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Multi-Level Fusion Processing Algorithm for Complex Radar Signals Based on Evidence Theory

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Abstract
As current algorithms unable to perform effective fusion processing of unknown complex radar signals lacking database, and the result is unstable, this paper presents a multi-level fusion processing algorithm for complex radar signals based on evidence theory as a solution to this problem. Specifically, the real-time database is initially established, accompanied by similarity model based on parameter type, and then similarity matrix is calculated. D-S evidence theory is subsequently applied to exercise fusion processing on the similarity of parameters concerning each signal and the trust value concerning target framework of each signal in order. The signals are ultimately combined and perfected. The results of simulation experiment reveal that the proposed algorithm can exert favorable effect on the fusion of unknown complex radar signals, with higher efficiency and less time, maintaining stable processing even of considerable samples.

Keywords
Complex Radar Signal, Evidence Theory, Multi-Level Fusion, Similarity

1. Introduction

Signal processing, as a significant technique in electronic information system, is of the essence for radar target recognition [1]. With the explosive development of radar technique and the occurrence of new radar systems, radar signals have become increasingly complex. Besides, parameters of radar signals represent varying combinations corresponding to diverse operating modes. Or even under the same operating mode, signal parameters are not fixed due to external noises [2]. All these make traditional processing dependent on single parameter or stepwise processing of different parameters unsuitable.

Current joint multi-parameter processing algorithm is primarily composed of grey correlation analysis, fuzzy identification algorithm and evidence theory. Grey correlation analysis compares the gray value of to-be-processed signals with that of reference signals. Despite its simpleness, the algorithm is not perfect in accuracy until its input was subsequently improved and its accuracy reached 91%. Its parameter type is nevertheless restricted to interval [3-5]. Fuzzy identification algorithm replaces similarity measure with fuzzy membership as the basis, providing a mathematical method for events of uncertain recognition in radar signal processing. However, the results of multiple observations on the same target may be inconsistent or even contradictory in practice [6,7]. And the above two algorithms merely separately

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process each radar signal, without fusion of signals drawn from different reconnaissance equipment in different times [8]. Evidence theory integrates all aspects of information of evidences to curtail information incompletion and impreciseness. Being accurate, this theory is at present massively applied in the fusion processing of radar signals. A contradiction between multiple input and high complexity however exists [9,10]. Current radar signal processing' relying on the template library entails a new processing approach as the result is not steady enough when the quantity of signal data is large.

A multi-level fusion processing algorithm for complex radar signals based on evidence theory is proposed therefrom. In this algorithm, a database is built by ourselves on the basis of to-be-processed radar signal data, and the corresponding decision rules are constructed and deduced. Then a reasonable similarity model which can reflect the similarity among parameters, describe the matching degree of multi-valued parameters and mark different signal modes of the same target, is established to extract similarity matrix. Next, radar signals are fused at parameter level with evidence theory and divided into multiple signal sets through correlation judgment. Evidence theory is subsequently applied to fuse the signal information of each signal set for validation. The simulation results manifest that effective integration of complex radar signals and corresponding classification and combination is possible by this algorithm, which makes radar signals more abundant and complete.

2. Parameter Processing between Radar Signals

In processing unknown radar targets, the specific types of radar parameters are summarized as single-value type, multi-value type and interval type due to the scarcity of prior knowledge [11], to curb the influence of parameter type judgment errors caused by equipment performance and noise, making calculation of parameter similarity of each target easier and more effective. Different types of similarity models are discussed as follows:

2.1 Similarity of Single-Value Parameter

Given reference parameter A, to-be-measured parameter B, and $\Delta = |A - B|$, then the similarity can be defined as:

$$\alpha = \begin{cases} 1 & \Delta \le r \\ (\Delta - 3r)^2 / (2r)^2 & r < \Delta \le 3r \\ 0 & \Delta > 3r \end{cases}, \tag{1}$$

In which r is the tolerance value of measured parameters, and its distribution is shown in Fig. 1.

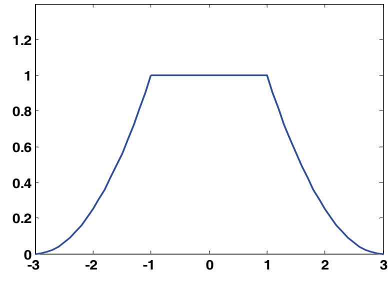

Fig. 1. Distribution of fixed value similarity.

