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An Automatic Digital Camouflage Pattern Generation Method based on Texture Structure

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Abstract

This article investigates the problem of scattered burst signal detection based on multiple sensors to obtain overall decisions. In the explosion detection system studied in the article, sensors independently transmit their decisions on measuring explosion information to the data fusion processing terminal, which provides overall decisions based on fusion rules. The researchers focus on the data fusion theory of the distributed parallel detection burst point data fusion system based on the Bayesian rule. This paper has obtained the data fusion rule and sensor decision criteria that make the overall system optimal, and proposed a nonlinear Gauss Seidel mathematical variable algorithm that optimizes the data fusion rule and multi-sensor decision criteria The data fusion problem when detecting burst point signals with two different and three identical types of sensors. The data fusion algorithm proposed in this article is validated and simulated through computer experiments on the detection of three types of sensors. The relevant experimental data show that the performance of a data fusion system based on Bayesian detection is significantly improved compared with the sensor acquisition of burst point information. In the experiment, the risk of Bayesian missing detection of burst point signal coefficient of the data fusion system using three sensors with the same performance is reduced by 32.7%.

Keywords

Data Fusion; Bayesian Rule; Scattered Detection; Computer Simulation.

1. Introduction

The common sensor detection burst point system is a highly integrated signal acquisition fusion system, the received signal is transmitted to the data fusion processing terminal, the data fusion processing terminal according to the sensor measurement of the burst point information, the formation of the best detection scheme for the shooting target. However, this detection system has a certain degree of limitations, even in the actual collection of shooting explosion point signal detection effect is not obvious. In the data fusion system in which distributed sensor groups detect the blasting point signal of live fire, each group sensor processes the information of detecting the blasting point target to form its own limited decision information. Therefore, the requirements on the bandwidth of the communication network are reduced during live firing, and the stability and survivability of the data fusion system for detecting the burst point are also improved [1].

At present, the distributed data fusion based on various performance rules has been deeply studied by scholars. The distributed Bayesian detection burst point data fusion system is a kind of system with the least risk in the detection of burst point signal in live firing, which is widely used in military communication network, submarine active sonar detection and radar detection. Tenney and Sandel first solved the problem of the distributed detection signal of the two sensors by using the minimum risk rule, and concluded that when the sensor measurement is

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independent and the fusion criterion is fixed, the optimal decision criterion of the sensor is the likelihood ratio detection [2]. Sarama and Rao discussed the problem of solving the limiting judgment threshold of three sensors [3]. Lauer and Sandel explored the problem of scattered detection of burst points when sensor measurements are not separate [4]. Teneketzis extends Wald's sequential analysis of sample sampling schemes to a distributed inspection system [5]. Sadjadi applied the conclusions of literature to the distributed detection signal system of the multi-data fusion processing terminal of a single sensor. Chair and Varshney discussed an improved fusion rule when the sensor decision criteria were fixed [6]. Ekchian and Tenney introduced a signal detection method using single-row distributed wireless network sensor system performance optimization [7]. Chair and varshney deduced the data fusion rule of the data fusion processing terminal when the decision threshold of the wireless network sensor is fixed. When the decision threshold of the wireless sensor is independent, the best data fusion rule is the likelihood ratio test for each sensor to detect the decision conclusion of two data values. They did not give the local decision threshold of the sensor and the detection performance of the system [8]. This paper tries to deduce the overall best decision criterion based on Bayes rule (i.e., the sensor and the data fusion processing terminal are the best at the same time) for detecting burst point signal, and obtains the mathematical calculation method for solving the data fusion rule and the decision rule for detecting burst point signal of wireless network sensors. The performance optimization algorithm of the parallel data fusion system is presented based on the terrain of the live firing range, and the algorithm is verified by computer simulation.

