The Algorithm of Comprehensive Support Degree for Sensor Array Based on Spectrum Consistency

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Abstract. Aiming at the problem of data fusion deviation caused by the uncertainty of observation information in the multi-sensor data fusion algorithm, this paper proposes an array comprehensive support algorithm based on the spectrum consistency of the observation information. Starting from the probability distribution function of the array observation model, the algorithm introduces a multi-sensor consistent data fusion method. Aiming at the empirical selection of data fusion thresholds, the algorithm discusses the consistency processing method of the symmetric distance function, and comprehensively considers the multi-sensor delay estimation, A comprehensive support degree algorithm for spectrum consistency is proposed. The hardware-in-the-loop simulation test of the quaternary acoustic array verifies that the proposed algorithm not only reduces the observation noise caused by the uncertainty data fusion deviation, but also realizes the effectiveness of the estimation of the multi-sensor observation signal under the condition of unknown prior signal.

1. Introduction
In the intelligent detection technology, the detection system includes parts such as target indication, target tracking, target solution, and follow-up control. Target indication is the basis of intelligent detection technology, and it is also the primary condition. The traditional way to perceive target indication information is to use a single sensor, such as radar sensors, photoelectric sensors, acoustic and infrared sensors, and so on. In practical engineering applications, it is difficult to collect target observation information due to the occlusion of environmental obstacles, single sensor failure, and the influence of uncertain random disturbance factors in the observation environment. In addition, due to factors such as transmission errors and calculation errors, the observation data will not be able to truly represent the position and status information of the target. In response to the above problems, relevant researchers have developed digital filters using parameter estimation methods, such as maximum likelihood estimation, least square estimation and maximum a posteriori estimation [1, 2], but in the above method, the prerequisite is that the effective detection probability of the sensor is 1, that is, the observation data is truly without loss. Subsequently, genetic algorithm, particle swarm algorithm, ant colony algorithm and other methods also have related research [3–6], but the setting of function fitness is subjective, which limits the application range of such algorithms.
Aiming at the uncertainty of multi-sensor observation data, Lou R C [7] proposed to use the confidence probability distance to measure the consistency of the description of the multi-sensor observation data, but the actual engineering setting needs to be considered in the structure selection of the confidence distance function. Literature [8] In order to study the degree of support between multi-sensor observation data, the concept of decision distance is proposed based on the membership function, the distance matrix and the relationship matrix are constructed, and the directed graph method is used to solve the largest sensor association group supported by data fusion. The optimal fusion is carried out according to the guidelines, but this algorithm requires the use of prior data to manually set the threshold, and at the same time reduces the utilization of the observed data in the binary judgment. Wang Lin [9] and others proposed the stability theory based on matrix eigenvectors to participate in multi-sensor data fusion algorithms. Jiao Zhuqing [10] and Yang Jia [11] respectively proposed multi-sensor consistent reliability fusion based on trust or proximity Methods. The commonality of the above methods is that the threshold value needs to be selected in advance to determine the relationship matrix between multiple sensors. Therefore, there are more human factors in defining the support of each sensor and the effective choice of data. The result of data use fusion depends on the parameter value. The choice of, causes data instability in the engineering application of the algorithm, thereby affecting the robustness of subsequent data processing. In view of the problems of the above algorithms, especially the problem of data fusion bias due to the uncertainty of observation information in the multi-sensor data fusion algorithm, this paper starts from the probability distribution function of the multi-sensor array observation model and introduces the multi-sensor consistent data Fusion method, aiming at the problem of artificial experience selection of data fusion threshold, establishes a consistency processing method of symmetric distance function, comprehensively considers the time delay estimation of multiple sensors, and proposes a comprehensive support degree algorithm for spectrum consistency. In addition, based on the preliminary research foundation of the research group [12,13], this paper verifies that the algorithm in this paper not only reduces the observation noise caused by uncertain data fusion bias, but also has unknown prior Realize the effectiveness of multi-sensor observation signal estimation under signal conditions.