2.2 Similarity of Multi-Value Parameter

Template parameters are $(A_1,\cdots A_i,\cdots A_n)$ in ascending order, and to-be-processed parameters $(B_1,\cdots B_i,\cdots B_m)$. Parameter deficiency due to various factors in practice makes $m \neq n$. The similarity of multi-value parameter is thus explored from the following aspects:

1. If $m = n$, the similarity can be defined as

$$\delta = \frac{nr\varepsilon D}{d(A,B) + nr\varepsilon}, \tag{2}$$

where $d(A,B) = \sqrt{\sum_{k=1}^{n}(A_k - B_k)^2}$ represents the Euclidean distance between template parameters and to-be-processed parameters, ε represents system measuring error, r tolerance value of measuring parameters, and D coincidence degree between intervals. The calculation method is as follows:

$$D = \begin{cases} 0 & (A,A)\bigcap(B,B) = \phi \\ \dfrac{\min(A_n,B_n) - \max(A_1,B_1)}{\max(A_n,B_n) - \min(A_1,B_1)} & (A,A)\bigcap(B,B) \neq \phi \end{cases}. \tag{3}$$

For different signal modes of the same radar targets, the pulse repetition period (PRI) values are not within the tolerance, but multiples are strict. As shown in Table 1, radio frequency (RF) and pulse width (PW) are identical, but PRI and Eq. (2) are not, and the PRI value of signal mode 1 is 2.4 times than that of signal mode 2. d and d(A, B) shall thus be altered as follows:

Given $\tau \approx A_1 / B_1 \approx \cdots \approx A_n / B_n$; $B_1' = B_1 - (\tau - 1)A_1$、$\cdots$、 $B_n' = B_n - (\tau - 1)A_n$, then

$$d(A,B) = \sqrt{\sum_{k=1}^{n}(A_k - \tau B_k)^2}, \tag{4}$$

$$D = \begin{cases} 0 & (A,A)\bigcap(B,B) = \phi \\ \dfrac{\min(A_n,B_n') - \max(A_1,B_1')}{\max(A_n,B_n') - \min(A_1,B_1')} & (A,A)\bigcap(B,B) \neq \phi \end{cases}. \tag{5}$$

Now add 11 to the similarity to obtain Eq. (6), marking possible different signal modes of the same target, as well as differentiating the matching degree of multi-value parameters below.

$$\delta = \frac{nr\varepsilon D}{d(A,B) + nr\varepsilon} + 11. \tag{6}$$

Table 1. Different signal modes of the same target

	RF (MHz)	PW (μs)	PRI (μs)
Signal mode 1	890	1+65	3352, 1978, 2894, 2207
Signal mode 2	890	1+65	1397, 750, 1206, 920

2. If $n \neq m$, the similarity is calculated as following:

1) Determine corresponding matching points. Uncertainty of the position of parameter deficiency entails rough matching between parameters A and B. The match takes effect when $|B_i - A_j| < r$.

2) Sequence well-matched parameter groups in ascending order as $(A_1, A_2 \cdots, A_{n'})$ and $(B_1, B_2, \cdots B_{n'})$, $n' \geq 2$ for calculation convenience.
3) Calculate the similarity between $(A_1, A_2 \cdots, A_{n'})$ and $(B_1, B_2, \cdots B_{n'})$ in the same way with case 1.
4) Mark the matching degree. If the matching coefficient is $\sigma = n'/\max(n, m)$, then $\delta' = \delta + \mathrm{fix}(10 * \sigma)$. As shown in Fig. 2, the obtained similarity reflects parameters' matching degree and the similarity degree between parameter groups, bring convenience for future calculation.

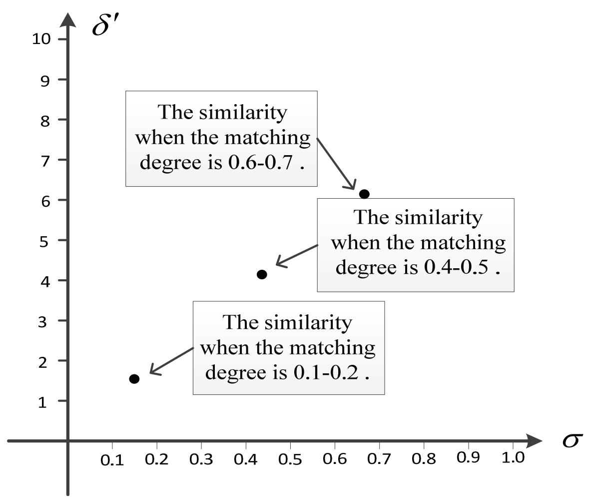

Fig. 2. Similarities after mark.

2.3 Similarity of Interval Parameter

Given template parameter Interval (A_1, A_n) and to-be-processed parameter Interval (B_1, B_m), the similarity can be defined as follows:

$$\delta = \frac{L\left[(A_1, A_n) \cap (B_1, B_n)\right]}{L(A_1, A_n) + L(B_1, B_n) - L\left[(A_1, A_n) \cap (B_1, B_n)\right]} \tag{7}$$

where L refers to the length of interval, and $(B_1, B_m) \cap (A_1, A_n)$ the intersection of two intervals.

2.4 Similarity Model Selection Principle

In practice, the type of to-be-processed radar signal parameters and that of template radar are impossibly hard to be identical, resulting in similarity model selection problem. Here, similarity model selection principles (shown in Fig. 3) are presented as follows.