2. Mathematical Model of Distributed Parallel Fusion System

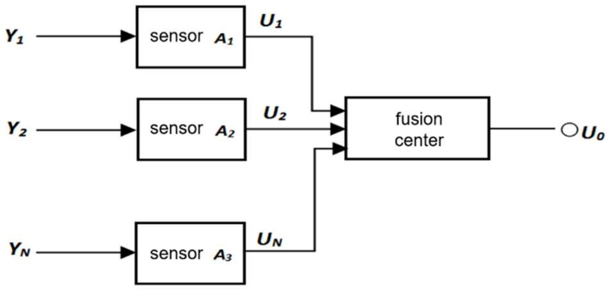

Figure 1. Frame diagram of the non-feedback distributed parallel fusion system

The non-feedback distributed parallel data fusion system is composed of A sensors and a data fusion processing terminal. The frame diagram is shown in Figure 1. The sensor collects and measures the random burst point signal source, and the detected signal data is quantified for collection Y_i according to certain decision rules. Y_i is a random variable conforming to the probability distribution, assuming that the value (i = 1, 2, ...N) on the measurable space (Φ_i, B_i), then the sensor randomly outputs Ui, i = 1,2, ..., N, then Ui is implemented in the set {1, 2, ..., N}. The sensor A = (A_1, A_2, ..., AN) resulting relativity U = (U_1, U_2, ..., U_N) is the limiting decision vector for sensor acquisition of burst point data, and the realization of the limiting decision is denoted as U. Will U_i (i =1, 2, ..., N) Collect the burst point information and transmit it to the data fusion processing terminal. The data fusion processing terminal uses U= (U_1, U_2, ..., U_N) is the "measurement" of its limited decision vector, conducts the detection of the virtual and real shooting target, and forms the final decision MU0, U0 is a random variable between A and U. Assuming $U_0 \in \{0,1\}$, U_0 =0, it means that the data fusion processing terminal determines that no shooting burst point appears. When U_0 = 1, it means that the data fusion processing terminal determines that there is a shooting point. Live firing target detection is a binary function hypothesis test problem. H0 is used to represent the original hypothesis that no live firing

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target appears, and H1 is used to represent the alternative hypothesis that there is a live firing target. Under these two hypotheses, the verification probabilities are P_0 =P(H_0), P_1 = P(H_1) respectively. The fusion probability density of the burst point sensor under the assumption H_f (f=0, 1) is $PY_f|H_f(y_f|H_f)$. N Detection The fusion probability density of the burst point sensor under the assumption of Hf (f=0, 1) is $P_{Y_1Y_2...Y_N}$ $|H_f$ (y_1 y_2 ... $y_N|H_f$).

Let's say γi, i = 1, 2, ..., N, is the decision function of the wireless network sensor in Part Yi to detect the burst point of live firing, namely, $U^i=\gamma^i(Y^i)$; γ^0; Gamma 0 is the decision function of the data fusion processing terminal, that is, $U^0 = \gamma^0(U^1, U^2, ..., U^N)$. Therefore, the fire detection burst point is a measurable mapping from the measurement space of the sensor to the decision space, that is:

$$u_i = \gamma_i(y_i), i = 1,2 \cdots, N \tag{1}$$

$$u_0 = \gamma_0(u_1, u_2 \cdots, u_N) \tag{2}$$

If Hf is true and Cif signal detection is missed (i =0, 1; f= 0, 1), which is the measurement statistics and decision criteria $\gamma= \{\gamma_0, \gamma_1, \gamma_2, ..., \gamma_N\}$. The core of the data fusion system is to select the decision function γ_0 of the sensor and the data fusion processing terminal, if $\gamma_1, \gamma_2, ..., \gamma_N$ is the average loss of the detection signal of the system, that is, the use of wireless network sensors in live firing to detect the risk of missing the burst point signal is minimal. Before deducing the mathematical formula, if the probability of verifying and detecting burst point signal is set as P_0 and P1 in advance, the Bayesian risk of missing burst point detection is:

$$R_B(\gamma) = \sum R(H_i\gamma)P(H_i) \tag{3}$$

Where γ is the decision function, if γ* exists in the decision function class Γ (the set of all possible decision functions).

$$R_B(\gamma^*) = \inf_{\gamma\in\tau} R_B(\gamma) \tag{4}$$

γ*(*) is called the decision function of the optimal detection burst point signal scheme under the Bayesian criterion for detecting burst point, or the solution of the Bayesian detection burst point binary equation function. To sum up, the method of solving the decision core of live firing burst point by using Bayesian system methodology is to assume that a set of wireless network sensors detecting burst point signal decision function (criterion) $\Gamma= (\gamma_0, \gamma_1, \gamma_2, \gamma_N)$, thereby reducing the data fusion processing terminal burst point missed Bayesian risk coefficient value is minimum, thereby reducing the probability of misjudgment, where γ_0 represents the decision function of the data fusion processing terminal,

$$R_B(\gamma) = \sum R(H_i\gamma)P(H_i) \tag{5}$$

Gamma γ_i (i=1, 2,...,N), represents the decision function of the i wireless network sensor, which is a measurable mapping from the detectable signal space to the decision space of the data fusion processing terminal, namely:

$$U_i = \gamma_i(x_i)\ i = 1,2, \cdots, N \tag{6}$$

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In (6), P_F =P (u_0 =1|H_0) is the virtual warning probability of the data fusion system, and PD =P (U_0 =1 |H_1) is the detection probability of the data fusion system. According to the above functional formula, the Bayesian risk of detecting burst point loss required to be minimized can be expressed as:

$$\begin{aligned} R_B &= \sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij}P_jP\left(U_0=i \mid H_j\right) \\ &= C_{00}P_0P\left(u_0=0 \mid H_0\right)+C_{01}P_1P\left(u_0=0 \mid H_1\right) \\ &+ C_{10}P_0P\left(u_0=1 \mid H_0\right)+C_{11}P_1P\left(u_0 \mid H_1\right) \\ &= \left(C_{10}-C_{00}\right)P_0P_F-\left(C_{01}-C_{11}\right)P_1P_D+C_{00}P_0+C_{01}P_1 \end{aligned} \tag{7}$$

