Scholar Publishing Group
International Journal of Neural Network
https://doi.org/10.38007/NN.2022.030201
ISSN 2790-2692 Vol. 3, Issue 2: 1-8

Fuzzy Neural Networks to Multi-source Information

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Keywords: Multi-source Information, Fuzzy Neural, Neural Network, Fire Detection

Abstract: The development of multi-source fusion technology is based on the intersection of different scientific disciplines and the high level of development in different fields, which inevitably requires enhanced collaboration in information fusion and deeper communication in related research fields. The aim of this paper is to explore the application of fuzzy neural networks to multi-source information. First, the structural characteristics of multi-sensors, their basic ideas and research values are outlined. Then, multiple information fusion techniques are introduced, and fuzzy theory and neural network algorithms are described in detail, their characteristics and application areas are explained. The application of fuzzy neural networks with multiple sources of information in fire detection systems is investigated, the system is simulated and evaluated, and the fuzzy neural network-based fire detection system is tested on test samples. The test results show that the fuzzy neural network system designed in this paper has good practicality for fire monitoring.

1. Introduction

Multi-source information fusion, also known as multi-sensor information fusion, combines and analyses incomplete environmental information collected in different forms and by different means in the local environment, and processes redundant or conflicting information collected by different means to achieve complementary information and analysis of information uncertainty, promoting a more complete and consistent representation of the system as a whole [1-2]. Combining multiple sources of information can improve the accuracy of emergency planning, decision-making and response, thereby reducing the risks associated with decision-making.

Fuzzy theory and neural network algorithms are two of the most important techniques that can be used to combine information from multiple sources, each with its own characteristics.Al-Muhammed M J offers a cryptographic technique with a new computational model. The model uses fuzzy neural networks to generate highly complex hidden codes from encryption keys. The computational model also uses substitution and distortion methods that rely on plaintext and chaotic noise, causing great confusion in the ciphertext [3]. Vo T proposed a novel integrated fuzzy neural architecture that uses a topic-driven text representation learning approach for SA tasks, called: TopFuzz4SA. Specifically, in the proposed TopFuzz4SA model, a topic-driven neural encoder-decoder architecture is first applied topic-driven neural encoder-decoder architecture combined with latent topic embedding and attention mechanisms in order to fully learn the rich contextual and global semantic information of the given text data [4]. Therefore, it is relevant to study the application of fuzzy neural networks with multiple sources of information [5].

This paper uses the means of multiple sensors to synthesise the parameters collected by each sensor to make a more accurate fire assessment, breaking through the traditional thinking of fire monitoring systems, and this integrated monitoring approach is of high practical value. The most commonly used sensors are temperature, smoke, CO and various combustible gas sensors, and the system uses multiple sources of information with a fuzzy neural network approach to get the results of whether a fire has occurred or not. It enables early detection with a high degree of accuracy and reliability in order to minimise the loss of life and property caused by fire.

2. Research on Multi-source Information and Fuzzy Neural Networks

2.1. Structural Features of Multi-sensors

A simple sensor, such as a thermometer, can provide an indication of the temperature at a specific point. However, the accuracy of sensor readings is limited; they can only be read to a certain extent and are subject to noise and other factors [6-7]. In order to provide a true, reliable and accurate response to environmental conditions, most advanced systems today often use multi-sensor architectures to compensate for the lack of accuracy and reliability of a single sensor [8-9].

Multi-sensor information fusion helps systems to compensate for these deficiencies by fusing input data from multiple sources and provides a way to address these issues to improve the accuracy and reliability of the system [10]. The multi-sensor system architecture diagram is shown in Figure 1.

