A Study of Weighted Average Method for Multi-sensor Data Fusion

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Abstract

With the development of sensor technology, multi-sensor data fusion has become an important research direction in the field of sensors. Among them, parametric classification algorithms have become the most intensively studied class of algorithms in the field of multi-sensor data fusion, and the weighted average method is the most important one among the parametric classification algorithms. This paper describes the composition and development of parameter classification algorithms, focusing on the process, steps and recent developments of the weighted average method, and uses the algorithm to fuse data from ultrasonic and infrared sensors. The simulation results prove that the weighted average method has a better fusion effect.

Keywords: multi-sensor, data fusion, parametric classification, weighted average method

1. Introduction

In order to meet the needs of data acquisition, a large number and various types of sensors are widely used in various fields such as military equipment, household appliances, automotive industry and medical and health care [1]. If the data that are collected by various sensors are processed separately and in isolation, it will not only increase the workload of data processing, but also cut off the intrinsic connection between the information of each sensor, which will eventually lead to the loss of key information after the combination of each sensor information. Therefore, it has become a research focus in the field of sensors to combine the data collected by multiple sensors organically by utilizing the complementary data characteristics of multiple sensors [2].

In nature, information fusion is an inherent characteristic of living organisms and is a fundamental function prevalent in humans and other animals. In the field of science and technology, the concept of "data fusion" was introduced in the 1960s, initially to address the need for multi-source correlation in military systems. In 1984, the U.S. Department of Defense established the Data Fusion Expert Group (DFS) to direct systematic research on multi-sensor information fusion technology. The International Society for Information Fusion was founded in the United States in 1998. In the 21st century, multi-sensor information fusion technology has gradually been widely used in non-military fields.

As one of the research hotspots of multi-sensor data fusion technology, fusion algorithms have received a lot of attention. Since multi-sensor data fusion involves many theories and technologies, there is no completely unified algorithm that can be adapted to all scenarios, so the appropriate algorithm needs to be selected according to different application contexts. Currently, multi-sensor data fusion algorithms are divided into the following three main categories: physical model-based methods, parameter-based methods, and cognitive theory-based methods. In this paper, we focus on the parameter-based methods.

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2. Parameter Classification Algorithm

Parametric classification algorithms are the most common, applied and studied class of algorithms in the history of multi-sensor fusion technology development. Such algorithms can be further divided into those based on statistics and those based on information theoretic techniques. Commonly used algorithms in this category are weighted average, Bayesian estimation, D-S evidence theory, entropy method, neural network, and cluster analysis.

2.1. Bayesian estimation

Bayesian estimation is a method of representing various uncertain information provided by multiple sensors as probabilities and processing them using the Bayesian conditional probability formula in probability theory.

Assume that the individual decisions contained in a sample space are independent of each other $A_1, A_2, A_3 \cdots A_n$, and assume that the observations for the system are B. By taking the prior probability $\mathrm{P}(A_i)$ and the conditional probability $\mathrm{P}(\mathrm{B}/A_i)$ through the nature of the sensor itself and a priori knowledge, the probability equation can be obtained.

$$\mathrm{P}(A_i/\mathrm{B}) = \frac{\mathrm{P}(A_i\mathrm{B})}{\mathrm{P(B)}} = \frac{\mathrm{P}(\mathrm{B}/A_i)\mathrm{P}(A_i)}{\sum_{j=1}^{m}\mathrm{P}(\mathrm{B}/A_j)\mathrm{P}(A_j)} \tag{1}$$

where $\mathrm{P}(A_i/\mathrm{B})$ is the posterior probability and $\mathrm{i} = 1,2 \cdots \mathrm{m}$.

This result can be generalized to the case of multiple sensors. When there are n sensors and the observation results are $B_1, B_2, B_3 \cdots B_n$ respectively, the posterior probability of each decision at n sensors can be obtained as equation (2), assuming that they are independent of each other and independent of the observed object condition.

$$\mathrm{P}(A_i/B_1 \wedge B_2 \wedge \cdots \wedge B_n) = \frac{\prod_{k=1}^{n}\mathrm{P}(B_k/A_i)\mathrm{P}(A_i)}{\sum_{j=1}^{m}\prod_{k=1}^{n}\mathrm{P}(B_k/A_j)\mathrm{P}(A_j)} \tag{2}$$

The final decision result can be obtained according to the corresponding specific rules [3].

Bayesian estimation is a common method for the multi-sensor low-level redundant data fusion, and can be better for incomplete information with the added Gaussian noise. By this method, the information collected from each data source is represented by a probability density function, and various constraints are assumed in advance to complete the fusion of uncertainty information.

2.2. D-S evidence theory

The D-S theory of evidence was originally proposed by Dempester in 1967 and was later expanded and developed by Shafer. It is eventually developed into one of the mathematical methods that can better handle uncertainty inference problems [4].

Evidence theory proposes the concepts of belief function Bel(A) and plausibility function Pl(A) to represent the degree of support and the degree of non-doubt for A, respectively, and the interval $[\mathrm{Bel(A)}, \mathrm{Pl(A)}]$ represents the uncertainty of premise A. For the synthesis of multiple confidence levels, let$m_1, m_2, \cdots m_n$denote the confidence allocation of n data respectively, and if they are obtained from mutually independent information, the fused Bel(A) can be expressed as Equation (3).

$$\mathrm{m(A)} = \frac{\sum_{\cap A_i = A}\prod_{i=1}^{n} m_i A_i}{1-k} \tag{3}$$

where $\mathrm{k} = \sum_{\cap A_i = A}\prod_{i=1}^{n} m_i A_i$ denotes the conflict between mass functions.