As shown in Fig. 3, for single-value parameters and multi-value parameters, the value of minimum difference between multi-value and single value is selected with equipment and environment taken into account. Yet chances are that only one of the multi-value parameters is detected or multiple single-value parameters are misjudged as multiple parameter values. For single-value parameters and interval parameters, the similarity between the median-value of interval parameters and that of single-value parameters is calculated by virtue of single-value similarity model, avoiding the case where similarity cannot be calculated with only one detected interval value. For multi-value parameters and interval parameters, it's simple and fast to take the interval between the maximum and the minimum of multi value, and similarity is obtained by interval similarity model.

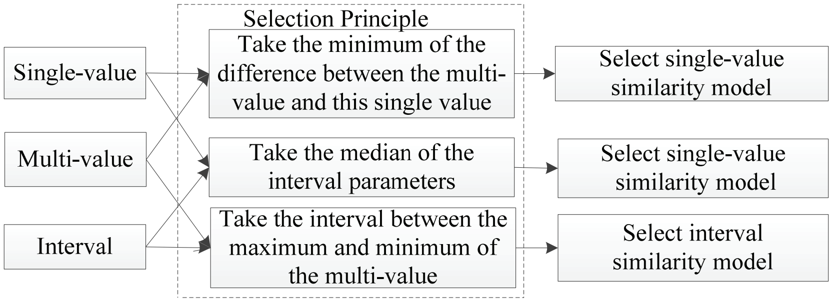

Fig. 3. Similarities model selection for inconsistent parameter types.

3. D-S Evidence Theory

D-S evidence theory is an effective way of processing imperfect information. By representing the identified target set with recognition framework U and defining the basic probability assignment function (BPAF) in U as m: → [0,1], it satisfies the following conditions:

$$\begin{cases} m(\Phi) = 0 \\ \sum_{A \subset U} m(A) = 1 \end{cases}, \tag{8}$$

where Proposition A, called focal element, is a non-empty subset of U, and $m(A)$ reflects the reliability of A.

$m_1, m_2, \cdots, m_n$ denote the BPAF of recognition framework U derived from n independent evidences, and then the BPAF of Proposition C under the interaction of n independent evidences is obtained by D-S combination rule [6,12].

$$m(C) = \begin{cases} 0 & C = \Phi \\ \dfrac{\sum_{\cap A_i = C} \prod_{j=1}^{n} m_j(A_i)}{1 - \sum_{\cap A_i = \phi} \prod_{j=1}^{n} m_j(A_i)} & \forall C \subset U, C \neq \Phi \end{cases}. \tag{9}$$

Making decision upon evidence combination has close ties with application. Pondering radar signals' lacking in prior conditions, a database is built with to-be-process radar signals, which at the same time are used as evidence to obtain the final trust value through data fusion. The same or similar trust values are determined as same targets, making threshold value ε approach to infinitesimal, and

$$\left|m(C_i)-m(C_j)\right|<\varepsilon . \tag{10}$$

If Eq. (10) is satisfied, then target C_i and C_j are determined as the same target. Following comes proof of the decision rule.

Eq. (11) denotes the similarity matrix among evidence sources, based on to-be-processed radar signals.

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

Providing that 1, 3, 5 are the same target data, the following results can be obtained in an ideal situation:

$$\begin{array}{c} s_{13}=s_{15}=s_{35}=1 \\ s_{21}=s_{23}=s_{25} \\ s_{41}=s_{43}=s_{45} \\ s_{61}=s_{63}=s_{65} \\ s_{71}=s_{73}=s_{75} \\ \vdots \\ s_{n1}=s_{n3}=s_{n5} \end{array} . \tag{12}$$

The similarities between evidence sources are taken as the input according to D-S evidence theory combination rule (see Eq. (13)).

$$m(A)=\frac{\sum\limits_{\cap A_i=A}\prod\limits_{t=1}^{n}m_t(A_i)}{1-\sum\limits_{\cap A_i=\phi}\prod\limits_{t=1}^{n}m_t(A_i)}=\frac{\sum\limits_{\cap A_i=A}\prod\limits_{t=1}^{n}m_t(A_i)}{1-k} . \tag{13}$$

All the to-be-processed signals are fused for respective trust function value ($m(1)$, $m(2)$,···,$m(n)$), in which:

$$m(1)=\frac{\prod\limits_{i=2}^{n}s_{i1}}{1-k}=\frac{\prod\limits_{i=2}^{n}s_{1i}}{1-k}=\frac{s_{12}\cdot s_{13}\cdot s_{14}\cdot s_{15}\cdot s_{16}\cdots s_{1n}}{1-k} . \tag{14}$$

$$m(3)=\frac{\prod\limits_{i=1\text{and}i\neq 3}^{n}s_{i3}}{1-k}=\frac{\prod\limits_{i=1\text{and}i\neq 3}^{n}s_{3i}}{1-k}=\frac{s_{31}\cdot s_{32}\cdot s_{34}\cdot s_{35}\cdot s_{36}\cdots s_{3n}}{1-k} . \tag{15}$$

$$m(5)=\frac{\prod\limits_{i=1\text{and}i\neq 5}^{n}s_{i5}}{1-k}=\frac{\prod\limits_{i=1\text{and}i\neq 5}^{n}s_{5i}}{1-k}=\frac{s_{51}\cdot s_{52}\cdot s_{53}\cdot s_{54}\cdot s_{56}\cdots s_{5n}}{1-k} . \tag{16}$$

