Research on fusion detection of centralized mobile target based on seismic wave sensor

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Abstract. Aiming at the limitation of single sensor detection and the deficiency of low information utilization rate in distributed fusion mode, according to the characteristics of strong energy and long propagation distance on free surface of seismic wave and the advantages of centralized fusion detection method, a centralized fusion detection algorithm based on Neyman-Pearson criterion is proposed. The probability formula of single sensor detection and centralized fusion detection is deduced and simulated. Through the experiment of ground maneuvering target, it is proved that the algorithm can effectively improve the detection probability and performance of the target.

1. Introduction

The ground target will excite energy-rich seismic wave signals during the maneuvering process, among which the interface wave signal transmitted along the ground surface attenuates slowly and has a long propagation distance. Therefore, the use of seismic wave sensors for ground moving target detection can achieve good results[1]. In the actual environment, the dimension of target information obtained by only a single sensor is very limited, compared with single sensor, multi-sensor fusion detection technology has the advantages of comprehensive information, high fault tolerance and wider coverage[2].

A multi-sensor fusion detection system consists of multiple sensors and fusion centers, including centralized and distributed[3]. In distributed fusion mode, each sensor is judged based on its own measurement data and transmitted to the fusion center. Most of the previous studies have proposed a distributed multi-sensor fusion detection[4]. In Aziz A M[5], propose a distributed multi-decision fusion rule to improve the detection performance and stability of the system, and deduce its application in the binary communication system. In Eritmen K and Keskinoz M[6], the distributed decision-making fusion rules of multi-layer wireless sensor networks are studied, including the sensor layer, the local cluster layer and the fusion center layer. First, the optimal likelihood ratio criterion is derived when the real-time state information of the fading channel is known, and then given the likelihood ratio detection criterion when the channel statistics are known is presented. In Luo J et al [7], a target detection data fusion algorithm based on tree topology is proposed, and combined with an ordered full binary tree, the optimal threshold fusion rule is discussed. In the centralized fusion mode, each sensor only preprocesses the detected target information. Then the data is transmitted to the fusion center. And finally, the fusion center processes and integrates all the transmitted data to form the final judgment. Compared with distributed fusion, Compared with the distributed fusion method, the centralized method can reduce the loss of information and the result of the fusion is more accurate.
In recent years, it has also been studied by many experts and scholars. In Xinbo Gao et al [8], two new centralized fusion algorithms are proposed to solve the problem of multi-sensor centralized fusion in the linear Gaussian model. In Hongliang Sun and Zejun Lu [9], combining a classic constant false alarm rate detector CA-CFAR with multi-sensor centralized detection, the detection probability of the two-sensor centralized constant false alarm rate detector and the three-sensor centralized constant false alarm rate detector is simulated, which effectively improves the sensor detection performance. In Xiaoying Wang et al [10], integrate multi-view sensor data into a centralized sensor network, successfully integrating information provided by multiple sensors with different fields of view. In Yangyang Li et al [11], a centralized asynchronous fusion algorithm for sensors with different resolutions based on DP-TBD is proposed. Compared with the performance of a single sensor, this algorithm greatly improves the performance of target tracking.

Based on this, this paper proposes a seismic wave sensor centralized maneuvering target fusion detection algorithm based on Neyman-Pearson criterion, the experimental results show that the algorithm can effectively improve the detection probability.

2. Mathematical Model of Target Detection Problem

Target detection can usually be regarded as a binary hypothesis test problem. There are two hypotheses: $H_0$ (no target) and $H_1$ (with target), which can be expressed as:

$$ \begin{cases} H_1: z = v + A \\ H_0: z = v \end{cases} $$

where $z$ represents the sensor observation value, $v$ represents the white Gaussian noise, $A$ represents the deterministic signal.