Suppose that C_{10} >C_{00}, C_{01} > C_{11}, that is, the cost of the wrong decision made by the data fusion system is greater than the cost of the correct decision made by the system. At this time, the virtual warning probability and correct detection probability of the system are respectively:

$$\begin{gathered} P_F = P(u_0=1 \mid H_0) = \sum_u P(u_0=1 \mid \boldsymbol{u})P(\boldsymbol{u} \mid H_0) \\ P_D = P(u_0=1 \mid H_1) = \sum_u P(u_0=1 \mid \boldsymbol{u})P(u \mid H_1) \end{gathered} \tag{8}$$

Σu in equations (7) and (8) represents the sum of the decision vector values U for all possible data fusion processing terminals. Substituting equations (7) and (8) into equation (6) yields:

$$\begin{aligned} R_B = C + C_F\sum_u P(u_0=1 \mid \boldsymbol{u})P(\boldsymbol{u} \mid H_0) - C_D\sum_u P(u_0=1 \mid \boldsymbol{u})P(u \mid H_1) = C + \\ +\sum_u P(u_0=1 \mid \boldsymbol{u})[C_FP(u \mid H_0) - C_DP(\boldsymbol{u} \mid H_1)] \end{aligned} \tag{9}$$

Where C is a constant independent of the decision.

3. Optimization of Decision Rules for Distributed Parallel Fusion Systems

The distributed data fusion detection system shown in Figure 1 can be regarded as a parallel decision problem composed of three distributed detection circles. The data fusion processing terminal is a member of one detection group, and the wireless sensor set of limited local detection is another member of the parallel multichannel detection square. The parallel multichannel detection array can be further regarded as a queue composed of each local detection wireless network sensor [9]. When optimizing one parallel multiplex detection square member, it is assumed that the other parallel detection square members have been optimized and remain unchanged. When optimizing and perfecting the decision criteria of the k detection burst point sensor, it is assumed that the decision criteria of the sensors of the remaining detection square array and the fusion criteria of the data fusion processing terminal have been optimized and perfected, and remain fixed.

$$p\left(y_k \mid H_1\right)\sum_{u^k}\int_{y^k} A\left(u^k\right)C_DP\left(u^k \mid Y^k\right)p\left(Y^k \mid y_k, H_1\right)dY^k \underset{u_k=0}{\overset{u_k=1}{\gtrless}} p\left(y_k \mid H_0\right)\sum_{u_k}\int_{Y^k} A\left(u_k\right)C_FP\left(u^k \mid Y_k\right)p\left(Y^k \mid y_k, H_0\right)dY^k \tag{10}$$

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It can be proved that in a distributed parallel fusion system, if the fusion criterion of the data fusion processing terminal has been determined, the sensor decision criterion that minimizes the Bayesian risk of detecting the burst point is to find the optimal fusion criterion of the data fusion processing terminal after obtaining the optimized decision criterion of finiteness detection of the burst point sensor, assuming that it keeps the fixed position unchanged. Assume that the conditional probability distribution $P(u|H_j)$, (j = 0, 1) is known. The fusion criteria of the data fusion processing terminal are:

$$\frac{P(u|H_1)}{P(u|H_0)} \underset{u_0}{\overset{u_0=1}{\gtrless}} \frac{C_F}{C_D} \tag{11}$$

3.1. Optimization of Decision Rules of Fusion System When Sensor Observation Conditions are Independent

Joint optimization of sensor decision criteria γ_i, i = 1, 2, ..., N. γ0 is very difficult under certain conditions. However, the problem of missing burst point detection can be simplified by introducing some statistical structure to the measurement of detecting burst point sensor. When detecting burst point sensor measurements $Y_1, Y_2, \ldots, Y_N$ condition independent, local decision criteria for sensors γ_i, i =1, 2, ..., N, reduced to a threshold test for the local likelihood ratio. When the measurement conditions of the detection burst point sensor are independent, the fusion level of the data fusion processing terminal.

$$\prod_{i=1}^{N} \frac{P(u_i|H_1)}{P(u|H_0)} \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \frac{C_F}{C_D} \tag{12}$$

When the measurement conditions of the detection burst point sensor are independent, if the fusion rule γ_0 of the data fusion processing terminal and the decision criteria of the remaining sensors are used, the fusion rule γ_i (i = 1, 2 ..., N, i ≠ k) has been given the timing, then the decision criterion for detecting the burst point sensor k is:

$$\frac{P(y_k|H_1)}{P(y_k|H_0)} = \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \frac{\sum_{u^k} C_F A(u^k) \prod_{i=1, i\neq k}^{N} P(u_i|H_0)}{\sum_{u^k} C_D A(u^k) \prod_{i=1, i\neq k}^{N} P(u_i|H_1)} \tag{13}$$

According to equations (12) and (13), the decision rules of the data fusion processing terminal and the wireless network sensor can be further simplified to the likelihood ratio test when the sensing signal condition of the wireless network sensor at the burst point of live firing is independent. Since u = ($U_1, U_2, \ldots, U_N$) has 2n different values, so the fusion center should perform 2n decision functions according to formula (12), that is:

$$P(u_0 = 1 \mid \boldsymbol{u}) = \begin{cases} 1, \Lambda(u) \geqslant C_F/C_D \\ 0 \end{cases} \\ u_i = 0.1; i = 1,2,\cdots,N \tag{14}$$

