Multi - Sensor Fire Control System Based on Bayesian Filter

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Abstract

With the popularity of the concept of intelligent fire protection, the development of faster, more accurate and safer fire protection system is becoming more and more important. According to the traditional idea of Bayesian filtering algorithm, combined with the characteristics of multi-sensor fusion technology, this paper proposes a set of multi-sensor data fusion technology applied in the fire scene. This technology makes some innovations to Bayesian filtering algorithm, which is of great significance for fire fighting and disaster relief and ensuring the safety of fire site personnel.

Keywords

Intelligent fire; Multi-sensor data fusion technology; Bayesian filtering.

1. INTRODUCTION

With more and more idioms such as smart city and intelligent fire protection being used in our daily life, intelligent development has become a necessary trend of social development in the future. The multi-sensor data fusion technology, as an important technology in today's intelligent development, also plays a crucial role in more and more scenes. As one of the important components of smart city construction, smart fire protection should conform to the trend of The Times. While ensuring safety, it should develop continuously towards the characteristics of faster and more accurate, so as to better protect our city.

In the past fire fighting, most of the use of a single sensor. Different sensors are used differently in different scenarios, each with its own advantages and disadvantages, and a single sensor is bound to misjudge in a particular situation [1]. The multi-sensor data fusion technology can make dynamic multidimensional prediction according to the current scene, with higher accuracy [2]. Therefore, this paper improves the application of multi-sensor data fusion technology in intelligent fire fighting, and makes innovative attempts in fire fighting based on the traditional idea of Bayesian filtering, so as to achieve the purpose of high precision, low error, less error and more safety.

2. TRADITIONAL IDEA OF BAYESIAN FILTERING

2.1. Three Probabilities of Bayesian Filtering

The data part of traditional Bayesian filtering is composed of three parts: prior probability, posterior probability and likelihood probability of data modification [3]. First of all, if there are several random variables x_1 , x_2 ,..., x_n in a random process that are not independent of each other, then a probability relation must be obtained:

$$P(x_n) = f(P(x_{n-1})) \tag{1}$$

But if you want to explore this random process, you must also select the initial value of a process, $p(x_1)$, to explore the whole random process. In most cases, the initial value of the system can not be obtained through random experiments, so the prior probability method is usually adopted to guess the initial value of the whole process. The prior probability is often based on life experience, or is summed up after many experiments. This leads to a certain subjectivity in the final results, and different prior probability guesses will lead to different results. In order to reduce the influence of subjective factors in the experimental process, traditional Bayesian filtering introduces external observation to correct and update the data. Objective data corrected by external observation is called a posterior probability.

Likelihood probability represents the accuracy of data observation. In the application of sensors, likelihood probability largely depends on the accuracy of sensors used. For example, when temperature sensors are used, the real temperature is 27 degrees, that is, $T_r = 27$. The current temperature obtained by the temperature sensor is 27.2 degrees, that is, $T_t = 27.2$. Then, the probability $P(T_t = 27.2|T_r = 27)$ of the temperature measured at 27 degrees is the likelihood probability of the current experiment. The likelihood probability and posterior probability under the same test are complete density function distribution, that is, the sum of probabilities of all cases is 1. [4]

2.2. The Application of Bayesian Filtering

In A random process, given that the state of the system is A and the observation of the system is B, a prior probability density will be obtained on the basis of guessing the prior probability. First, the variance of prior probability density is determined as the calculation of subsequent prior probability weights to achieve the purpose of allocating the proportion of prior probability in the final result. Then the observation is introduced to calculate the likelihood probability. The likelihood model is usually introduced when calculating the probability density function of the likelihood probability. The general likelihood model satisfies the normal distribution and the variance is the precision of the sensor.

Suppose that the prior probability function satisfies $f_x(x)$ and the likelihood function satisfies $f_{y|x}(y|x)$, then the posterior probability function is:

$$f_{X|Y}(x|y) = \eta f_X(x) f_{Y|X}(y|x)$$
(2)

$$\eta = \frac{1}{\int f_X(x) f_{Y|X}(y|x) dx}$$
(3)

Thus, we can obtain the probability model of Bayesian filtering as follows:



Figure 1. Bayesian filtering probability model

The variance of the results obtained by Bayesian filtering is significantly reduced, and the uncertainty is correspondingly reduced, and the obtained results are more likely to be the real results. [5]

3. OVERALL DESIGN OF MULTI-SENSOR BASED ON FIRE FIGHTING SYSTEM

At present, our country has a variety of sensors used in the fire alarm system, such as temperature sensor, smoke alarm, flame sensor, infrared sensor and so on, but most of the sensors are set independently, which leads to in some cases, a single abnormal data will cause the wrong alarm sensor, and such a wrong alarm lack of verification method, It not only leads to unnecessary human resource mobilization caused by false information, but also causes people's anxiety.