Eq. (12) is substituted into Eq. (15) and Eq. (16):

$$m(1)=\frac{s_{12}\cdot 1\cdot s_{14}\cdot 1\cdot s_{16}\cdots s_{1n}}{1-k}=\frac{s_{12}\cdot s_{14}\cdot s_{16}\cdots s_{1n}}{1-k} . \tag{17}$$

$$m(3) = \frac{s_{31} \cdot s_{32} \cdot s_{34} \cdot s_{35} \cdot s_{36} \cdots s_{3n}}{1-k} = \frac{s_{13} \cdot s_{23} \cdot s_{34} \cdot s_{35} \cdot s_{36} \cdots s_{3n}}{1-k} \\ = \frac{1 \cdot s_{12} \cdot s_{14} \cdot 1 \cdot s_{16} \cdots s_{1n}}{1-k} = \frac{s_{12} \cdot s_{14} \cdot s_{16} \cdots s_{1n}}{1-k} . \tag{18}$$

$$m(5) = \frac{s_{51} \cdot s_{52} \cdot s_{53} \cdot s_{54} \cdot s_{56} \cdots s_{5n}}{1-k} = \frac{s_{15} \cdot s_{25} \cdot s_{35} \cdot s_{45} \cdot s_{56} \cdots s_{5n}}{1-k} \\ = \frac{1 \cdot s_{12} \cdot 1 \cdot s_{14} \cdot s_{16} \cdots s_{1n}}{1-k} = \frac{s_{12} \cdot s_{14} \cdot s_{16} \cdots s_{1n}}{1-k} . \tag{19}$$

Then Eq. (10) is proved.

$$m(1) = m(3) = m(5) \qquad \Rightarrow \qquad |m(1) - m(3)| < \varepsilon \,\&\&\, |m(1) - m(5)| < \varepsilon .$$

It's therefore theoretically feasible to exercise fusion processing of to-be-processed signals with evidence theory. Except that the information from all sides are made into full use to curtail the impact of incompletion and accident caused by single evidence, this algorithm also solves the problem that D-S evidence theory fails to sort out irrelevant evidence [13].

4. Algorithm Description

The overall processes of the proposed algorithm are shown in Fig. 4, and specific steps are as follows:

1) Establish a template library based on to-be-processed radar target signals and describe parameter type numerically. The specific rule and arrangement order are presented respectively in Table 2 and Fig. 5. Being clear and definite, numbers facilitate the algorithm design, avoiding wrong description of parameter type caused by lack of prior knowledge.
2) Select corresponding similarity model on the basis of parameter type and calculate similarity matrix as shown in Fig. 4.
3) Optimize the similarity. Mark the signal parameters of different modes and same target selected by similarity. Then adjust the similarity according to the matching degree of multi-value parameters to be closer to the description of actual signals. Optimization rule is shown in Table 3.

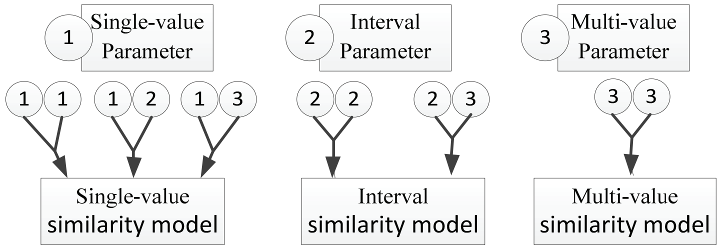

Fig. 4. Similarity model selecting.

R F	RF parameter type	PW	PW parameter type	PRI	PRI parameter type

Fig. 5. Parameter setting.

Table 2. Parameter type rule

Parameter type	Parameter value	Type representation
Fixation	a	1
Multi-value	$(a_1, a_2, \cdots, a_n)$	2
Interval	$[a_{\min}, a_{\max}]$	3

Table 3. Similarity optimization

Similarity state	State description	Optimization method
$11 < s_{PRI}(i,j) \le 12$ ($s_{PRI}(i,j)$ is the PRI similarity between the evidence *i* and the target *j*).	The radar targets may be the same and the signal patterns are different.	Save *i*, *j*, and $s_{PRI}(i,j) = s_{PRI}(i,j) - 11$
$0.9 \le s_1 \le 1$ and $0.9 \le s_2 \le 1$; s_3 is an arbitrary value (s_1, s_2, s_3 represent RF, PW, PRI similarity randomly).	Arbitrary two parameters of radar target are highly similar.	$s_3 = s_3 - \mathrm{fix}(s_3)$
$s_1 < 0.9$ or $s_2 < 0.9$ and $s_3 > 1$ (s_1, s_2, s_3 represent RF, PW, PRI similarity randomly).	The similarity between Radar target parameters is unstable.	$s_3 = s_3 * (\mathrm{fix}(s_3)/10)$

fix(·) represents the integral part.

