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Research on Radar Emitter Signal Feature Extraction Method Based on Fuzzy Entropy

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Abstract:

With the rapid application of the new radar system, radar signal sorting based on conventional parameters has not achieved the desired results. Therefore, new features need to be extracted for signal sorting. In response to this problem, the paper proposes to use the entropy theory to extract the fuzzy entropy characteristics of the radar signal to determine the uncertainty of the radar source signal. Experiments with test signals show that the fuzzy entropy characteristics are less affected by noise over a wide range of SNR.

Keywords: radar emitter signal, feature extraction, Fuzzy Entropy, fuzzy set.

1 Introduction

At present, in order to solve the problem of radar signal sorting in the modern electronic countermeasure environment, the sorting method combined with the intra-pulse feature extraction of radar signals has become a research hotspot. By analyzing the intrapulse data of radar signals, this method studies the intentional modulation features and unintentional modulation features in the pulse, constructs a new radar signal sorting model based on short-term observation data, expands the parameter space, and reduces the overlapping probability of multi-parameter space. To achieve fast and accurate sorting identification signals.

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Devijver [1] defined generalized feature extraction as: extracting the most relevant information (or features) from the original data, and the proposed information should have the property of minimizing intra-class and enhanced inter-model variability. For the in-pulse feature extraction, the feature with the intra-class aggregation and inter-class separation is extracted from the intrapulse data, so that the features between the signals are clearly distinguished, so as to prepare for sorting and identifying the radar signal. Considering that the radar signal envelope is greatly affected by noise and multipath interference, and the feature extraction method has different application scopes, it is necessary to find a suitable feature extraction algorithm for analysis, so that the identification of the radiation source can be better sorted. The feature extraction method of radiation source signal based on entropy feature compensates for the insufficiency of the classical method to a certain extent. In [2], the approximate entropy and norm entropy are used to form the feature vector and the neural network classifier is used for classification and recognition. Recognition effect. In this paper, the entropy feature extraction method of radar emitter signal is studied.

On the basis of studying the entropy characteristics, this paper supplements the new characteristic parameters other than the conventional five parameters, and proposes the fuzzy entropy as the new feature of the radiation source signal. The entropy parameter is used to describe the uncertainty of the radiation source signal.

2 Analysis of Fuzzy Entropy

Entropy represents the average uncertainty of the source in information theory. It can be used to measure the ambiguity of a fuzzy set in fuzzy subset theory. Therefore, the fuzzy entropy (FzzyEn) can be used to represent the uncertainty of the fuzzy set.

Assume U is the set of finite universes $U=\{x_1,x_2,...,x_n\}$, the set of all fuzzy sets on it is $F(U)$, $P(U)$ is recorded as the set of all the distinct sets on it. For $A\in F(U)$, the degree of membership of the fuzzy set A at the point x is recorded as $\mu_A(x)$, the complement of A is A^c, namely $\forall x\in U$, $\mu_{A^c}(x)=c(\mu_A(x))$. Here the function c is a generalized complement function, commonly $c(x)=1-x$. The distinct modification (sharpening) of A is A^*, defined as: when $\mu_A(x)\geq 1/2$, $\mu_{A^*}(x)\geq\mu_A(x)$; when $\mu_A(x)\leq 1/2$, $\mu_{A^*}(x)\leq\mu_A(x)$; $A=[m]$ is meaning $\forall x\in U$, $\mu_A(x)=m$ [3].

If $A\in P(U)$, at that time $x\in A\ or \notin A$, the element x belongs to or does not belong to a distinct set, then obviously the ambiguity of the distinct set should be 0; if $A\in F(U)$, at that time $A=[1/2]$, the state of whether the element x belongs to the set A is the most difficult to determine, then the ambiguity at this time should be the largest. Intuitively, the fuzzy set A is the same as A^c to the distance $[1/2]$, that is, the degree of blurring is the same for A and A^c. In addition, the fuzzyness of the fuzzy set A should have the property of monotonous change, that is, the closer to $[1/2]$, the greater the ambiguity A has, the more the deviation to $[1/2]$, the smaller the ambiguity A has. Based on the above analysis, the general definition of fuzzy entropy is as follows [4]:

Definition 1 Fuzzy entropy F_e is the mapping of $F(U)$ to $R^+=[0,+\infty)$, which satisfies the following four conditions:

(1) $F_e(A)=0$ *iff* $A\in P(U)$;

(2) $F_e(A)=\max_{A\in F}F_e(A)$ *iff* $A=[1/2]$;

(3) If A^* is the clearly modified of A, then $F_e(A^*)\leq F_e(A)$;

(4) $\forall A\in F(U)$, $F_e(A^c)=F_e(A)$.

