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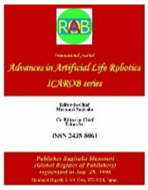

Research Article

A Study on Multi-sensor Data Fusion Algorithm

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ABSTRACT

As an important research direction in the field of sensors, multi-sensor data fusion has received greater attention and development in areas such as robotics and autonomous driving. This paper provides a comprehensive introduction to the physical model-like and parameter-based data fusion algorithms that are often used in current engineering. Meanwhile, the process, steps and recent developments of the weighted average method and the extended Kalman filter method are highlighted, and multi-sensor data fusion experiments are conducted for each of the two algorithms. The simulation results prove that the data fusion algorithm has a good fusion effect.

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]. It is very important to effectively process and analyze the data acquired by the sensors and to obtain accurate information about the system itself and the environment. To date, no sensor can be guaranteed to provide accurate and completely reliable information when used alone. 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, data fusion is an essential characteristic inherent to living organisms and is the basis for their environmental perception and behavioral actions. 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 the 21st century, multi-sensor information fusion technology has gradually been widely used in non-military fields. From a non-military perspective, multi-sensor data fusion is defined as the synthesis of incomplete information about an environmental characteristic provided by multiple sensors and information sources to form a relatively complete and consistent sensory description for more accurate identification and judgment functions.

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. Among them, the physical model class and parameter-based data fusion algorithms are more widely used in engineering practice, and this paper mainly introduces these two types of algorithms.

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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. Commonly used algorithms in this category are weighted average, Bayesian estimation, D-S evidence theory and neural network.

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. The method combines the association probability distributions of each sensor into a joint posterior probability distribution function. Provides the final fused value of the multi-sensor data by minimizing the likelihood function of the joint distribution function.

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].

Bayes estimation is a common method for fusing multi-sensor low-level redundant data in static environments, and can be better for incomplete information with the added Gaussian noise. When the observation coordinates of multiple sensors agree, the sensor measurement data can be fused directly. However, in most cases, the sensors need to describe the same object from different coordinate frames, when the sensor data are to be fused with information in an indirect way using Bayes estimation. Bayes method is suitable for redundant data, but it requires that the probabilities are independent and that the prior and conditional probabilities are given, which is difficult in engineering practice.

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.

D-S evidence theory describes the data information of a sensor in terms of a trust function that not only represents the known and certainty of the information, but is also able to distinguish between unknowns and uncertainties. At the same time, the trust function is built without a direct specification of probabilities, which is very suitable for those cases where probabilities are difficult to obtain.

2.3. Artificial neural network

Artificial 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.

To implement multi-sensor information fusion in artificial neural networks, the input information of sensors is processed into a global input function, and the function mapping is defined as a mapping function of the relevant units, which is defined as a mapping function of 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. Especially in the case of sensor data fusion system without function model, the neural network can get the network structure and mapping relationship by a large number of training, and has good self-adaptability, which is very suitable for the scenario of complex multi-sensor data fusion.

2.4. Weighted average method

The weighted average method is one of the simplest and most intuitive real-time fusion methods for multi-sensor data fusion algorithms. The method takes the redundant information from different sensors and averages them in a weighted way, and the resulting weighted value is the result of data fusion.

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 $\mathrm{i} = 1,2,\cdots \mathrm{n}$, 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.

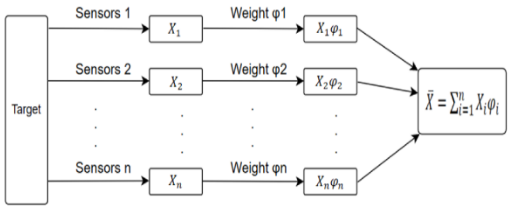


Fig.1 Weighted average method model structure

When using this method, a detailed analysis of the system and sensors must first be performed to obtain the correct weights to ensure a more accurate final fusion result.

3. Physical Model Based Classification

Such algorithms are based on physical models to observe the results and obtain the feature correlation between them and the real observed objects, and judge the degree of matching between the two by a pre-set coefficient threshold [6]. The most prominent representatives of this class of algorithms are Kalman filtering methods and their extensions.

3.1. Kalman filter

The Kalman filter is a recursive optimal estimation algorithm [7]. The method uses the statistical properties of the measurement model to recursively derive the optimal fusion data under statistical significance. If the system has a linear dynamics model and both the system noise and sensor noise are Gaussian-distributed white noise models, Kalman filtering can provide the only optimal estimate for statistically significant information fusion. The recursive nature of Kalman filtering allows the system to perform fusion processing without requiring large amounts of data storage and computation. Therefore, Kalman filtering is generally used to fuse low-level real-time dynamic multi-sensor redundant data and effectively remove interference information.

3.2. Extended kalman filter

The Kalman filter algorithm is used for linear systems where the prediction and observation models are performed under the assumption of Gaussian distribution and linearity. Simple Kalman filtering must be applied to systems that conform to a Gaussian distribution, but in reality not all systems conform to this. For example, nonlinear problems caused by external disturbances to the physical model, the presence of nonlinearities and pathological variance matrices all make the traditional Kalman filtering algorithm no longer applicable. Therefore, there is an urgent need to improve the Kalman filtering algorithm to obtain a Kalman filtering technique applicable to nonlinear systems.