However, with the continuous progress of science and technology, more and more fields have realized the correlation of multi-sensors to ensure the timely acquisition of information and disaster prevention. For example, in the meteorological department, pressure sensors, gas sensors and other timely detection of weather conditions to prevent changeable weather. Although the mutual fusion of multiple sensors increases the amount of calculation to a certain extent, the requirements for monitoring equipment are improved, but the accuracy of information acquisition is greatly improved. [6] On the basis of reducing error reports, the use of multi-sensor has become the first line of defense to protect people's safety, and will certainly receive more and more social recognition and use.

Therefore, on the basis of the traditional single sensor fire alarm system, this paper provides a multi-sensor fire alarm system based on the idea of promoting the wide application of multi-sensor fire alarm system.

The multi-sensor fire alarm system designed in this paper is mainly composed of lower computer including sensor and main control board, alarm system and working background including upper computer. [7]

Firstly, different sensors are used to detect the data of various scenarios, and the data is sent to the main control board for calculation, fusion, and processing. If the data judged after fusion reaches the threshold set by the fire warning, the system will start alarm soon, and at the same time, the real-time data of the fire site will be transmitted to the upper computer, so as to facilitate the monitoring center to carry out real-time observation and determination of the background data, and finally take corresponding measures.



Figure 2. Multi-sensor fire alarm system

4. FUSION AND IMPROVEMENT OF MULTI-SENSOR DATA FUSION TECHNOLOGY AND BAYESIAN FILTERING

After real-time monitoring of fire site data by different sensors, data processing needs to be carried out on the main control board. In this paper, the multi-sensor data fusion is completed based on Bayesian filtering.

Because Bayesian filtering has certain limitations in use, such as prior probability speculation with a certain degree of subjective inference, a value needs to be set in advance, but in different fire sites there are many changes, it is difficult to reduce the influence of prior probability on the final filtering results as much as possible through a static value, which will cause a certain degree of error to the experimental results. As well as different types of sensors used in different scenarios, this paper makes some improvements on the basis of Bayesian filtering.

In the same scene, it is obviously unrealistic to realize data fusion after each sensor performs Bayesian filtering, which not only requires a large amount of advance observation of the scene to obtain the prior probabilities of different sensors, but also wastes a lot of time in calculation, which is difficult to ensure the timeliness of information transmission when the fire occurs. Therefore, this paper intends to adopt the method of serial Bayesian filtering. After Bayesian filtering is performed on a specific sensor, the output posterior probability is directly used as the prior probability of the next sensor for filtering, which can ensure the accuracy of the prior probability of subsequent sensors and reduce the error impact of the prior probability of the first sensor. This requires the same physical quantity when multiple sensors are fused. Therefore, we need to adjust the output data of all sensors to the probability of fire occurrence before multi-sensor data fusion.

Because the method of serial Bayesian filtering is adopted, a prior probability x_0 and multiple likelihood probabilities y_0 , y_1 y_n are required. Thus, the model of multi-sensor series-linked Bayesian filtering is as follow:



Figure 3. Multi-sensor cascade Bayesian filtering model

In this model, x_n is the posterior probability obtained by the previous sensor after modification, which is also the prior probability of the input of the next sensor, and x_0 is the prior probability of the guess.

But even so, it still only reduces the number of prior probabilities that need to be set, and still fails to solve the problem that it is impossible to set a fixed prior probability according to experience to satisfy all situations in different scenarios. Therefore, this paper intends to adopt dynamic data extraction of main sensors to set the prior probability of the whole system.

The principle is to set up a main sensor, extract the probability density function of the fire probability obtained by a large number of experiments of the main sensor, as the prior probability input of the whole system, reduce the variance of the input data of the main sensor, so as to improve the proportion of the result obtained by the final data fusion of the main sensor, and the filtering of the subsequent system as the data correction of the main sensor. To verify the main sensor on the occurrence of fire judgment, if the judgment of fire, then the system alarm.

The modified multi-sensor tandem Bayesian filtering model is the same as the figure above, except that the guessed prior probability is modified into the experimental data of the main sensor. In this way, the problem that it is difficult to determine a static threshold to judge the occurrence of fire in different scenarios is solved. At the same time, due to the different causes of fire in different scenarios, the setting of the main sensor has greater flexibility, making the judgment result more accurate.

5. CONCLUSIONS

This paper studies and improves the multi-sensor fire alarm system based on the traditional idea of Bayesian filtering. In the future, I believe that both the combined application of different sensors in different scenarios and the research on different algorithms of data fusion between sensors will become the focus of the development of intelligent fire protection. Through the updating and creation of successive generations of algorithms, the multi-sensor technology with higher accuracy and faster efficiency will certainly flourish. I believe that the fire protection system based on multi-sensors will certainly bring people a better future.

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