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$C_F = P_0\left(C_{10} - C_{00}\right), C_D = P_1\left(C_{01} - C_{11}\right), C = C_{00}P_0 + C_{01}P_1, \Lambda(u) = \prod_{i=1}^{N} \frac{P\left(u_i \mid H_1\right)}{P\left(u_i \mid H_0\right)}$. The data fusion system criteria can be equivalent to:

$$\frac{P\left(u_1, u_2 \cdots u_N \mid H_1\right)}{P\left(u_1, u_2 \cdots u_N \mid H_0\right)} \underset{u_0}{\overset{u_0=1}{\gtrless}} \frac{C_F}{C_D} = \eta \tag{15}$$

The parameter of detecting the burst point signal by sensor is expressed as:

$$\begin{aligned} &\prod_{S_1} \frac{P\left(u_i = 1 \mid H_1\right)}{P\left(u_i = 1 \mid H_0\right)} \prod_{S_0} \frac{P\left(u_i = 0 \mid H_1\right)}{P\left(u_i = 0 \mid H_0\right)} \\ &= \prod_{S_1} \frac{P_{Di}}{P_{Fi}} \prod_{S_0} \frac{1 - P_{Di}}{1 - P_{Fi}} \underset{u_0}{\overset{u_0=1}{\gtrless}} \eta \end{aligned} \tag{16}$$

Where S_j = {i: Ui = j, i =1, 2, ..., N}, j =0, 1. If we take the logarithm of both sides of formula (16), we have:

$$\sum_{i=1}^{N} \left[u_i log \frac{P_{Di}}{P_{Fi}} + \left(1 - u_i\right) log \frac{1 - P_{Di}}{1 - P_{Fi}} \right] \underset{u_0=0}{\overset{u_0=1}{\gtrless}} log\eta$$

After finishing:

$$\sum_{i=1}^{N} \left[log \frac{P_{Di}\left(1 - P_{Fi}\right)}{P_{Fi}\left(1 - P_{Di}\right)} \right] u_i \underset{u_0=0}{\overset{u_0=1}{\gtrless}} log\left[\eta \prod_{i=1}^{N} \frac{\left(1 - P_{Fi}\right)}{\left(1 - P_{Di}\right)} \right] \tag{17}$$

Therefore, the optimal data fusion system criterion is realized by comparing the burst point signal with a threshold after weighting the burst point detection sensor's decision. The value weighting and threshold of detection burst point data are determined by the performance of many sensors, that is, the detection burst point signal probability and virtual warning probability of the sensor. The threshold is also related to the prior probability and the cost (loss) of Bayesian missed burst signal. For the training range to use many burst point detection sensor groups, it is necessary to determine N decision thresholds.

$$Th_k = \frac{\sum_{u^k} C_F A\left(u^k\right) \prod_{i=1,k\neq k}^{N} P\left(Y^k | x_k H_0\right)}{\sum_{u^k} C_D A\left(u^k\right) \prod_{i=1,i\neq k}^{N} P\left(Y^k | x_k, H_1\right)} \; k = 1,2,\cdots,N \tag{18}$$

$$Th_k = \frac{\sum_{u^k} C_F A\left(u^k\right) \prod_{i=1,k\neq k}^{N} P\left(Y^k | x_k H_0\right)}{\sum_{u^k} C_D A\left(u^k\right) \prod_{i=1,i\neq k}^{N} P\left(Y^k | x_k, H_1\right)} \; k = 1,2,\cdots,N \tag{19}$$

In order to obtain the overall optimal solution of the data fusion system, N +2N nonlinear equations with the strongest data coupling given by equations (15) and (18) must be solved.

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$$\begin{aligned} P_D = p\left(u_0 = 1 \middle| H_1\right) &= \sum_u p\left(u_0 = 1 \middle| u, H_1\right) \bullet p\left(u \middle| H_1\right) \\ &= \sum_u p\left(u_0 = 1 \middle| u\right) \bullet p\left(u \middle| H_1\right) \\ P_F = P\left(u_0 = 1 \middle| H_0\right) &= \sum_u P\left(u_0 = 1 \middle| u, H_0\right) \bullet p\left(u \middle| H_0\right) \\ &= \sum_u P\left(u_0 = 1 \middle| u\right) \bullet P\left(u \middle| H_0\right) \end{aligned} \tag{20}$$

3.2. Optimization of Decision Criteria for the Same Sensor Data Fusion System

Under the condition that the performance of the burst point detection sensor decision criteria is the same, the data fusion system criterion becomes the K -out -of -N rule, that is, when there are K or more wireless network sensors that detect the burst point of live fire, the decision system is judged as 1, that is, the data fusion processing terminal is judged as 1. That is, U_0 =1, the solution of the binary equation can further simplify the complexity of the calculation. Because the performance parameters of local wireless network sensors for detecting burst point signal are basically the same, their detection probability P_{Di} and false alarm probability P_{Fi} are the same under the condition of independent scattered observation. That is, the detection probability and false alarm probability of $P_{Di} = p_d, P_{Fi} = p_f,\ i = 1,2,\ldots,N,$ system are