The theory uses Bel(A) rather than probabilities in the metric, and uses methods that constrain the probability of certain events to construct trust functions without directly accounting for probabilities, making it very suitable for situations where probabilities are difficult to obtain.

2.3. Artificial neural network

Artificial neural network are proposed on the basis of modern neuroscience research results. Neural network is the nonlinear network system that is composed of interconnected neurons with learning, memory, computational capabilities, various processing and intelligent recognition capabilities [5]. In a multi-sensor system, there is some uncertainty in the environmental information provided by individual sensors. In contrast, artificial neural network can be expressed in the network structure in terms of network weights based on the similarity of the samples received by the current system.

The implementation of multi-sensor data fusion in artificial neural network begins with the selection of the model, topology and learning rules of the neural network according to the requirements of the intelligent system and the form of sensor data fusion. The input information of the sensor is processed into a global input function, and the function mapping is defined as

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the mapping function of related units and this function mapping is defined as a mapping function for the relevant units. The statistical laws of the environment are reflected into the structure of the network itself through the interaction of the artificial neural network with the environment, and then the sensor output information is learned, understood, and the assignment of weights is determined to complete knowledge acquisition and information fusion.

2.4. Weighted average method

The weighted average method is the most easily understood and most used method in the parameter classification fusion algorithm. The weighted average method is a simple and intuitive way to fuse data by weighting the data from each sensor.

The main steps are: assume that the number of sensors is n and these sensors jointly monitor the same target, the data collected by the sensors is x_i, where $i = 1,2,\cdots n$, then the weighted average of all the collected data is obtained.

$$\bar{x} = \sum_{i=1}^{n} \varphi_i x_i \tag{4}$$

Where φ_i is the weighting factor for each sensor.

The structure of the weighted average method model is shown in Fig.1.

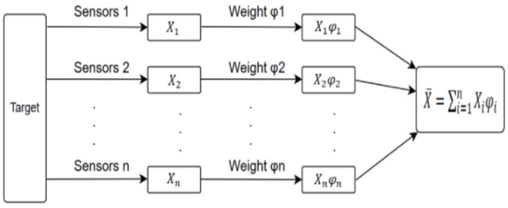

Fig.1 Weighted average method model structure

When using this method, it is necessary to reasonably determine the weighting coefficients of each sensor to ensure that the final fusion results are more accurate.

3. Test of Weighted Average Method

The main purpose of multi-sensor data fusion is to synthesize incomplete data provided by multiple sensors about a particular environmental feature to form a relatively complete and consistent sensory description for more accurate recognition and judgment functions.

In this paper, the data fusion simulation of data from two sets of sensors is performed under Windows 10 based on MATLAB 2019b software using weighted average method.

The distance data collected from ultrasonic and infrared sensor simulations were first fused. Five sets of typical data were grabbed from all fused data for comparative analysis, whcih is shown in Table 1.

Table 1. Motor parameters

Test value (cm)	Fusion results (cm)	Error
80	80.143	0.18%
80	79.856	0.18%
80	80.541	0.68%
80	79.992	0.01%
80	80.471	0.59%

From the data in the table, it can be seen that the fusion results of ultrasonic sensor and infrared sensor range data have less than 1% error, which shows the better fusion effect of the weighted average method.

At the same time, the image data fusion test was performed on the image information collected by the two vision sensors using the weighted average method.

In the first test, the values of weights for the high color vision sensor were set to larger, and the test is shown in Fig.2, where the top left image is taken by the high resolution but color distorted vision sensor, the top right image is taken by the good color but low resolution vision sensor, and the bottom image is the test result after fusion of these two vision sensor data.

Fig.2 High color image fusion test

As can be seen from the above figure, the images captured by the two vision sensors are weighted by the image data fusion, and the fused images are more vivid in color and have a certain improvement in resolution.

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But we still can see that the details of the objects in the test result are rather blurred. Therefore, in the second image data weighting fusion, the weights of the high-resolution vision sensors are set larger, and the fusion result is shown in Fig.3.

Fig.3 High definition image fusion test

As can be seen from the above tests, after the second fusion, although some areas of the image are not full of color, the overall fusion effect is satisfactory because the details of the objects are clearer and the colors are brighter.

4. Conclusion

This paper presents the theory and development of parameter classification algorithms in multi-sensor data fusion techniques. In particular, the Bayesian estimation, D-S evidence theory, artificial neural networks and weighted averaging are introduced. At the end of the paper, the weighted average method is tested for data fusion simulation, and the test results show that the method has obvious fusion effect and has strong practicality.

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Authors Introduction

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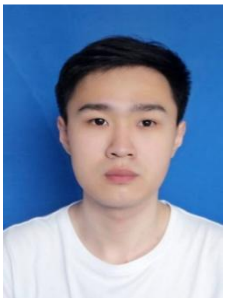

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He received an M.E. and Doctor of Engineering (PhD) from the Beijing Institute of Technology, China in 1998 and Oita University, Japan in 2004 respectively. His main research interests are artificial intelligence, pattern recognition and robotics. He worked in National Institute of Technology, Matsue College, Japan from 2003 to 2009. Since October 2009, he has been the staff in the College of Electronic Information and Automation, Tianjin University of Science and Technology, China.