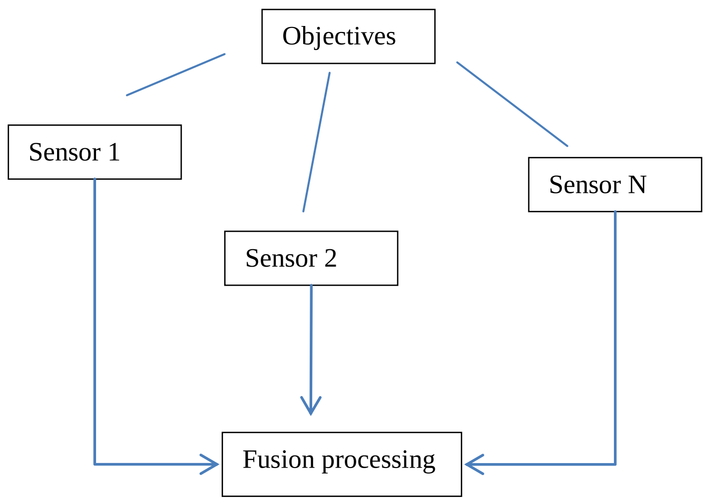

Figure 1. Multi-sensor system architecture

2.2. Information Fusion Techniques

The main advantages of the information fusion function are estimation and recognition [11-12].

The key technologies for information fusion are mainly focused on fuzzy set theory and neural networks [13-14].

(1) Fuzzy set theory

Membership in a particular set can be determined by applying generalised set theory [15]. Fuzzy set theory provides an algebraic algorithm for the transformation of fuzzy sets and their elements (e.g. merged sets, logical or even fuzzy matrices). Fuzzy set theory is also beginning to be used in analyses that contain imprecise facts [16].

(2) Artificial neural networks

Artificial neural networks are essentially a continuous distributed numerical computational process [17-18]. For target recognition systems with information fusion, it is better suited to handle the fusion of feature layers. As feature spaces consisting of multiple source features are usually very large, artificial neural networks have great potential to solve these problems [19-20].

3. Fuzzy Neural Networks with Multi-source Information in Fire Detection Systems

3.1. Fuzzy Neural Network based Fire Detection System

The fire monitoring system in this paper requires data acquisition from the site, as well as alarm control and the use of GSM networks to send SMS messages to designated mobile phone numbers, all of which is done by a microcontroller, where the data acquisition is processed by the ZigBee's own microcontroller and all data is transmitted to a master control node, which runs the algorithms to produce results and outputs.

The inputs to the system are smoke and temperature signals from an optical smoke sensor and a solid-state temperature sensor, which are processed by a fuzzy system and fed into a neural network. There are many ways to integrate fuzzy systems and neural networks, but this fire detection system uses a tandem fuzzy neural network. Its block diagram is shown in figure 2:

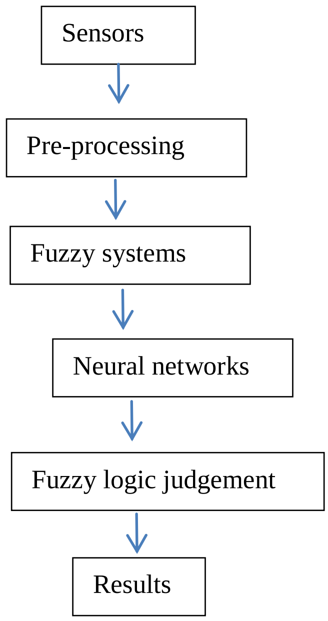

Figure 2. Tandem fuzzy neural network detection system

As can be seen from Figure (2), a fuzzy system is connected in series before and after the neural network. The structure of the neural network is a three-layer BP network with a feed-forward function and two outputs, namely the probability of open fire and the probability of negative fire.

These are fed into the fuzzy logic judge to obtain the corresponding affiliation degrees, and finally a certain alarm time delay and judgement threshold is set to determine the outcome of open and negative fires.

3.2. Design of BP Neural Network

(1) Network structure, the design uses a three-layer network structure, that is, the input layer is one layer, the signal variables of fire characteristics are ambient temperature, smoke concentration and CO concentration three, so the number of nodes in the input layer is three.

(2) The gradient descent function was chosen as the training function.

(3) The activation function of the hidden layer is chosen as a hyperbolic transfer function of type s.

(4) For other parameters, the initial learning rate is set to 0.5, the error limit is set to 0.0001, and the maximum number of training steps is 15000.