2. Comprehensive support algorithm of acoustic array spectrum consistency

2.1. Consistent data fusion algorithm

For the problem of multi-sensor acoustic arrays, tThe number of sensors is \( N \), which measure independently. It is assumed that the observation value of the first sensor is \( x_i \), the observation accuracy is \( \sigma_i \), and it obeys the normal distribution. The observation model can generally be expressed by the normal distribution:

\[
P(x_i) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma_i^2}\right)
\] (1)

\[
D_{ij} = 2 \int_{x_i}^{x_j} P_i(x \mid x_i) dx = P\left( |Z| \leq \frac{|x_i - x_j|}{\sigma_i}\right)
\] (2)

\[
D_{ji} = 2 \int_{x_j}^{x_i} P_j(x \mid x_j) dx = P\left( |Z| \leq \frac{|x_j - x_i|}{\sigma_j}\right)
\] (3)

Where, \( P(x \mid x_i) \) is conditional probability, is random Variable, which obeys the normal distribution. Thus, the confidence distance matrix can be obtained as:
Given experience or the results of multiple tests, a threshold is given $\epsilon_j$, so

$$s_{ij} = \begin{cases} 1 & D_{ij} \leq \epsilon_j \\ 0 & D_{ij} > \epsilon_j \end{cases} i=1,2,\ldots N$$

(5)

Then from the confidence distance matrix between the acoustic sensors, the support matrix between the acoustic sensors can be obtained as

$$S = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nn} \end{bmatrix}$$

(6)

In this way, the largest acoustic sensor group participating in the fusion can be determined, and the observation data of the acoustic sensor in the largest acoustic sensor group is data fused, which eliminates the influence of inaccurate acoustic sensors and reduces the impact caused by severely distorted acoustic sensors. Big error. In this algorithm, when the measurement accuracy of the acoustic sensor is different from that of the acoustic sensor, the confidence distance is different, which is inconsistent with the symmetry requirement in the usual distance definition, and the threshold is determined based on experience, which is very subjective. In addition, improper selection of the threshold may have a great impact on the results.

2.2. Consistency algorithm using symmetric distance

Due to the above-mentioned problems in the above-mentioned consensus algorithm, it has been improved. Considering that the confidence distance is the key to the fusion of consistent data, a new confidence distance is defined.

So:

$$D_{ij} = \frac{1}{2} \left[ 2 \int_{x_j}^{x_i} P_i(x | x_j)dx + 2 \int_{x_j}^{x_i} P_j(x | x_j)dx \right]$$

(7)

$$D_{ij} = \int_{0}^{\frac{|x_i-x_j|}{\sigma_i}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx + \int_{0}^{\frac{|x_i-x_j|}{\sigma_j}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

(8)

$$D_{ji} = \int_{0}^{\frac{|x_j-x_i|}{\sigma_j}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx + \int_{0}^{\frac{|x_j-x_i|}{\sigma_i}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

(9)

So, $D_{ij} = D_{ji}$. The confidence distance defined in this way overcomes the inconsistency when the observation accuracy is different.
\[ s_{ij} = 1 - D_{ij} \]  

This overcomes the subjective error caused by artificially defined thresholds, blurs the degree of mutual support of the measured data of various acoustic sensors, and can effectively reduce the changes in observation data caused by various disturbance factors.

Calculate the support matrix of all acoustic sensors, there is the largest modulus eigenvalue and the corresponding eigenvector \( Y \), \( Y = (y_1, y_2, \cdots, y_n)^T \) has \( SY = \lambda Y \), expanded into \( \lambda y_k = y_1 s_{k1} + y_2 s_{k2} + \cdots + y_n s_{kn} \), where, \( k = 1, 2, \cdots, N \)

\[
\phi_k = \frac{\lambda y_k}{\sum_{i=1}^{N} \lambda y_i} = \frac{y_k}{\sum_{i=1}^{N} y_i}
\]  

Then it is the comprehensive support of the first acoustic sensor, and the final data fusion value as follow:

\[
x = \sum_{k=1}^{N} \phi_k x_k
\]  

