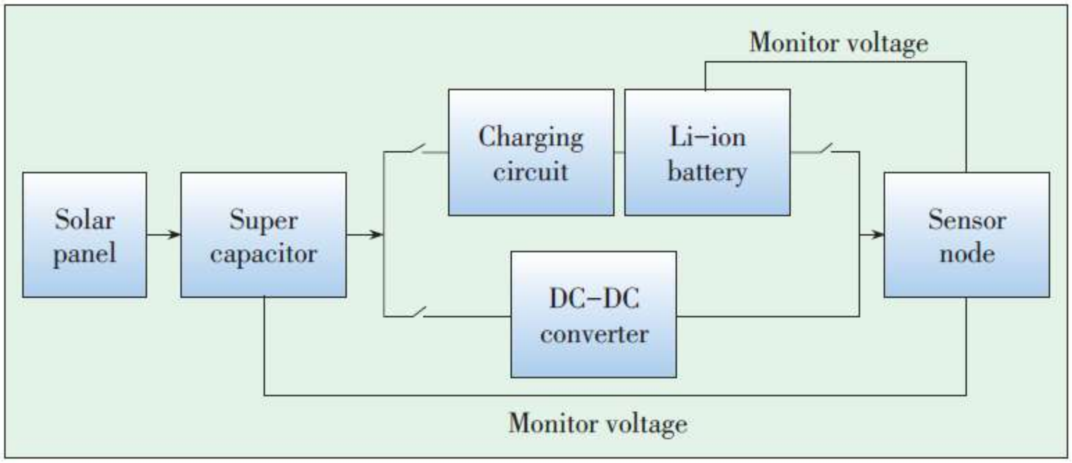

Figure 1: The solar battery architecture.

On the contrary, the super capacitor has almost infinite charge discharge cycles and is ideal for frequently pulsing applications.Here we discuss implementation of the solar battery in detail. The solar panel of the battery is 110 × 95 mm and comprises eight cells connected in parallel and generating 550 mAat 2 V. Theoretically, the maximum energy generated in onehour can sustain a sensor node for 26 days, i.e., 1100 mAh/(0.53 mA × 3.3 V × 24 h), provided that the sensor nodes workon a 10% duty cycle with an average current of 0.53 mA. Energy from the solar panel is buffered by two 150 F 2.5 V supercapacitors wired in parallel. A 3.7 V 700 mAh Li-ion battery isused to continually save energy. The fully charged Li-ion battery can power a sensor node working on a 10% duty cycle for55 days, i.e., 700 mAh/(0.53 mA×24 h) . We choseMAX1674 and ISL6292 integrated circuits as the DCDC converters, which have a conversion efficiency ofaround 90%.

Fire Detection Module

The fire detection module is responsible for multi criteria detection. The module comprisesfive TelosB sensor nodes, four of which monitorthe forest fire. That is, they convert the attributes of a forest fire into sensing data. The multi layer back propagation artificial neural network is implemented on each individual sensor node because the sensor node is endowed withfour types of sensing units. However, for thepurpose of analysis, raw sensing data besides the fire alarm are transmitted to users. The lastsensor node acts as the base station, collectingsensing data and the fire alarm from the otherfour sensor nodes.

For simplicity, four sensornodes communicate with the base station directly in one hop communication. Each TelosB sensor node has a 16 bit 8 MHz microcontroller, anRF transceiver compliant with IEEE 802.15.4,and four sensing units. These sensing unitsense temperature (-40 °C-123.8 °C), relative humidity (RH), infrared light (320 nm-1100nm), and visible light (320 nm-730 nm). Hence, each sensornode can monitor the four attributes of a forest fire. The architecture of the artificial neural network is shown in Figure. 2.The back propagation artificial neural network in the fire detection module is a two layer network. There are four neurons in the first layer, because of the four sensing units in a TelosBsensor node, and one neuron in the second layer. The transferfunction for the first layer is log sigmoid function (f1 in Figure. 2)and is given by:

$$f(x)=1/(1+e^{-x}) \quad (7)$$

The transfer function for the second layer is a linear function (f2 in Figure. 2) and is given by:

$$f(x)=x \quad (8)$$

User Interface Module

The user interface module is responsible for displaying theraw sensing data to the user. First, the sensing data and firealarm are transmitted from the base station to the user. The data flow is shown in Figure.3. Sensing data from sensor nodes aretransmitted to the base station by wireless communication. Thebase station is a gateway between WSNs and the Internet and forwards the sensing data to a user client. The medium between the base station and user client is the Internet. Therefore, the user may be located far away from the fire detection system. Socket communication is facilitated by Java.

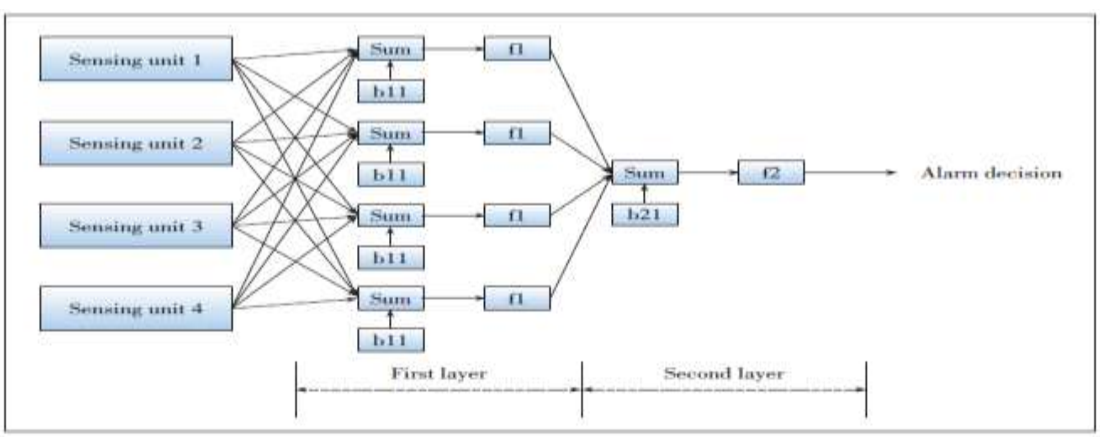

Figure 2: The back propagation artificial neural network.