When there is k or more k 1s in u, P (u_0 =1|u) = 1, and for each K value, N sensors have C_N^K combination, namely:

$$P_D = \sum_{i=K}^{N} C_N^i (p_d)^i (1 - p_d)^{N-i} \tag{21}$$

Thus, can be obtained.

$$\begin{aligned} R_B\left(K\right) = C + \sum_{i=N}^{N} C_N^i \Big[& C_F\left(p_f\right)^i \left(1 - p_f\right)^{N-1} \\ & - C_D\left(P_d\right)^i \left(1 - P_d\right)^{N-i} \ \Big] \end{aligned} \tag{22}$$

When K increases by 1, the increment of risk RB can be expressed as:

$$\begin{aligned} R_B(K+1) - R_B(K) = C_N^K \big[& C_D(p_d)^i (1 - p_d)^{N-K} \\ & - C_F\left(p_f\right)^i \left(1 - p_f\right)^{N-K} \big] \end{aligned} \tag{23}$$

Assuming pd ≥ pf, it is easy to prove that there is a single minimal point of Bayesian risk. If:

$$\left(\frac{p_d}{p_f}\right)^K \left(\frac{1-p_d}{1-p_f}\right)^{N-K} \geqslant \frac{C_F}{C_D} \tag{24}$$

Then R_B (K +1) ≥R_B(K), otherwise R_B (K +1) <R(K). Take the logarithm of both sides of (24), then:

$$K \geqslant \frac{\log\left\{\left(\frac{C_F}{C_D}\right)\left[\left(1-p_f\right)/\left(1-p_d\right)\right]^{\ N}\right\}}{\log\left\{p_d\left(1-p_f\right)/\left(1-p_d\right)\right\}} \Delta K^* \tag{25}$$

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So, R_B (K +1) ≥R_B(K). Otherwise, R_B (K +1) < R(K). Therefore, the optimal K value Kopt for the, K -out -of -N rule is given by the following formula:

$$K_{Opt} = \begin{cases} \left[K^*\right], if K^* \geq 0 \\ 0, else \end{cases} \tag{26}$$

In equation (25), the [] symbol represents the smallest integer whose value is greater than K^*. K -out -of -N data fusion processing rules can be implemented by logical functions. The data fusion criterion "AND", fusion criterion "OR" and multiple groups of data fusion criterion "MAJOITY" commonly used are all special cases of the basic data fusion criterion where K is N=1 and N= 1/2 in the K -out -of -N data fusion processing rule.

$$\begin{gathered} P_F = \sum_{i=K}^{N} C_N^i \left(p_f\right)^i \left(1-p_f\right)^{N-1} \\ C_N^i = \frac{N!}{i!\left(N-i\right)!} \end{gathered} \tag{27}$$

4. Parallel Multiplex System Optimization Algorithm

According to equations (11) and (12), it is a set of strongly coupled nonlinear binary equations to solve the optimal data fusion criterion for the minimum risk coefficient of Bayesian missed live fire burst point and the optimal decision rule of wireless network sensor for detecting live fire burst point. The optimal data fusion rule and the optimal decision rule of wireless network sensor can be further simplified into the likelihood ratio criterion when the in-situ measurement signal Yi condition of wireless network sensor is independent. At this time, the difficulty coefficient of data fusion system optimization decreases significantly. However, it is still necessary to solve N +2N coupled nonlinear binary equations, and it is generally impossible to obtain the analytic value of the function [10]. The binary equation function numerical optimization method is usually used to determine the optimal data fusion criteria and the optimal decision rules of wireless network sensors for detecting live firing burst points. There are two main difficulties in the optimization of data fusion system: one is nonlinear binary equations, the other is the mutual coupling of decision rules of data fusion. The data fusion criteria for reducing the minimum risk of the burst point miss coefficient value of live firing using the distributed Bayesian methodology and the corresponding detection of the burst point wireless network sensor threshold are calculated as follows:

(1) Select a set of data fusion criteria from all data fusion criteria;

(2) Select an iterative method (Newton method, Gauss-Newton method, etc.) to calculate the threshold of detecting the burst point sensor and the corresponding Bayesian risk;

(3) Compare the values of Bayesian missed burst point risk coefficient under various data fusion criteria, select the data fusion criteria corresponding to the method of minimum risk detection of burst point data and the sensor threshold decision of detection of burst point wireless network, which is the global optimal solution of data fusion system. For the distributed Bayesian detection burst point data fusion processing terminal, the purpose of system optimization is to obtain the corresponding fusion criteria γ0 of the data fusion processing terminal and the decision rules γi (i =1, 2,..., n) to minimize the risk coefficient of Bayesian missed burst point detection in the data fusion system. When the measurement conditions of each burst point detection sensor are independent, the optimization of the performance of the data fusion system becomes the data fusion criterion γ0 of the data fusion processing terminal and the threshold decision of a set of burst point detection sensors. Th1, Th2, ..., ThN, and