2.3. Comprehensive support algorithm for spectrum consistency of multi-acoustic sensors

Aiming at the problem of multi-acoustic sensor acoustic array positioning, the observation data between the acoustic sensors is time lag, and the difference is unknown before the time delay estimation, so the multi-acoustic sensor fusion observation data cannot be directly calculated using equation (12). In addition, within a certain observation time \( T \), the time delay difference is much smaller than the observation time \( T \). Therefore, it can be considered that the frequency spectrum between the signals of the multi-acoustic sensors during the observation time \( T \) is similar. However, due to the interference of the noise signal, the spectrum of the global observation signal is not the same. Under this condition, it is difficult to estimate the accuracy of the acoustic sensor. Based on the above analysis and combined with the characteristics of the acoustic sensor array, a new measure of support is defined, that is, the frequency domain support:

\[
s_{ij} = 1 - \frac{1}{\omega^2 - \omega_1^2} \sum_{\omega=\omega_1}^{\omega^2} | F_i(\omega) - F_j(\omega) | \]

Among them are the normalized frequency spectrum of the signal, and each is the frequency distribution interval of the observation information within the observation time \( T \).

Equation (13) expresses the approximate degree of the two acoustic sensor observation signals in the frequency domain, and calculates its comprehensive support degree according to its support matrix.

3. Verification of multi-element array fusion algorithm

3.1. Test design

In order to verify the effectiveness of the comprehensive support degree algorithm for spectrum consistency of multi-acoustic sensors proposed in the article, a four-element acoustic array directional hardware-in-the-loop simulation experiment was designed. In the test, a high-fidelity speaker is used to play the tank noise during driving to simulate the target sound source. Because the speaker is small in size, the sound source can be considered as a spherical sound source from the observation distance. A
A variable-structure acoustic array device is designed and installed on a three-axis turntable to simulate the movement posture of the array. In the semi-physical simulation test, the four-element array is uniformly arranged in a circular shape, the diameter of the array is 1m, and the sampling frequency is 12,500 Hz. Figure 1 shows the layout of the quaternary acoustic array.

![Image of acoustic array layout]

**Fig 1.** The variable structured of acoustic array.

### 3.2. Analysis of algorithms

Take the measured signal. For a signal that meets the estimated length of the delay, the four channel signals and their spectra are shown in Figure 4. From the figure, it can be seen that the signal spectrum of channel 1# is obviously different. It may be that the frequency response bandwidth of the acoustic sensor is different from the other three. The channel data is different, it is also possible that the channel frequency response of the channel is different, or even the acoustic sensor completely fails.

According to formula (13), the support matrix is calculated as:

\[
S = \begin{bmatrix}
1.0000 & 0.8676 & 0.8505 & 0.7918 \\
0.8676 & 1.0000 & 0.9185 & 0.8735 \\
0.8505 & 0.9185 & 1.0000 & 0.8748 \\
0.7918 & 0.8735 & 0.8748 & 1.0000 \\
\end{bmatrix}
\]  

(14)

The characteristic value of the calculation support matrix is:

\[
\lambda = \begin{bmatrix}
0.0802 & 0.1200 & 0.2102 & 3.5896 \\
\end{bmatrix}
\]  

(15)

The eigenvector corresponding to the largest eigenvalue is:

\[
Y = \begin{bmatrix}
-0.4885 & -0.5102 & -0.5079 & -0.4930 \\
\end{bmatrix}^T
\]  

(16)

The comprehensive support degree of each acoustic sensor calculated according to the maximum eigenvector is:

\[
\phi = \begin{bmatrix}
0.2443 & 0.2551 & 0.2540 & 0.2466 \\
\end{bmatrix}
\]  