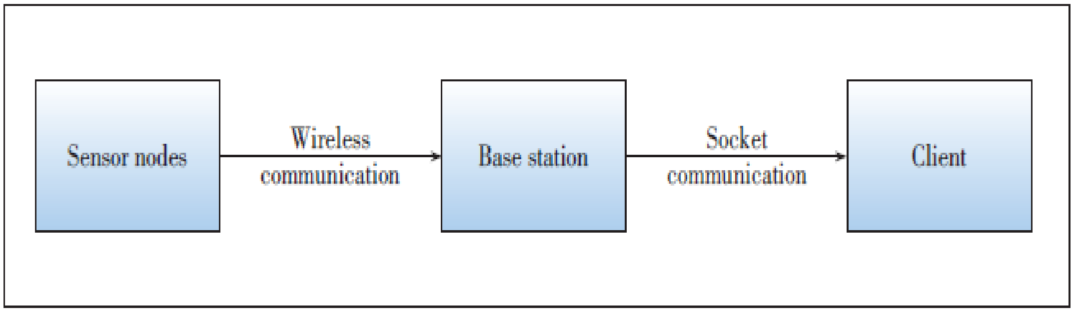

Figure 3: Data flow.

Next, the user interface module displays the sensing data to the user.The graphical interface draws curves for each typed of sensingdata over time. The graphical interface is refreshedaccording to the arrival of new sensing data. Therefore, the curves of thegraphical interface are synchronous with the sensing units onsensor nodes. Each type of sensing data is displayed by a tab in the graphical interface.

CONCLUSION

A forest fire can threaten forest resources and human life.This threat can be mitigated by timely and accurate alarms.WSNs are widely used for environmental monitoring; therefore, we use a WSN for forest fire detection. To increase the accuracy of the detection system, we propose multi-criteria detectionfor forest fires. In this paper, multi criteria detection is implemented by the artificial neural network algorithm. To powerthe sensor nodes in the forest where only intermittent sunlightis available, we develop a solar battery module. We developed anarchetypeof the proposed system comprising solar battermodule, fire finding module, and user interface module.

References

[1] Fernandes, A. Utkin, A. Lavrov, and R. Vilar, "Development ofNeural Network Committee Machines for Forest Fire Detection UsingLidar," Pattern Recognition, vol. 37, no. 10, pp. 2039-2047, 2004.

[2] Snow, P. Rastogi, and G. Weckman, "Assessing dependability of wireless networks using neural networks," in Military Communications Conference. IEEE, 2005, pp. 2809–2815 Vol. 5.

[3] Hong and V. K. Prasanna, "Optimizing a Class of In-networkProcessing Applications in Networked Sensor Systems," in Proceedingsof IEEE International Conference on Mobile Ad-hoc and SensorSystems, October 2004.

[4] G. Guo and M. Zhou, "Using MODIS Land Surface Temperature toEvaluate Forest Fire Risk of Northeast China," IEEE Geoscience andRemote Sensing Letters, vol. 1, no. 2, April 2004.

[5] J. Zhang, W. Li, N. Han, and J. Kan, "Forest fire detection system based on a ZigBee wireless sensor network," Frontiers of Forestry in China, vol. 3, no. 3, pp. 369–374, 2008. View at Publisher · View at Google Scholar · View at Scopus

[6] K. Bouabdellah, H. Noureddine, and S. Larbi, "Using Wireless Sensor Networks forReliable Forest Fires Detection," *Procedia Computer Science.*, vol. 19, pp. 794–801,2013.

[7] R. Lippmann, "An introduction to computing with neural nets," ASSP Magazine, IEEE, vol. 4, no. 2, pp. 4–22, 1987.

[8] S. E. Page, F. Siegert, J. O. Rieley, H. V Boehm, A. Jaya, and S. Limin, "The amount ofcarbon released from peat and forest fires in Indonesia during 1997," *Nature*, vol. 420, pp.61–65, 2002.

[9] Shuang Lai, "Game theory and generalized Vickrey auction based bandwidth resource allocation in IEEE 802.16 networks", Proceedings of 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), Zhengzhou, China, pp.7088-7091, August 2011.

[10] T. J. Lynham, C. W. Dull, and A. Singh, "Requirements for space-basedobservations in fire management: a report by the Wildland Fire HazardTeam, Committee on Earth Observation Satellites (CEOS) DisasterManagement Support Group (DMSG)," in IEEE InternationalGeoscience and Remote Sensing Symposium, vol. 2, pp. 762-764, June2002.

[11] Z. Li, S. Nadon, and J. Cihlar, "Satellite-based detection of Canadian Boreal forest fires: development and application of the algorithm," International Journal of Remote Sensing, vol. 21, no. 16, pp. 3057–3069, 2000. View at Publisher · View at Google Scholar · View at Scopus

[12] Kalaivanan M., and K. Vengatesan." Recommendation system based on statistical analysis of ranking from user. International Conference on Information Communication and Embedded Systems (ICICES), pp.479-484, IEEE, (2013).

[13] K. Vengatesan, S. Selvarajan: The performance Analysis of Microarray Data using Occurrence Clustering. International Journal of Mathematical Science and Engineering, Vol.3 (2) .pp 69-75 (2014).