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minimize the risk coefficient value of Bayesian missed burst point data in the data fusion system.
(1) Suppose that the data fusion system detects the initial value of live firing burst point data $\gamma 0^{(0)}$, $Th1^{(0)}$, ..., $ThN^{(0)}$ allows the wireless network sensor to detect the error ε of the burst point signal, set j: = 1, l: = M, where M is the number of iterations;

(4) The fixed data fusion system burst point detection data value is $\{Th1^{(j-1)}, ..., ThN^{(j-1)}\}$ solves the data fusion system criterion $\gamma 0^{(j)}$ according to formula (12);

(5) For data fusion system burst point detection wireless network sensor k, k =1, 2, ..., N, its fixed detection burst point value $\{\gamma 0^{(j)}, Th1^{(j)}, Th2^{(j)}, ..., Thk\text{-}1^{(j)}, Thk+1^{(j-1)}, ..., ThN^{(j-1)}\}$, according to (18), the functional decision threshold of wireless network sensor k is calculated as $Thk^{(j)}$, l = l -1;

(6) Calculation with$\{\gamma 0^{(j)}, Th1^{(j)}, Th2^{(j)}, ..., ThN^{(j)}\}$ corresponds to the risk coefficient value $RB^{(j)}$of the Bayesian missed live fire burst point signal, if $|RB^{j-1} - RB^{j}| < \varepsilon$, or l = 0, then stop, and $\{\gamma 0^{(j)}, Th1^{(j)}, Th2^{(j)}, ..., ThN^{(j)}\}$, which is the overall optimal solution value of the data fusion system; Otherwise, j = j +1 and returns to formula (2).

5. Experimental Verification

Considering the parallel multichannel data fusion system, it is assumed that the measurement conditions of each detection burst point wireless network sensor are independent, the detection burst point of many wireless network sensors follows Gaussian distribution, and the detection signal conditional probability density is:

$$\begin{gathered} P_{Y_1|H_1}(y_i \mid H_1) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(y_i - m_i)^2}{2}\right) \\ p_{Y\ i}|_0(y_i \mid H_0) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{y_i^2}{2}\right) \end{gathered} \tag{28}$$

Let $C_{00} = C_{11} = 0, C_{01} = C_{10} = 1$ take the Bayesian missed burst point signal risk (here is the minimum error probability) as the optimized and perfect detection of burst point objective function, and complete the optimization of data fusion criteria and many sensor detection signal thresholds according to the signal detection algorithm provided in this paper.

(1) Considering the data fusion criterion of a set of parallel wireless network sensors to detect the burst point signal of live fire, and assuming M1 = M2 =1. At this time, the data fusion system performs computer experimental data simulation verification and the test results are shown in Figure 2 and Figure 3. As can be seen from Figure 2, when the signal detection performance systems of the two groups of wireless network sensors are basically the same, the optimal data fusion criterion of the data fusion system is related to the prior probability P0 of the wireless network sensor detecting the burst point of live fire. When P0 ≤0.5, the optimal data fusion criterion basically conforms to the "or" data fusion criterion in the Bayesian methodology, that is, as long as any one of the two wireless network sensors detects the burst point of live fire, the data fusion system considers that the wireless network sensor has detected the burst point signal. When 0.5 < P0≤1, the optimal data fusion criterion of the data fusion system is basically in line with the "and" data fusion criterion in the Bayesian methodology, that is, only when two wireless network sensors detect the burst point, the data fusion system considers that the wireless network sensor has detected the burst point signal. Figure 3 shows the change of the decision threshold for detecting the burst point sensor with the prior probability P0. As can be seen from Figure 3, since the burst point detection performance of the two wireless network sensors is basically the same, their functional decision thresholds are basically the same. The function threshold decision of the wireless network sensor also detects the jump of the burst point signal of live firing at the stage value P0 = 0.5.

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(2) Consider the data fusion criteria of the two detection wireless network sensors of the blast point, assuming M1 =1, M2 =2. The computer simulation experiment verification results of the data fusion system are shown in FIG. 4 and 5. As can be seen from FIG. 4, when the performance of the sensor in detecting the burst point wireless network is different, the decision threshold of the sensor in detecting the burst point wireless network is also different, but at the same time, the burst point signal of live firing is detected to change when P0 = 0.5. Therefore, it can be seen from the computer simulation results that the performance of the data fusion system is close to that of the higher-quality detection wireless network sensor when the performance difference between the two detection wireless network sensors is large.