For same radar targets of different signal patterns, it can be derived from Eq. (6) that its similarity interval is (11,12], and the similarity input of evidence fusion is between interval (0,1], it is thus possible to optimize the similarity to interval (0,1], acquiring marks while reflecting the similarity degree of evidence signals and targets. In case similarity is affected by parameter deviation caused by inevitable factors such as errors while other parameters are not, if the extracted similarity satisfies $0.9 \le s_1 \le 1$ and $0.9 \le s_2 \le 1$, then the other similarity has to be restored to minimize the impact of matching degree on proper data; while if the extracted similarity satisfies $s_1 < 0.9$ or $s_2 < 0.9$ and $s_3 > 1$ then it shows that radar signals share high uncertainty due to varying factors in practice. In this case, the similarity shall be optimized as Table 3 to be more realistic, dampening the effect of uncertainty.

4) Respectively integrate the similarity of each radar target parameter in accordance with evidence fusion rule (Eq. (9)) to obtain the trust value of each evidence fusion parameter to target framework and determine their types. Relevant determination rules have been illustrated in Section 2. Uncertainty of evidence signals in practice renders alteration of proved rules (Eq. (20)) necessary. Despite the uncertainty of signals, and since the i^{th} evidence shares the same signal with the i^{th} target, s_{ii} is the maximum value. Compare other trust values of the same column with the maximum value, and set ε in accordance with signal processing accumulation.

$$\begin{cases} s_{\max} = s_{ii} \\ \left| s_{ii} - s_{ij} \right| \le \varepsilon \\ k \subset [1,n] \quad and \quad j \ne i \end{cases} . \tag{20}$$

If the signal similarity in column *i* satisfies Eq. (20), where s_{ii} constitutes the similarity of the i^{th} signal corresponding to the i^{th} target, then *j* and *i* are the same target; s_{jj} and s_{jk} in column

j is derived in the same way.

$$(i,j)\bigcap(j,k)\neq\phi \tag{21}$$

If Eq. (21) is satisfied, then target i, j, k, are classified into the same equivalent set.

5) Perform signal-level fusion verification for each equivalent set obtained in Step 4 using the D-S evidence fusion rule (Eq. (9)). The verification rule is listed as follows. Given that equivalence set 1 contains n' signals, s'_{av} and $s'_{\max}$ are as Eq. (22), and s'_{ij} represents the trust value against target j upon fusion of the i^{th} equivalence set signal, if $\left|s'_{av}-s'_{\max}\right|\leq\left|s'_{av}-s'_{ij}\right|$ then signal j is element of equivalence set i. This signal-level fusion processing takes signal fusion results as basis, depressing wrongful influence of signals caused by contingency or uncertainty. Signals belonging to equivalence set around average value are therefore extracted by value of the difference between the maximum and the mean. The feasibility of this verification rule has been proved with 500 Monte Carlo simulation experiments.

$$\begin{cases} s'_{\text{av}}=\dfrac{1}{n'}\displaystyle\sum_{j=1}^{n'}s'_{ij} \\ s'_{\max}=\max(s'_{ij})\quad(1\leq j\leq n') \end{cases} \tag{22}$$

For further improvement in signal integrity, signals belonging to the same target (including the same signal of different patterns) are fused and parameters supplemented.

5. Simulation Experiment

5.1 Fusion Processing Simulation

The fusion results of unknown radar signals detected by electronic warfare reconnaissance equipment would exert direct influence on further recognition. The sets of simulation experimental data are shown in Table 4, in which each target signal is depicted by RF, PRI and PW, tolerance value of each parameter is 15 MHz, 0.3 μs, and 3 μs, and measuring error 5 MHz, 0.1 μs, and 1 μs. Parameter type is composed of multi value, single value and interval type. In this simulation, cases of similar parameter, cross parameter, and same signal in different modes are all devised.

A database is established according to Table 4 and corresponding similarity model is selected based on parameters types to calculate the similarity among radar signals, such as PRI similarity as shown in Table 5. This similarity model can reflect the similarity degree among parameters and the matching degree among multi-value parameters, as well as same targets in different patterns. To take a case in point, s_{27} = 11.79, then signal parameters follow strict relations as 2.24 times of each other.

The similarity is optimized in accordance with Step 3. Then parameter similarity of evidences is fused according to Step 4 to obtain the trust value of each signal relative to the target framework as shown in Table 6. It can be observed from the table that D-S evidence is of substantial assistance in fusing the similarity of parameters to obtain the trust values of the target. And for the same target, its trust value is basically the same. As in Table 6, the trust values of signal 1 to target 4 and 5 are both 0.19. The simulation results are thus in line with the theoretical decision rules.