For two different hypotheses, the probability density function (pdf) can be expressed as:

$$ p(z | H_0) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{z^2}{2}\right] $$

$$ p(z | H_1) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{(z-A)^2}{2}\right] $$

To judge whether $z$ belongs to $H_0$ or $H_1$, the following judgment rules can be adopted:

$$ \Lambda(z) = \frac{p(z | H_1)}{p(z | H_0)} = \frac{p(H_0)C_{10}}{p(H_1)C_{01}} = \eta $$

Where $\Lambda(z)$ is likelihood ratio, $\eta$ is likelihood threshold, $p(H_i)$ is the priori probability of $H_0$ and $H_1$, and $C$ is the cost factor.

However, in some cases, neither a priori probability nor a given cost factor can be predicted, and the losses caused by missing alarms in military applications are often more serious than false alarms. In this case, the Neyman-Pearson criterion is usually selected [12]. In Neyman-Pearson criterion, the probability of detection is maximized for a given pre-specified probability of false alarm.

For a given pre-specified false alarm probability ($P_F = \alpha$), in order to maximize the detection probability ($P_D$), we use the Lagrangian method to construct the objective function

$$ F = P_D - \lambda(P_F - \alpha) = \int_z \left( p(z | H_1) - \lambda p(z | H_0) \right) dz + \lambda \alpha $$

In order to maximize $F$, we should assign the positive value of integral $z$ to $Z$, that is, if $p(z | H_1) - \lambda p(z | H_0) > 0$, we can determine that $z$ belongs to $H_1$, otherwise, $z$ belongs to $H_0$, and the final judgment can be expressed as:
where, the threshold $\lambda$ is determined by the following:

$$\alpha = \int_{\lambda}^{\infty} p[\Lambda(z) \mid H_{0}] d\Lambda(z)$$

3. Fusion Algorithm

The $N$ observations of the signal by the sensor can be expressed as:

$$p(z[n] \mid H_0) = \left(\frac{1}{\sqrt{2\pi\sigma}}\right)^N \exp\left[-\frac{\sum_{n=0}^{N-1} z[n]^2}{2\sigma^2}\right]$$  \hspace{1cm} (1)

$$p(z[n] \mid H_1) = \left(\frac{1}{\sqrt{2\pi\sigma}}\right)^N \exp\left[-\frac{\sum_{n=0}^{N-1} z[n] - s[n]^2}{2\sigma^2}\right]$$  \hspace{1cm} (2)

The likelihood ratio can be derived as:

$$\Lambda(z) = \frac{p(z \mid H_1)}{p(z \mid H_0)} = \exp\left[\frac{1}{\sigma^2} \left(\sum_{n=0}^{N-1} z[n] - s[n]^2\right)\right]$$  \hspace{1cm} (3)

The judgment can be derived as:

$$T(z) = \left(\sum_{n=0}^{N-1} z[n]s[n]\right) - \frac{1}{2} \sum_{n=0}^{N-1} s[n]^2 < \sigma^2 \ln \lambda = \gamma$$  \hspace{1cm} (4)

The threshold($\gamma$) is determined by the false alarm probability($P_f$), i.e.:

$$P_f = \int_{\gamma}^{\infty} p(T(z) \mid H_0)dz = \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(T(z)+\frac{1}{2}\varepsilon)^2}{2\sigma^2\varepsilon}\right)dz = Q\left(\frac{\gamma + \varepsilon}{\sqrt{\sigma^2\varepsilon}}\right)$$  \hspace{1cm} (5)

$$\gamma = \sigma^2 \varepsilon Q^{-1}(P_f) - \frac{1}{2} \varepsilon$$  \hspace{1cm} (6)

where: $\varepsilon = \sum_{n=0}^{N-1} s[n]^2$, $Q(x) = \int_{x}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right)du$.