The extended Kalman filter solves the nonlinear problem by local linearity. The continuous nonlinear equations are first linearized and discretized to approximate the nonlinear model using a first-order Taylor expansion. The nonlinear state and observation equations are then expanded into Taylor series around the obtained estimates, and the linearized model is obtained by taking a first-order approximation, thus enabling the continued use of the standard Kalman filter recursive system. The biggest difference between the extended Kalman filter and the Kalman filter is that the state transfer matrix and the observation matrix of the extended Kalman filter are both Jacobi matrices of state information when calculating the variance.

4. Test

In order to verify the fusion effect of two types of multi-sensor fusion algorithms, this paper applies the weighted average method and the extended Kalman filter method to simulate the data fusion of multiple groups of sensors, respectively.

4.1. Test of weighted average method

The distance data collected from the ultrasonic and infrared sensor simulations are first fused using the weighted average method. 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.

As can be seen from Fig. 2, when the weights of the high color vision sensor are set to larger weights, the fused image is more vivid, but the details of the objects in the image are less sharp. 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.

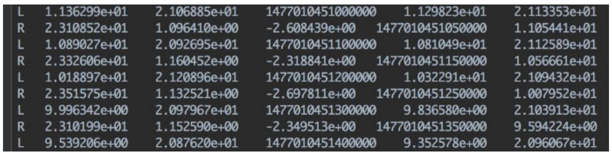
Fig.3 High definition image fusion test

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.

4.2. Test of weighted average method

This paper tests the fusion effectiveness of the extended Kalman filter fusion algorithm with data from LIDAR and millimeter wave radar used in the Udacity course when detecting the same obstacle.

The measurement scenario for the data is to fix a LIDAR and a millimeter wave radar with the same frequency at the origin, followed by alternate triggering of the two radars to detect the same moving obstacle. Some of the data are shown in Fig 4. The first letter of each line of data indicates which sensor the data comes from L is short for Lidar and R is short for Radar.



L	1.136299e+01	2.106885e+01	1477010451000000	1.129823e+01	2.113353e+01
R	2.310852e+01	1.096410e+00	-2.608439e+00	1477010451050000	1.105441e+01
L	1.089027e+01	2.092695e+01	1477010451100000	1.081049e+01	2.112589e+01
R	2.332606e+01	1.160452e+00	-2.318841e+00	1477010451150000	1.056661e+01
L	1.018897e+01	2.120896e+01	1477010451200000	1.032291e+01	2.109432e+01
R	2.351575e+01	1.132521e+00	-2.697811e+00	1477010451250000	1.007952e+01
L	9.996342e+00	2.097967e+01	1477010451300000	9.836580e+00	2.103913e+01
R	2.310199e+01	1.152590e+00	-2.349513e+00	1477010451350000	9.594224e+00
L	9.539206e+00	2.087620e+01	1477010451400000	9.352578e+00	2.096067e+01

Fig.4 Sensor data

The trajectory of the obstacle obtained after simulation is shown in Fig 5.

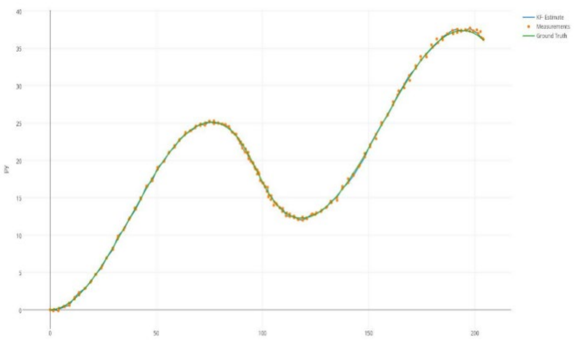


Fig.5 Obstacle target detection simulation results

In the figure, the blue line is the estimate of the target position by the extended Kalman filter algorithm, the orange points are the measurements from LIDAR and RADAR, and the green line is the true position of the target. As can be seen from the figure, the measurement of the obstacle position by a single sensor is inaccurate, while using the extended Kalman filter algorithm to fuse the two sensor measurements can obtain an estimate that is very close to the actual position state of the target

.

5. Conclusion

This paper introduces the physical model class and parameter-based class multi-sensor data fusion algorithms commonly used in engineering practice. At the same time, two typical algorithms, the weighted average method and the extended Kalman filter method, were tested for data fusion simulation. The test results show that the use of multi-sensor fusion algorithms can make full use of the advantages of each sensor and help the sensor system to obtain more accurate measurements. This will certainly make the application of multi-sensor data fusion technology in engineering practice more widespread and its research prospect will be more optimistic.

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Authors Introduction

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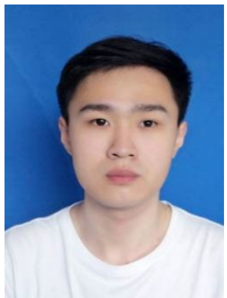

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