(17)
As shown in Table 1, it is the support data of the four acoustic sensors. According to the average comprehensive support of 0.25, it can be seen that the observation signal of the 1# sensor is distorted, which is consistent with the observation result. In addition, calculate the six delay values of this group of signals as shown in the T2 row in Table 2. It can be seen from the results of the time delay estimation: when two acoustic sensors with relatively low support degrees perform the time delay estimation, the error of the result is large, and the error of acoustic sensor 1 is the largest. In this regard, the statistics of the measured data of the four acoustic sensors show that the error of the time delay estimation with the acoustic sensor 1# is obviously too large. Therefore, it is necessary to estimate the support of the acoustic sensor first. Under the condition that the number of acoustic sensors is redundant, the acoustic sensor with high comprehensive support should be selected for orientation or distance fixation. The method proposed in this paper relies on the measured data to evaluate the signals of the multi-acoustic sensors. The measured signals can be estimated under the condition of unknown prior signals, and the acoustic sensor signals with high comprehensive support are given. The algorithm is simple and effective.

|  | 1# | 2# | 3# | 4# |
|---|---|---|---|---|
| T1 | 0.2472 | 0.2512 | 0.2492 | 0.2524 |
| T2 | 0.2443 | 0.2551 | 0.2540 | 0.2466 |
| T3 | 0.2515 | 0.2445 | 0.2519 | 0.2521 |
| T4 | 0.2483 | 0.2488 | 0.2513 | 0.2516 |
| T5 | 0.2499 | 0.2467 | 0.2496 | 0.2537 |
| T6 | 0.2496 | 0.2478 | 0.2513 | 0.2514 |
| T7 | 0.2509 | 0.2449 | 0.2509 | 0.2534 |
| T8 | 0.2476 | 0.2524 | 0.2508 | 0.2492 |
| T9 | 0.2521 | 0.2491 | 0.2462 | 0.2526 |
| T10 | 0.2500 | 0.2494 | 0.2480 | 0.2526 |

| Time delay | Observation | τ_{31} | ms | τ_{42} | ms | τ_{34} | ms | MST_{21} | ms | MST_{32} | ms | MST_{41} | ms |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Theoretical value | 1.4641 | 0 | 0.7138 | 0.7504 | 0.7138 | 0.7504 |
| T1 | 1.4256 | 0.0272 | 0.7120 | 0.6736 | 0.8016 | 0.6224 |
| T2 | 1.4096 | 0.0272 | 0.7056 | 0.6768 | 0.7334 | 0.2924 |
| T3 | 1.3456 | 0.0304 | 0.7024 | 0.6576 | 0.8240 | -1.896 |
| T4 | 1.3776 | 0.0496 | 0.6992 | 0.6800 | 0.7600 | 1.2144 |
| T5 | 1.3584 | 0.0400 | 0.6764 | 0.6832 | 0.7312 | 1.1984 |
| T6 | 1.3328 | -0.0304 | 0.6920 | 0.6476 | 0.7184 | 0.0272 |
| T7 | 1.3712 | -0.0272 | 0.6992 | 0.6896 | 0.7280 | 1.1728 |
| T8 | 1.3936 | -0.0432 | 0.6992 | 0.6992 | 0.7312 | 0.6448 |
| T9 | -2.2032 | -0.0592 | 0.6672 | 0.5680 | 0.7344 | -6.5808 |
| T10 | -0.5776 | -0.0528 | 0.6928 | 0.6864 | 0.7344 | 0.6416 |

4. Conclusion
The realization of target identification, location and tracking based on the sound source signal observed by the multi-sound array is a key link in the intelligent sound detection technology of weapon equipment. This paper aims at the problem of data fusion deviation caused by the uncertainty of multi-sensor observation information. Starting from the probability distribution function of the observation model, a
multi-sensor consistent data fusion method is introduced. Combining the actual situation of multi-sensor time delay estimation, a comprehensive support algorithm of acoustic array based on the spectrum consistency of observation information is proposed. The hardware-in-the-loop simulation experiment of the quaternary acoustic array verifies the necessity of estimating the support degree of the acoustic sensor first, and also confirms the effectiveness of the algorithm in this paper to estimate the observed signal under the condition of unknown prior signal. At the same time, under the condition that the number of sensors in the acoustic array detection is redundant, the acoustic sensors with high comprehensive support should be selected for orientation or distance.

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