3.3. Fuzzy Logic Judgement

The output of the neural network is the probability of fire and ignition, which only indicates how likely a fire is to occur. In order to approximate reality and simulate human judgement, the output of the neural network is further processed using fuzzy inference methods. Since the hardest interval for fire probability is around 0.5, the membership function should be suitably extended for input values around 0.5 so that a normal distribution can be used as the fuzzy membership function.

$$A(x)=\begin{cases}0, x \le a \\ 1-e^{\frac{-(x-a)^2}{b}}, x > a\end{cases} \tag{1}$$

where X is the probability of an open or ignition fire, A(X) denotes the fuzzy size of the corresponding participation function, and α and β are used to adjust the shape of the participation function (α = 0, 0.5, 1, corresponding to large, medium and small participation functions).

To improve the resilience of the system, the concept of a fire probability duration function d(n) is introduced in this paper.

$$d(n)=[d(n-1)+1]*u(A(x)-T_d) \tag{2}$$

Where $u(\cdot)$ is the unit jump function and Td is the crisis threshold, here taken as 0.5. d(n) is accumulated when the fire probability A(X) exceeds Td, otherwise d(n) = 0 and n is a discrete time variable.

4. Analysis and Research on the Application of Fuzzy Neural Networks for Multi-source Information

4.1. Protection Range of Fire Detectors

For a particular detector, the protection radius is a "fixed value", while the protection range is a "variable value" that varies according to the actual protection area. In practice, the protection radius of a fire detector is the core indicator, while the protection range is a subordinate, secondary indicator and is limited by the protection radius. In this paper only the radius of protection of the detector is considered.

The DSl624 temperature detector selected in this paper has a protection radius of 3.6m when the height of the indoor space is not greater than 8m; the MQ-2 smoke detector has a protection radius of 5.8m when the indoor space is less than 6m; and the MQ-7 CO detector has a protection radius of 3.5m in an indoor environment.

4.2. Fire Monitoring Environment

In order to simulate the system, this paper selected the length and width of 7m, 9m, 2.8m high laboratory to simulate the home living room environment, because the living room has sofas, televisions and other wood products, leather products and flammable household appliances, burning will produce a lot of smoke and gas, so the test can be used in place of waste towels, waste wood and waste plastic, and prepared in advance to extinguish the fire equipment. From simple calculations, it can be seen that the living room needs to be laid out with the number of detectors as listed in Table 1. Figure 3 for the living room hall roof plan, the layout of the detector set up for: E point to place a MQ-2 and two MQ-7, A, B, C, D four points were placed a DSl624 and a MQ-2, so as to meet the principle of comprehensiveness, but also to meet the principle of economy.

Table 1. Number of detectors required in the simulation environment

Detector types	Detector type	Quantity (only)
Temperature detectors	DS1624	4
Smoke detectors	MQ-2	5
CO detectors	MQ-7	2

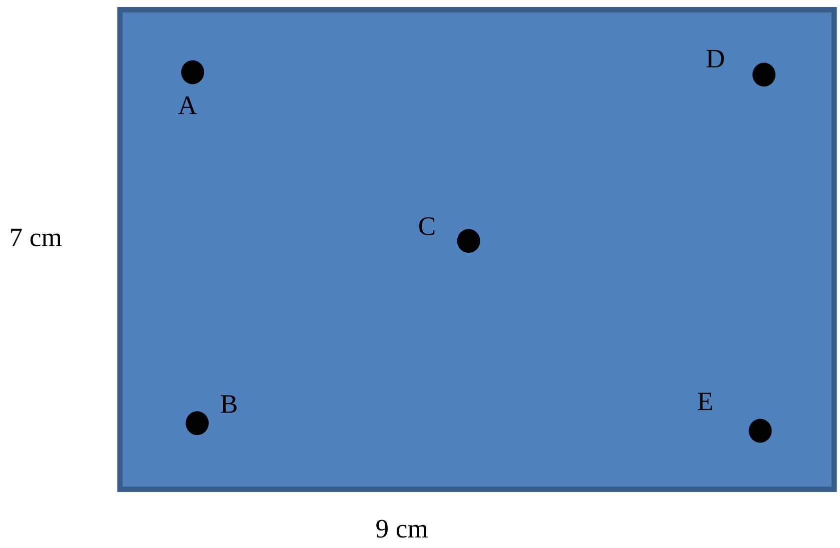

Figure 3. Detector layout in the simulation environment

The accuracy of the system was tested using 90 sets of test data, which were collected by the system in real time, including 30 sets of no fire data, anion fire data and open fire data respectively, the test data and test results are shown in Table 2:

Table 2. False alarm rate and accuracy of real-time data collected by the system

Test Status	Number of false alarms	Accuracy
No fire	1	97%
Ignition	2	94%
Open fire	0	100%

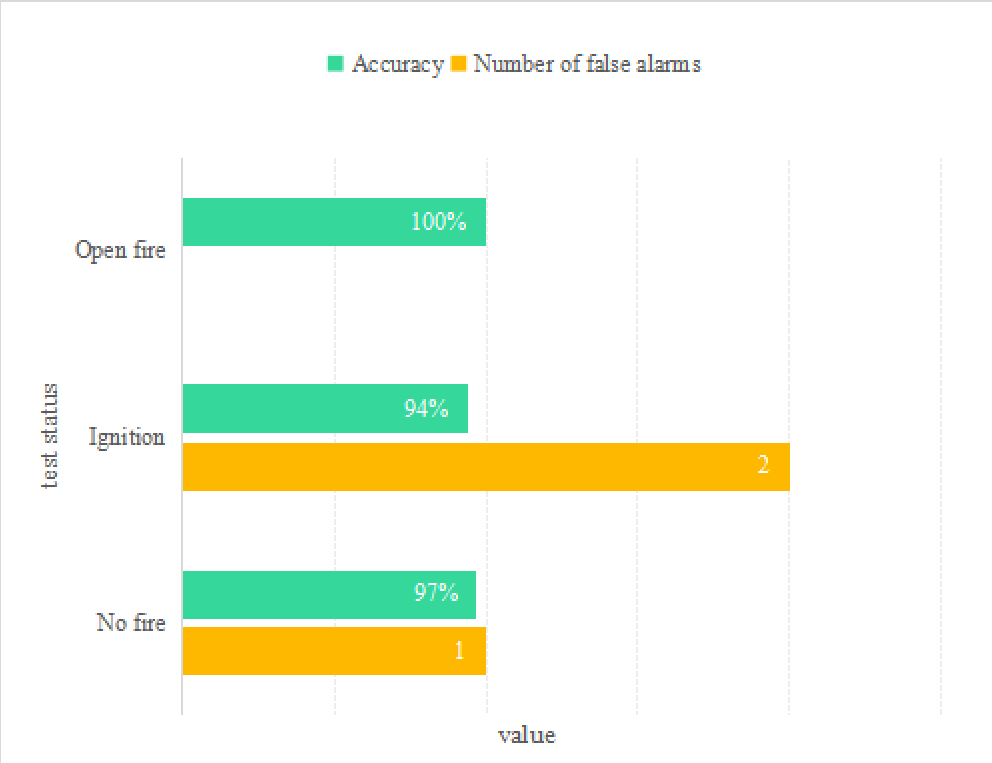

Figure 4. Test results

The test results show that the algorithm of the system designed in this paper has high accuracy in monitoring fires, but from the results it can be seen that the system still has false alarms and missed alarms, 1 false alarm in 30 groups of fire-free data, 2 missed alarms in 30 groups of inside-burning fire data and no false alarm in 30 groups of open fire data, with a high accuracy rate of 100%, as shown in Figure 4, which has high practical application value.

5. Conclusion

With the continuous development of science and technology, multi-source information fusion technology is bound to move further forward. With the continuous development of fuzzy neural networks, as well as the current great development of science and technology in various countries and the instability of the local environment, multi-source information fusion technology is bound to be further developed and will play an unprecedented role in the identification of fires. In this paper, we have designed a fire monitoring system from the aspect of fire monitoring, using a fuzzy neural network system to design the algorithm, however, the fire monitoring system designed in this paper needs further improvement and refinement. The system can also be studied and extended in depth from the following aspects:There is still room for optimisation of the algorithm; wireless voice video can be added to the system, which can provide a clear understanding of the fire situation.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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