Detection probability at this time is:

$$P_D = \int_{\gamma}^{\infty} p(T(z) \mid H_1)dz = Q\left(\frac{\gamma - \varepsilon}{\sqrt{\sigma^2\varepsilon}}\right) = Q\left(Q^{-1}(P_f) - \frac{\varepsilon}{\sqrt{\sigma^2\varepsilon}}\right)$$  \hspace{1cm} (7)

The pdf of centralized fusion detection under the two assumptions is:

$$p(Z \mid H_1) = \left(\frac{1}{(2\pi)^{\frac{\Sigma}{2}}}\right)^N \exp\left[-\sum_{n=0}^{N-1} \frac{1}{2}(Z - \overline{S})^T \Sigma^{-1} (Z - \overline{S})\right]$$  \hspace{1cm} (8)
\[
p(Z \mid H_0) = \left(\frac{1}{(2\pi)^{N/2}}\right)^N \exp\left[-\sum_{n=0}^{N-1} \frac{1}{2} (Z_n^T \Sigma^{-1} Z_n)\right]
\]

where, \( Z = \begin{bmatrix} z_1[n] \\ z_2[n] \end{bmatrix}, \ S = \frac{1}{2}(S_1 + S_0), \ S_1 = \begin{bmatrix} s_1[n] \\ s_2[n] \end{bmatrix}, \ S_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \) \( \Sigma \) is the covariance matrix.

The measurement noises of the two sensors are independent and uncorrelated. Therefore, the mutual covariance \( \sigma_{ij} = 0 \) between them, so the covariance matrix can be expressed as:

\[
\Sigma = \begin{bmatrix} \sigma^2 & 0 \\ 0 & \sigma^2 \end{bmatrix}
\]

The likelihood ratio can be derived as:

\[
\Lambda(z) = \exp\left(\sum_{n=0}^{N-1} (Z_n - S_n)^T \Sigma^{-1} (S_n - S_0)\right) = \exp\left(\frac{1}{\sigma^2} \sum_{n=0}^{N-1} (z_1[n]s_1[n] + z_2[n]s_2[n]) - \frac{1}{2}(\epsilon_1 + \epsilon_2)\right)
\]

The judgment can be derived as:

\[
T(z) = \sum_{n=0}^{N-1} (z_1[n]s_1[n] + z_2[n]s_2[n]) - \frac{1}{2}(\epsilon_1 + \epsilon_2) > c_{\gamma} \ln \lambda = \gamma,
\]

It can be seen from the likelihood ratio that \( T(z) \) obeys the Gaussian distribution. It can be deduced that when \( z \) belongs to \( H_0 \), \( T(z) \sim N(-\frac{\epsilon_1 + \epsilon_2}{2}, \beta) \), otherwise, \( T(z) \sim N(\frac{\epsilon_1 + \epsilon_2}{2}, \beta) \),

where, \( \beta = \sigma^2(\epsilon_1 + \epsilon_2) \).

The threshold(\( \gamma \)) is determined by the false alarm probability(\( P_f \)), i.e.:

\[
P_f = \int_{\gamma}^{\infty} P(T(z) \mid H_0) \, dT(z) = Q\left(\frac{\gamma + \frac{\epsilon_1 + \epsilon_2}{2}}{\sqrt{\beta}}\right)
\]

\[
\gamma = \sqrt{\beta} Q^{-1}(P_f) - \frac{\epsilon_1 + \epsilon_2}{2}
\]

Detection probability at this time is:

\[
P_d = \int_{\gamma}^{\infty} P(T(z) \mid H_1) \, dT(z) = Q\left(\frac{\gamma - \frac{\epsilon_1 + \epsilon_2}{2}}{\sqrt{\beta}}\right) = Q\left(Q^{-1}(P_f) - \frac{\epsilon_1 + \epsilon_2}{\sqrt{\sigma^2}}\right)
\]

4. Simulation Analysis

From the detection probability formula of centralized fusion detection and the detection probability formula of single sensor detection, the detection probability is all related to the background noise power, the number of observations and the probability of false alarms. Below we simulate the above situations respectively. According to the envelope characteristics of the signal collected by the seismic wave sensor, set the simulation signal to be a sinusoidal signal(\( \sin \frac{\pi T}{2} \)), the signal duration is 2 seconds,
the sensor sampling frequency is 5Hz and 10Hz, and the false alarm probability ($P_F$) is 0.01 and 0.05.

Figure 1 shows the relationship between the background noise power and single sensor detection and fusion detection when the sensor sampling frequency is 5Hz. Figure 2 shows the relationship between the background noise power and the single sensor detection and fusion detection when the sampling frequency is 10Hz.