Table 4. Parameter of unprocessed radar signal

Unprocessed radar signal	RF	PW	PRI
Signal 1	6615, 6620, 6780	45, 49, 68.8, 62.5, 86.4	20.5, 23.1
Signal 2	6606, 6653, 6792	37.8, 28.8, 48.7, 55.7	27
Signal 3	5321, 5678	35, 40, 45, 50	20, 27
Signal 4	6615, 6620, 6780	45, 68.8, 62.5	20.9, 23.3
Signal 5	6607.3–6787.2	44, 49, 68.8, 62.5	20.7, 23.3
Signal 6	6607, 6658, 6801	37.8, 28.8, 86.4	27.2
Signal 7	6606, 6658, 6798	64.7, 86.6, 103.5, 125.32	27.4
Signal 8	5321	35, 40, 45	20, 27
Signal 9	6601.8–6778.7	37.8, 28.8, 48.7, 55.7	27.7
Signal 10	6607–6797.2	44, 49, 68.8, 86.4	20.6, 23.2
Signal 11	5678	35, 40, 45	20, 27

Table 5. The similarity between PRI parameters

	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target 10	Target 11
Signal 1	1	0.53	5.69	11	10.89	0.75	5.48	0.75	0.53	10.09	0.75
Signal 2	0.53	1	0.54	0.26	0.56	7.52	11.79	6.99	1	0.53	6.99
Signal 3	5.69	0.54	1	0.75	1.57	0.43	0.00	11	0.51	0.48	11
Signal 4	11	0.26	0.75	1	10.86	0.00	0.43	0.75	0.26	7.49	0.75
Signal 5	10.89	0.56	1.57	10.86	1	0.00	0.32	0.59	0.53	1	0.59
Signal 6	0.75	7.52	0.43	0.00	0.00	1	0.72	0.43	7.67	0.75	0.43
Signal 7	5.48	11.79	0.00	0.43	0.32	0.72	1	0.00	11.79	11.48	0.00
Signal 8	0.75	6.99	11	0.75	0.59	0.43	0.00	1	7.17	0.59	1
Signal 9	0.53	1	0.51	0.26	0.53	7.67	11.79	7.17	1	0.56	6.93
Signal 10	10.90	0.53	0.48	7.49	1	0.75	11.48	0.59	0.56	1	0.59
Signal 11	0.75	6.99	11	0.75	0.59	0.43	0.00	1	6.93	0.59	1

Table 6. The trust values of each parameter relative to the target framework

	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target 10	Target 11
Signal 1	0.28	0.03	0.00	0.19	0.19	0.03	0.02	0.00	0.06	0.19	0.00
Signal 2	0.05	0.24	0.00	0.04	0.09	0.14	0.17	0.00	0.18	0.09	0.00
Signal 3	0.09	0.07	0.19	0.06	0.04	0.06	0.02	0.19	0.05	0.04	0.19
Signal 4	0.21	0.01	0.00	0.34	0.23	0.01	0.02	0.00	0.03	0.15	0.00
Signal 5	0.17	0.04	0.00	0.19	0.27	0.02	0.04	0.00	0.04	0.22	0.00
Signal 6	0.05	0.14	0.00	0.02	0.05	0.26	0.19	0.00	0.18	0.11	0.00
Signal 7	0.03	0.18	0.00	0.03	0.04	0.18	0.28	0.00	0.19	0.07	0.00
Signal 8	0.00	0.00	0.39	0.00	0.00	0.00	0.00	0.39	0.00	0.00	0.20
Signal 9	0.06	0.17	0.00	0.05	0.07	0.17	0.17	0.00	0.24	0.06	0.00
Signal 10	0.19	0.05	0.00	0.12	0.22	0.06	0.05	0.00	0.05	0.27	0.00
Signal 11	0.07	0.12	0.21	0.06	0.05	0.06	0.02	0.12	0.03	0.06	0.21

Tag: The signal 2 and 7, 7 and 9, 7 and 10 may be the same target in different signal mode.

Given preceding signal $\varepsilon = 0.1$, each column is determined and classified according to Eqs. (20) and (21). Targets within threshold are extracted as shown in Fig. 6 and the results in Fig. 7. It is clear that radar signals are roughly separated, yet signal overlapping still exists. Signal 2, for instance, appears in both set 2 and 3 simultaneously (Table 7). The reason lies in that in this step fusion is performed at the level of signal parameter, which can only distinguish the similarity between each independent to-be-processed signal and the target signal. The processing result is considerably affected by signal data quality, and data processing results with contingency and uncertainty are error-prone. Here thus comes the next step: fuse signals from each signal set, curbing the effects exerted by data contingency and uncertainty.

