A novel design of algorithm and framework for decentralized CFAR signal detection without prior information

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Abstract. In this paper, a fusion detection algorithm that focuses on decentralized CFAR (Constant False Alarm Rate) signal detection problem without prior information is proposed. In the algorithm, the threshold and test statistic of the detection fusion algorithm derive from the conventional CFAR detection method. At last a framework for decentralized CFAR signal detection is designed corresponding to the fusion algorithm. Simulation results illustrate that an almost optimal detection performance is obtained by the proposed algorithm.

1 Introduction

It is a significant problem to fulfil detection in distributed information fusion system. This problem must be up against no matter in multi-static radar or other multi-sensor cooperation detection system [1-3], in which what information to transport and how to design the framework is the key in the system.

Conventional method makes the detection fusion with the entire detectors' result in which a little quantity of information can be used. So it restricts the detection centre's performance [4-7]. As [8] combines the detection results of each detector, and optimize the weight coefficients for any given knowledge to improve the detection performance. With the development of communication ability, a means of double threshold detection arises for distribution detection [9-11]; it must be known that the signal noise rate (SNR) or the detection performance of every detector for reaching the optimal performance [12-14]. If making fusion information directly without the prior knowledge (SNR), the result must lead to a decrease performance for the entire system.

According to the information theory, every detection practice has a positive information in average, so the fusion with decreasing performance shouldn't be applied [15-16]. Of course there are some detection fusion methods without prior information. Reference [17] supposes the prior information deciding the weight of the each detector's detection result, in which the weight is confirmed by probability distribution. Although its performance is below the optimal obviously, the stability of this method is well. On the whole, the number of article is rather less and their performance is unsatisfying in the detection fusion without prior information.

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This paper puts forward a detection fusion algorithm without prior information. It's significant to make the research for the decentralize detection.

2 Decentralize CFAR Detection Fusion Algorithm

2.1 False Alarm Likelihood Function (FALF)

According to CFAR threshold detection criterion, assuming judgment method as (x_1 is the test statistic):

$$\begin{cases} H_1 : x_1 > th \\ H_0 : x_1 < th \end{cases} \quad (1)$$

We set the test statistic x 's FALF defined:

$$P_f(x_1) = \int_{x_1}^{\infty} p(x|H_0)dx \quad (2)$$

We can get that each test statistic x is corresponding a certain FALF $P_f(x)$. According to aforementioned article, if set the $P_f(x_1)$ as a new test statistic index, the detection is equal to:

$$\begin{cases} H_1 : P_f(x_1) < P_{fa} \\ H_0 : P_f(x_1) > P_{fa} \end{cases} \quad (3)$$

Next the decentralize detection fusion algorithm based on FALF will be introduced:

2.2 Detection Fusion Algorithm

As the aforementioned description, supposing $C=P_{fa}$, when $P_f(x_1)<C$, the algorithm return H_1 , else return H_0 , C is connected only with P_{fa} . The judgment correspond to the Neyman-Pearson criterion.

Fig. 1. Single detector.

P_f^{-1} is the inverse function to the FALF (figure 1). Then considering double element detection fusion problem, each receive signal's FALF set as: $P_{1f}(x_1) = \int_{x_1}^{\infty} p_1(x|H_0)dx$ & $P_{2f}(x_2) = \int_{x_2}^{\infty} p_2(x|H_0)dx$ When $P_{1f}(x_1)P_{2f}(x_2)<C$, the algorithm return H_1 , else H_0 . C is a function only connected with P_{fa} , assuming Ω (figure 2: Area H_1) is the area of $P_{1f}(x_1)P_{2f}(x_2)<C$, and different detector is independent with each other. So the expression of P_{fa} is offered as next integration:

Fig. 2. Double element detector.

$$P_{fa} = \int_{\Omega} p_1(x_1|H_0) \cdot p_2(x_2|H_0) dx_1 dx_2 \quad (4)$$

The relation between P_{fa} and C is $P_{fa}=C(1-\ln C)$ (Appendix A), $0<C<1$. When P_{fa} is a constant, the C is a constant too. In this way, we get the detection probability (P_d) as:

$$P_d = \int_{\Omega} p_1(x_1|H_1) \cdot p_2(x_2|H_1) dx_1 dx_2 \quad (5)$$

Next a generalize method is introduced for N element detection fusion, supposing the FALF of i^{th} detector receiving signal is defined as:

$$P_{yf}(x_i)=\int_{x_i}^{\infty} p_i(x|H_0)dx \tag{6}$$

When $\prod_{i=1}^N P_{yf}(x_i) < C$, the fusion system return H_1 , else return H_0 , as the aforementioned paper, assuming Ω is the area of H_1 , so the P_{fa} as:

$$P_{fa} = \int_{\Omega} \prod_{i=1}^N [p_i(x_i|H_0)] dx_1 \cdots dx_N \tag{7}$$

The relation between P_{fa} and C is $P_{fa} = C \cdot \sum_{i=0}^{N-1} \frac{(-\ln C)^i}{i!}$ (Appendix B), $0 < C < 1$. When $P_{fa} \& N$ is confirmed, the C is confirmed too. So C is the function of P_{fa} and N (the number of element for detection fusion). In this way, we get the detection probability (P_d) as:

$$P_d = \int_{\Omega} \prod_{i=1}^N [p_i(x_i|H_1)] dx_1 \cdots dx_N \tag{8}$$

When making an N element detection fusion, the C should be got firstly, and then the judgment is made by comparing the product of N FALF and C . We offer a series of C with the change of the P_{fa} in multi-element detection fusion as figure 3 and table 1:

Fig. 3. The relation among C and $P_{fa} \& N$.

Table 1. The value of C when confirming $P_{fa} \& N$.

$\begin{matrix} N \\ P_{fa} \end{matrix}$	1	2	3	4
10^{-1}	10^{-1}	2.05×10^{-2}	4.88×10^{-3}	1.25×10^{-3}
10^{-2}	10^{-2}	1.31×10^{-3}	2.24×10^{-4}	4.34×10^{-5}
10^{-3}	10^{-3}	9.77×10^{-5}	1.33×10^{-5}	2.12×10^{-6}
10^{-4}	10^{-4}	7.84×10^{-6}	8.93×10^{-7}	1.23×10^{-7}

3 The Detection Framework Based on The Algorithm

3.1 Centralize Detection Framework

Centralize framework is efficient for detection fusion [2]; the structure as the figure 4:

Fig. 4. Structure of centralize detection.

From the figure 4, every detector transmits its FALF rather than the judgment or initial signal and the fusion centre make the judgment through a product calculation. According to the framework design the algorithm as table 2:

Table 2. Algorithm Process.

import	The false alarm probability P_{fa} The Receiving signal x_i of detector i
algorithm	1. Calculate the FALF of x_i 2. Get the value of C relying on P_{fa} &N 3. Compare and judgment
export	Detection result

3.2 Sequential Detection Construction

The previous detection framework is a rather rigid structure such as some detector in breakdown. So it is essential to design a flexible structure for realistic environment. Designing a sequential detection framework as figure 5 :

Fig. 5. Sequential detection fusion algorithm structure.

When making the judgment of H_1 , it is no need to fusion all the element detection actually. Only if product of part element’s FALF reaches the threshold, can the judgment be made. In this way, the system can still fulfil the detection if some detector is missed.

3.3 Adaptive Threshold Detection Framework

Design an adaptive detection structure in which each detector’s threshold is based on other detector’s FALF. The structure is shown as figure 6:

Fig. 6. Adaptive threshold detection.

This framework shows that each detector’s threshold will be adjusted after receiving FALF from other detector, and guarantee the entire system’s CFAR characteristic. This method will get the same detection performance as the centralize method in 3.1. The communication is essential to make interaction in all detectors in this structure. And algorithm should refer to the previous indicate and adjust the part of corresponding threshold.

4 Simulation and Analysis

4.1 The Detection under Gaussian Distribution

Set the detector’s detection SNR, set detector 2’s SNR reach from -5dB to 8dB as the base, the detector 1 less 1.5dB than the base, the detector 3 more 1.5dB. Set the $P_{fa}=10^{-2}$. The optimal detection curve is the Bayes method result with the prior SNR information, the result as figure 7 & figure 8:

Fig. 7. The P_d .

Fig. 8. The P_{fa} .

When fusion detection P_d reaches from 0.5---0.9 by the algorithm of this paper, each performance of detector and the fusion P_d with known SNR by Bayes detection as table 3,

Table 3. The value of P_d .

	P_d				
The fusion P_d with unknown SNR	0.5	0.6	0.7	0.8	0.9
The P_d of detector 1	0.08	0.10	0.12	0.15	0.19
The P_d of detector 2	0.16	0.20	0.24	0.29	0.39
The P_d of detector 3	0.32	0.41	0.49	0.58	0.71
The fusion P_d with known SNR	0.56	0.67	0.76	0.84	0.93

After Monte Carlo simulation, the detection algorithm is proved a CFAR method. The performance of this method is close to the optimal from the simulation.