![Detection probability map](image1)

![Detection probability map](image2)

Figure 1  $f = 5$Hz Detection probability map  
Figure 2  $f = 10$Hz Detection probability map

It can be seen from Figure 1 and Figure 2 that under the same false alarm probability, with the continuous increase of noise power, the detection probability of single sensor and centralized fusion detection decreases, and the detection probability of centralized fusion detection is always much higher than that of a single sensor. Compare Figure 1 and Figure 2, when the sensor sampling frequency is higher, the detection probability of single sensor and centralized fusion detection is greater.

5. Experimental analysis

In order to verify the detection performance of the seismic wave sensor centralized moving target fusion detection method, the experimental analysis is carried out in the experimental scene shown in Figure 3. According to the characteristics of typical battlefield targets such as tanks and armored vehicles, we selected the tested object as a truck with a speed of 30km/h and a load of about 20 tons. The road is a hard, slightly curved mud road. Two seismic wave sensors are arranged at the same position 10 meters away from the road surface. The sensor adopts MEMS series acceleration sensor. This model has the characteristics of high sensitivity and good low-frequency detection characteristics. The acquisition card adopts USB-6211 of NI Company, and the data sampling frequency is set to 455Hz.

![Field layout](image3)

![No background noise signal](image4)

Figure 3  Field layout  
Figure 4  No background noise signal

The sensor detects the seismic wave signal without background noise as shown in Figure 4. According to the noise characteristics of different interfering targets (pedestrians, bicycles, motorcycles, small cars, guns, etc.) passing by, add Gaussian white with signal-to-noise ratios of 7dB, 3dB, 0dB, -3dB, -7dB to this signal Noise, as shown in Figure 5.
In the case of false alarm probability $P_f = 0.05$ and $P_f = 0.01$, the single sensor detection probability and centralized fusion detection probability of different signal-to-noise ratios are shown in Tables 1 and 2:

**Table 1 $P_f = 0.05$ Probability of Detection**

| SNR (dB) | The detection probability of single sensor | The detection probability of fusion |
|----------|------------------------------------------|-----------------------------------|
| 7        | 0.72                                     | 0.94                              |
| 3        | 0.41                                     | 0.64                              |
| 0        | 0.26                                     | 0.41                              |
| -3       | 0.17                                     | 0.26                              |
| -7       | 0.12                                     | 0.16                              |

**Table 2 $P_f = 0.01$ Probability of Detection**

| SNR (dB) | The detection probability of single sensor | The detection probability of fusion |
|----------|------------------------------------------|-----------------------------------|
| 7        | 0.46                                     | 0.80                              |
| 3        | 0.18                                     | 0.37                              |
| 0        | 0.09                                     | 0.18                              |
| -3       | 0.05                                     | 0.09                              |
| -7       | 0.03                                     | 0.04                              |

It can be seen from Table 1 and Table 2 that when $P_f = 0.05$ and the signal-to-noise ratio is 7dB, the detection probability of centralized fusion detection can reach more than 0.9; when $P_f = 0.01$ and the signal-to-noise ratio is 3dB, the probability of centralized fusion detection can reach twice that of single-sensor detection; under the same signal-to-noise ratio, the probability of centralized fusion detection is significantly higher than that of single-sensor detection, that is, the performance of
centralized fusion detection is better than that of single-sensor detection.

6. Conclusions
The use of multi-sensor fusion detection technology has become a promising research direction in the information field. Compared with the shortcomings of distributed fusion detection in target detection, centralized fusion detection can make full use of the measurement data information of each sensor, and the information utilization rate is high. This paper proposes a centralized multi-sensor fusion detection method based on Neyman-Pearson criterion. First, the detection probability formula of single sensor and centralized fusion detection is given and simulation analysis is carried out. Then, using seismic wave sensors to experiment with maneuvering targets, simulations and experiments show that the algorithm can effectively improve the detection performance, and provide ideas for how to effectively improve the detection probability under unknown parameter signals and complex environments.

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