(3) Consider the data fusion criteria for three-way detection of the burst point wireless network sensor, assuming $M_1 = M_2 = M_3 = 1$. The Bayesian risk of the optimal data fusion system and the detection of the burst point wireless network sensor changes with the prior probability P_0 (the probability that the target does not appear), as shown in Figure 6. Figure 7 shows the change of the threshold of the wireless network sensor with the prior probability P_0. As can be seen from Figure 7, the threshold for detecting the burst point of the wireless network sensor twice detected continuous jump in the burst point signal of live firing, and the three burst point signals showed continuous segments. Each detected burst point signal presents a continuous segment, which actually corresponds to a different data fusion criterion. When $0 \leq P_0 \leq 0$, the optimal data fusion criterion conforms to the "or" data fusion criterion in Bayes methodology. That is, when more than one wireless network sensor detects the burst point, the data fusion system is judged as the wireless network sensor has detected the burst point signal. When $0.1 \leq P_0 \leq 0.9$, the optimal data fusion criterion conforms to the 2 -out -of -3 methodological criterion (the K-out of -N criterion, a special case when K = 2, N = 3). At this time, when two or more wireless network sensors detect the burst point signal of live fire, the data fusion system is judged as the wireless network sensor has detected the burst point signal. When $0.9 \leq P_0 \leq 1$, the optimal data fusion criterion is in accordance with the "and" data fusion criterion in Bayesian methodology. That is, only when three wireless network sensors detect the burst point signal at the same time, the data fusion system will judge that the wireless network sensor has detected the burst point signal. The above optimal data fusion criteria are in line with the intuitive observation of the commander. When $0 \leq P_0 \leq 0.1$, the prior probability value of the explosion point detected by live firing is still very high. At this time, as long as a wireless network sensor finds the explosion point signal of live fire, it can be announced that the wireless network sensor has detected the explosion point signal. When $0.1 \leq P_0 \leq 0.9$, the prior probability of target occurrence decreases. At this time, at least two wireless network sensors must find the target at the same time, and the data fusion processing terminal can determine the existence of the live fire explosion point signal. When $0.9 \leq P_0 \leq 1$, the prior probability of the burst point signal of live firing is very small, only three wireless network sensors find the target at the same time, and the data fusion processing terminal can be identified as the wireless network sensor has detected the burst point signal of live firing.

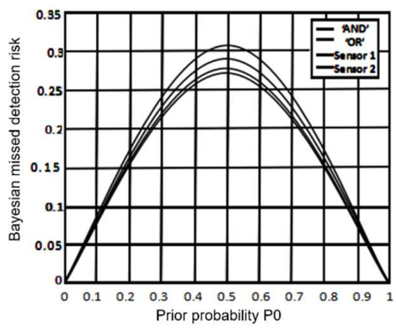

Figure 2. Bayesian missed detection risk when two identical sensors are fused

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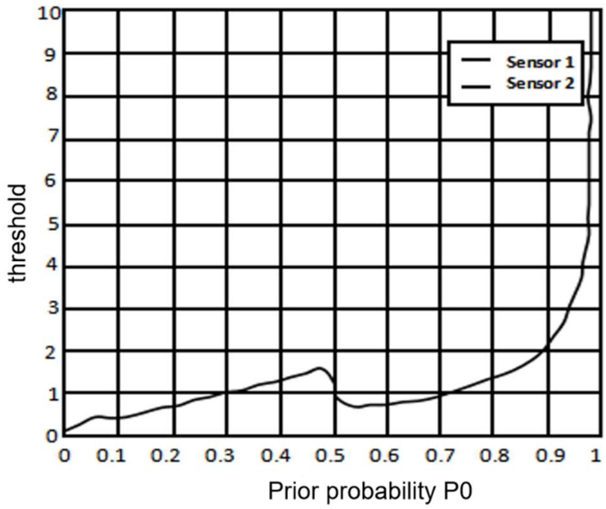