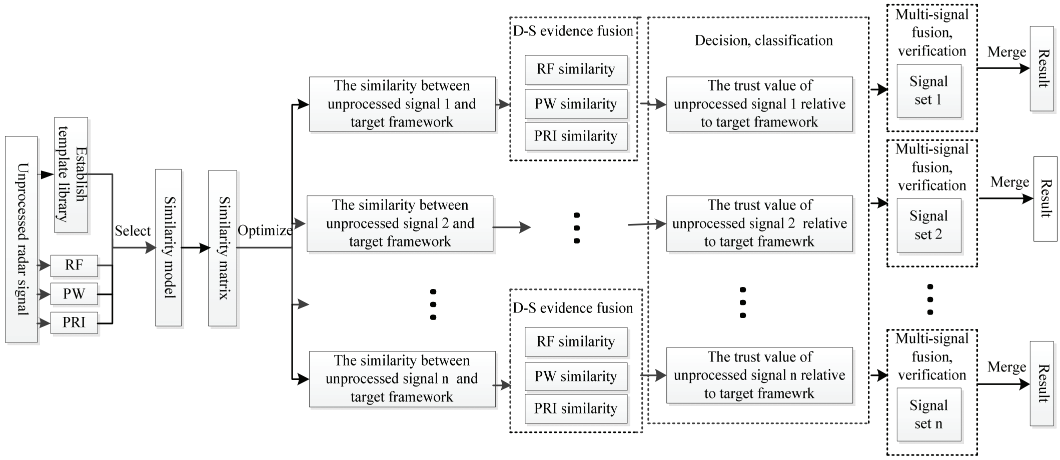

Fig. 6. Algorithm flow.

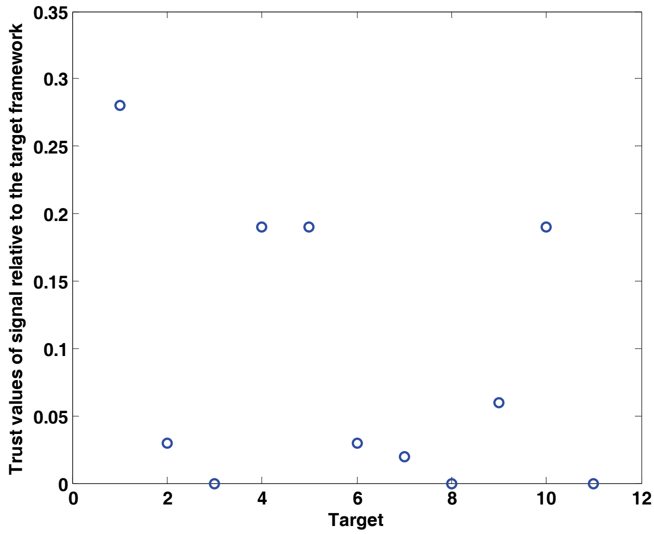

Fig. 7. Decision process.

Table 7. Classification result

	Target value
Signal set 1	1, 4, 5, 10
Signal set 2	2, 6, 7, 9
Signal set 3	3, 8, 11, 2

Tag: The signal 2 and 7, 7 and 9 may be the same target in different signal mode.

Fusion verification is exercised to each signal set according to Step 5 and the results are shown in Table 8. It can be seen that for the same signal, the trust value changes upon fusion, fluctuating within the range of 0.1. This is related to the effects of reconnaissance environment and equipment, i.e. even for the same target signal, precision and accuracy of signal parameters are different due to disparate devices [14]. The result is however in accord with theoretical decision rules.

Table 8. Trust value of multi-signal fusion

	Trust value
Set 1	Target 1 (0.24), Target 4 (0.21), Target 5 (0.29), Target 10 (0.26)
Set 2	Target 2 (0.22), Target 7 (0.26), Target 9 (0.27), Target 6 (0.25)
Set 3	Target 3 (0.45), Target 8 (0.32), Target 11 (0.23), Target 2 (0.00)

Through multi-signal fusion, the signal set obtained in Step 4 can be verified by making full use of each signal data, combining signals with each other to determine target frame. Misclassified signals influenced by accident and noise are eliminated to realize the processing of complex radar signals with multiple-type parameters. Finally, signals belonging to the same target are merged to be more complete. To take a case in point, through multi-signal fusion of trust value, target 2 are properly eradicated from signal set 3 and classified into signal set 2 as shown in Table 9.

Table 9. Fusion result

	RF (Hz)	PW (μs)	PRI (μs)	Radar signal
Radar 1	6607–6697	45, 49, 68.8, 62.5, 86.4	20.7, 23.2	1, 4, 5, 10
Radar 2	6601.8–6778.7	28.8, 37.2, 48.7, 55.7 / 64.7, 86.6, 103.5, 125.32	27.4	2, 6, 7, 9
Radar 3	5321, 5678	35, 40, 45, 50	20, 27	3, 8, 11

The algorithm can correctly realize the fusion processing of unknown complex radar signals, which is effectively deal with the limit that the existing algorithms cannot accurately realize fusion processing without database.

5.2 Analysis of Algorithm Performance

In consideration of the purpose of radar signal fusion processing algorithm, effective parameters of fusion processing will be defined to evaluate the performance of the algorithm. Effective parameter is defined as follows:

$$J = \frac{N_1}{N} \times 100\% , \tag{23}$$

In which N represents the total quantity of radar signal implemented in fusion processing, and N_1 the quantity of correct results obtained in algorithm processing.