4.2 The Detection under Rice Distribution

Next we make the simulation the detection fusion under the Rice distribution. It is a common distribution in an envelope detector. Set two orthogonal signals of every detector in which each signal’s SNR agree with the 4.1 chapter in the corresponding detector. The simulation result as figure 9 & figure 10:

Fig. 9. The P_d . Fig. 10. The P_{fa} .

When P_d reach from 0.5---0.9, each performance of detector as table 4.

Table 4. The value of P_d .

The fusion P_d with unknown SNR	0.5	0.6	0.7	0.8	0.9
The P_d of detector 1	0.07	0.08	0.10	0.12	0.16
The P_d of detector 2	0.16	0.20	0.24	0.30	0.39
The P_d of detector 3	0.39	0.47	0.56	0.67	0.82

The fusion algorithm performs a better detection performance than each detector.

5 Conclusion

In this paper, a novel detection fusion method without prior information is proposed after the analysis of problem in decentralizes detection, which test statistic is from the FALF of receiving signal. And several frameworks for the fusion are offered. Simulation results illustrate that an almost optimal detection performance is obtained by the proposed algorithm. In which the optimal detection fusion performance is the Bayes method result with the prior SNR information. Although only the threshold detection is researched in the paper, we can transform the non-threshold detection into the threshold detection. Moreover, the further work should offer the optimal detection method in the Rice distribution.

6 Appendices

6.1 Appendix A

considering: $P_{fa} = \int_{\Omega} p_1(x_1|H_0) p_2(x_2|H_0) dx_1 dx_2$, Ω is the area of $P_{1f}(x_1)P_{2f}(x_2) < C$,

supposing $P_{1f}(x_1) = \int_{x_1}^{\infty} p_1(x|H_0) dx$ and $P_{2f}(x_2) = \int_{x_2}^{\infty} p_2(x|H_0) dx$.

Proof:

$$\begin{aligned} P_{fa} &= \int_{\Omega} p_1(x_1|H_0) \cdot p_2(x_2|H_0) dx_1 dx_2 \\ &= \int_{-\infty}^{P_{2f}^{-1}(C)} p_2(x_2|H_0) \int_{f(x_2)}^{\infty} p_1(x_1|H_0) dx_1 dx_2 + \int_{P_{2f}^{-1}(C)}^{\infty} p_2(x_2|H_0) dx_2 \\ &= \int_{-\infty}^{P_{2f}^{-1}(C)} p_2(x_2|H_0) \frac{C}{P_{2f}(x_2)} dx_2 + C \\ &= -C \cdot \ln \left[P_{2f}(x_2) \right] \Big|_{-\infty}^{P_{2f}^{-1}(C)} + C \\ &= C(-\ln C + 1) \end{aligned}$$

Because of $C \in (0, 1)$, When P_{fa} is a constant, the C is a constant too.

6.2 Appendix B

Proof:

$$P_{fa} = \int_{\Omega} \prod_{i=1}^N [p_i(x_i|H_0)] d\Omega = C \cdot \sum_{i=0}^{N-1} \frac{(-\ln C)^i}{i!}, \Omega \text{ is the area of } \prod_{i=1}^N P_{if}(x_i) < C,$$

$$P_{if}(x_i) = \int_{x_i}^{\infty} p_i(x|H_0) dx, \text{ supposing } f_N(C) = C \cdot \sum_{i=0}^{N-1} \frac{(-\ln C)^i}{i!}$$

Mathematical Induction: when $N=1$, assuming $N=k$ it is true too, to calculate the formula when $N=k+1$:

$$\begin{aligned} P_{fa} &= \int_{\Omega} \prod_{i=1}^{k+1} [p_i(x_i|H_0)] d\Omega \\ &= \int_{-\infty}^{P_{kf}^{-1}(C)} p_{k+1}(x_{k+1}|H_0) \int_{\Omega'} \prod_{i=1}^k [p_i(x_i|H_0)] d\Omega' dx_{k+1} + C \\ &= \int_{-\infty}^{P_{kf}^{-1}(C)} p_k(x_k|H_0) f_k \left(\frac{C}{P_{kf}(x_k)} \right) dx_k + C \\ &= C \cdot \left(\int_1^C f_k(t) \cdot \frac{1}{t^2} dt + 1 \right) \\ &= C \cdot \left[-\sum_{i=0}^{k-1} \frac{(-1)^i (\ln C)^{i+1}}{(i+1)!} + 1 \right] \\ &= C \cdot \sum_{i=0}^k \frac{(-\ln C)^i}{i!} \end{aligned}$$

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