Figure 3. Decision threshold for fusion of two identical sensors

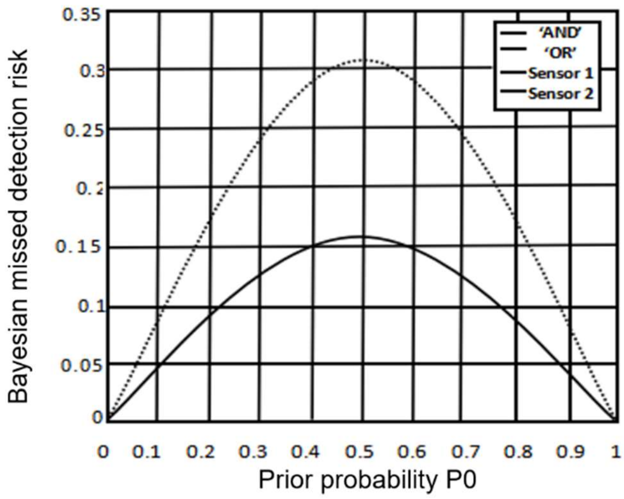

Figure 4. Risk of Bayesian missed detection when two different sensors are fused

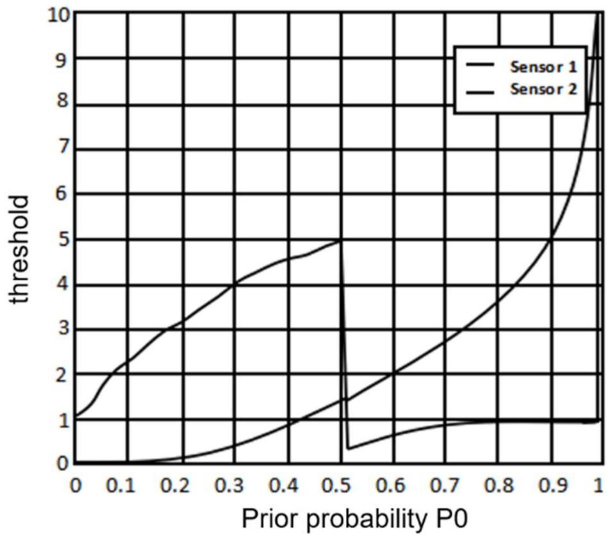

Figure 5. Decision threshold for fusion of two different sensors

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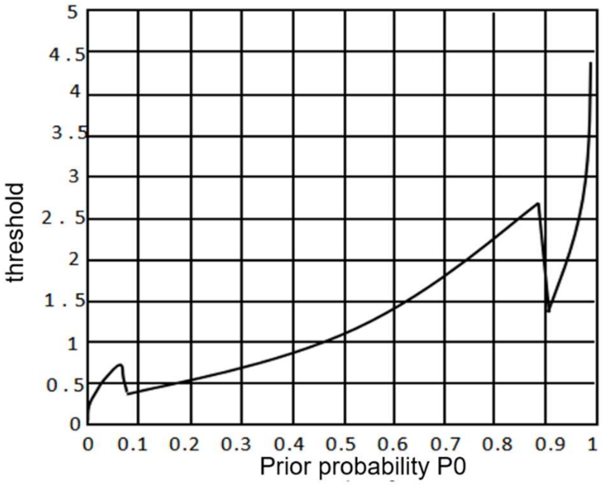

Figure 6. Risk of Bayesian missed detection when three identical sensors are fused

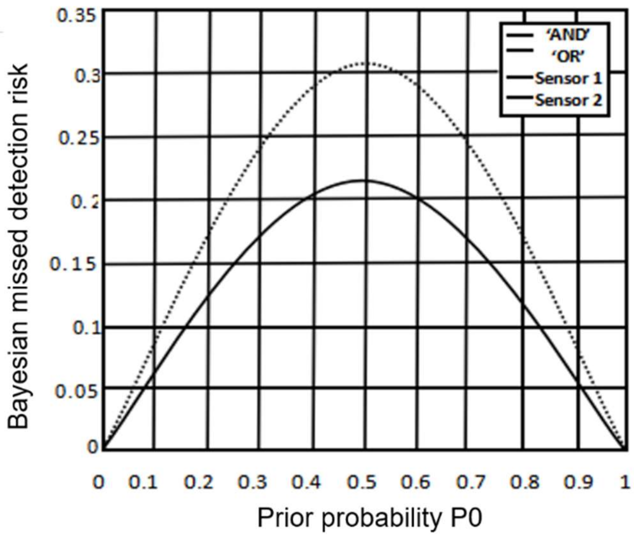

Figure 7. Decision thresholds for fusion of three identical sensors

6. Conclusion

Multi-group wireless network sensor data fusion detection of live ammunition shooting blast point has a large degree of practical application cases in the application of vehicle-mounted sonar, gun position calibration radar and communication signal detection system. This paper systematically studies the data fusion theory of distributed parallel multichannel detection data fusion system based on Bayes criterion. The data fusion criteria and the decision rules of wireless network sensor which make the whole system best are given. The nonlinear Gauss-Seidel algorithm is used to optimize and perfect the calculation method of detecting the burst point signal in the data fusion system. Combined with the wireless sensor data fusion system designed in this paper, several sets of computer simulation experiments are carried out. The simulation results show that the performance of the data fusion system is significantly improved compared with that of the wireless network sensor in detecting the burst point signal. The data fusion system using three same sensors to detect the burst point signal group reduces the risk system value of the Bayesian missed burst point signal by 32.7%. In addition, the computational simulation experiment shows that when the performance of one or more groups of wireless network sensors is basically the same, the performance of the data fusion detection

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system is significantly improved, while when the performance of one or more groups of wireless network sensors is significantly different, the performance of the data fusion system is not significantly improved, close to the performance of high-quality wireless network sensors. This conclusion can be extended to the general case where the number of wireless network sensors is greater than 3. There are usually: (1) The measurement data of multiple wireless network sensors in the data fusion system with poor quality (detecting low signal to noise ratio of burst point or detecting low probability of burst point when giving false warning probability) will not significantly improve the performance of the data fusion system; (2) The data fusion system has a number of high quality wireless network sensor measurement data, and the performance of the system is not significantly improved; (3) When the number of wireless network sensors is too large (N >15), and then increase the number of wireless network sensors, the system detection of burst point performance is not significantly improved; (4) The data fusion of 5-10 medium quality wireless network sensors to detect the burst point signal has a very significant improvement in system performance.

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