1) The impact of radar signal amount on effective parameters

Fifty radar target signals are selected, and 2, 5, 8, 11, 14, 17, 20, 23, 26 samples from each target signal are extracted to form 9 signal processing data sets. Each data set is processed with the proposed algorithm, fuzzy recognition algorithm and interval grey relation algorithm, then effective rate and processing time are counted. Experimental data are randomly altered and the simulation is repeated for 100 times, then the mean value of processing efficiency and time are calculated. The results are shown in Figs. 8 and 9.

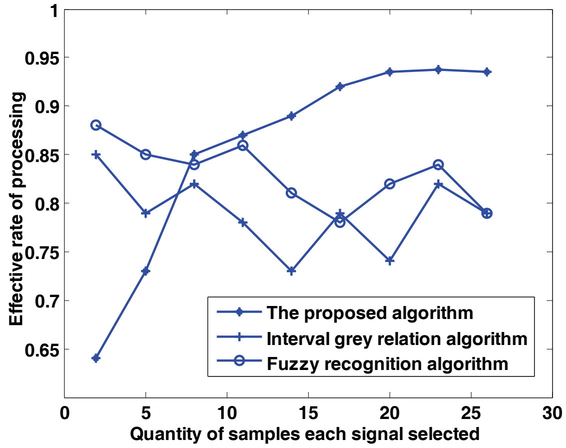

Fig. 8. Efficiency change along with the quantity.

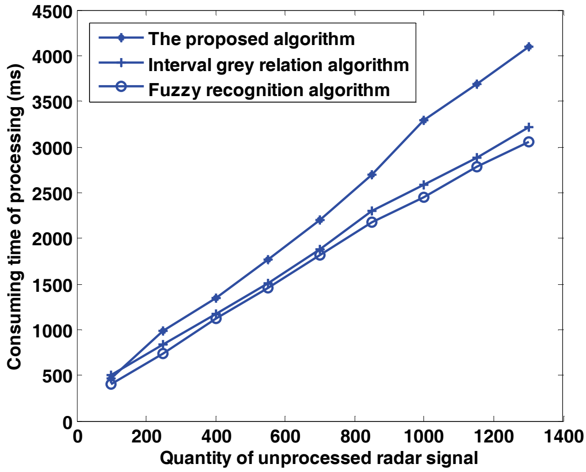

Fig. 9. Relations between total number of radar signals and time.

As shown in Fig. 8, when the samples are small in amount, the effective rate of this algorithm is about 0.25 lower than the other two algorithms, as the interval grey relation algorithm and fuzzy recognition algorithm's separate processing of radar signals will drive processing efficiency high. However, once the amount of samples increases, the effective rate of the proposed algorithm will increase and stabilize eventually, fluctuating around 0.93. It can be further verified that the proposed algorithm can process unknown signals by full signal integration, and maintain stable high efficiency under large sample data. While the other two algorithms are restricted to the comparison between single independent signals and target frame, without integration of signals. Under such circumstances, increased sample results in decreased and unstable efficiency. The proposed algorithm can exert favorable effect on the fusion of unknown complex radar signals, with higher efficiency, and maintaining stable processing even of considerable samples, which is what other two algorithms cannot get.

As shown in Fig. 9, the proposed algorithm is the most time-consuming due to the application of D-S evidence theory, thus the most complex than the other two algorithms. Yet adopting multi-level processing approach, this algorithm implements fusion decision on signal parameters at first, and then perform verification by fusing signals according to the decision, reducing exponentially growing calculating complexity, i.e., the contradiction between multiple input and high complexity [15].

Therefore, when the sample number reaches 100, the time consumed is nearly equal to that of the other two methods. And when the sample number is up to 1,300, the time consumed in this algorithm is only 27.54% more than that of grey relation algorithm, and 37.71% of fuzzy recognition algorithm. Time difference has narrowed.

6. Conclusion

The D-S evidence theory algorithm based on similarity can be of substantial assistance in fusion processing of unknown radar signals. A database concerning to-be-processed signals is initially established in real time to break the limitations of the lack of database, and the corresponding decision rules are constructed and deduced; then establish reasonable similarity model to obtain the similarity matrix, finally multi-parameter fusion processing and multi-signal fusion processing is performed successively through the agency of D-S evidence theory. It can be concluded from simulation experiment that the proposed algorithm is expert in processing unknown radar signals lacking template library, and maintaining a stable processing rate with considerable samples and less time consumed. Fusion processing renders radar signals more complete and abundant, decreasing the redundancy of radar signal and laying foundation for further signal recognition, which can effectively reduce the storage equipment's consumption.

This algorithm supports fusion processing with conventional parameters such as radio frequency, pulse width and repetition period provided. The ever-developing intra-pulse analysis technique in time frequency domain brings accuracy and reliability in the extraction of intra-pulse parameter, constituting a powerful evidence in signal processing. Future research on recognition of radar signal targets will take intra-pulse parameters into account, enhancing accuracy while maintaining effective and stable processing with large sample data.

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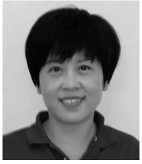

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