Where, *iff* means "if and only".

The definition of fuzzy entropy axiomatization described in Definition 1 has been widely adopted and has become a criterion for defining some new fuzzy entropy. The following definitions of related fuzzy entropy are based on the above concepts.

Definition 2 For $\forall A\in F(U)$, define A_{near} and A_{far} as the "nearest" distinct set and the "farthest" distinct set of the fuzzy set A respectively, then:

$$A_{near}(x)=\begin{cases}1, & A(x)\geq\frac{1}{2}\\ 0, & A(x)<\frac{1}{2}\end{cases} \tag{1}$$

$$A_{far}(x)=\begin{cases}0, & A(x)\geq\frac{1}{2}\\ 1, & A(x)<\frac{1}{2}\end{cases} \tag{2}$$

Obviously $A_{near}^{c}(x)=A_{far}(x)$.
Considering that the intersection of A and A^c is not empty, Yager defines the fuzzy entropy [5]:

$$F_{e_Y}(A)=1-\frac{l_p(A,A^c)}{n^{1/p}} \tag{3}$$

Assumeing $\forall A, B\in F(U)$, $p\geq 1$, then The definition of l_p can be written as:

$$l_p(A,B)=\left[\sum_{i=1}^{n}\left|A(x_i)-B(x_i)\right|^p\right]^{1/p} \tag{4}$$

When $p=1$, l_p become the Hamming measure:

$$l_p(A,B)=\sum_{i=1}^{n}\left|A(x_i)-B(x_i)\right| \tag{5}$$

Based on definition 2, Kaufmann also defines the fuzzy entropy [6]:

$$F_{e_{Kau}}(A)=\frac{1}{n^{1/p}}l_p(A,A^c)=\frac{1}{n^{1/p}}\left[\sum_{i=1}^{n}\left|A(x_i)-A_{near}(x_i)\right|^p\right]^{1/p} \tag{6}$$

Denoting a as the distance from the fuzzy set A to the "nearest" distinct set A_{near}, that is $a=l_1(A,A_{near})$, b as the distance from fuzzy set is A to A_{far}, that is $a=l_1(A,A_{far})$, the proportional fuzzy entropy can be defined as [7]:

$$F_{e_{Ko1}}(A)=\frac{a}{b}=\frac{l_1(A,A_{near})}{l_1(A,A_{far})} \tag{7}$$

From 0 to 1 in the unit hypercube, where the entropy of the vertex is 0, indicating no blur, the entropy of the midpoint is 1, which is the maximum entropy. From the vertex to the midpoint, the entropy gradually increases. Consider the proportional form of entropy from the geometry shown in Figure 1:

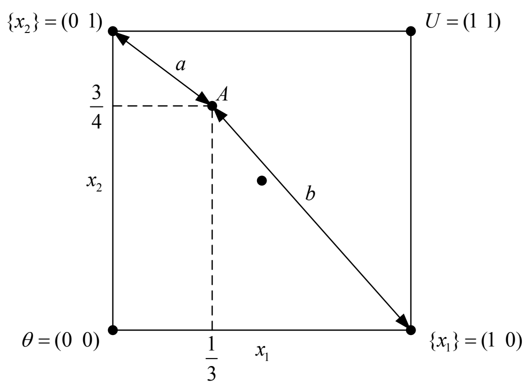

Figure 1 Proportional fuzzy entropy geometry

Obviously $A=(\frac{1}{3},\frac{3}{4}),\ A_{near}=(0,1),\ A_{far}=(1,0),\ a=\frac{1}{3}+\frac{1}{4}=\frac{7}{12},\ b=\frac{2}{3}+\frac{3}{4}=\frac{17}{12},\ F_{e_{Ko1}}(A)=\frac{7}{17}$.

In addition, according to Definition 1, Dubois defines the potential of the fuzzy set. If assuming $U=\{x_1,x_2,...,x_n\}$, the potential of the fuzzy set A on the domain U is [8]:

$$M(A)=\sum_{i=1}^{n}A(x_i) \tag{8}$$

Obviously $M(U)=n$, $M([1/2])=n/2$.

According to the concept of fuzzy set, Kosko defines fuzzy entropy using the concepts of overlap and underlap [7]:

$$F_{e_{Ko2}}(A)=\frac{M(A\cap A^c)}{M(A\cup A^c)}=\frac{\sum_{i=1}^{n}[A(x_i)\wedge A^c(x_i)]}{\sum_{i=1}^{n}[A(x_i)\vee A^c(x_i)]} \tag{9}$$

The geometrical representation of the fuzzy entropy is shown in Figure 2. From the symmetry, the distances from the four points of the complete fuzzy square to the nearest nearest vertex and the farthest vertex are equal.

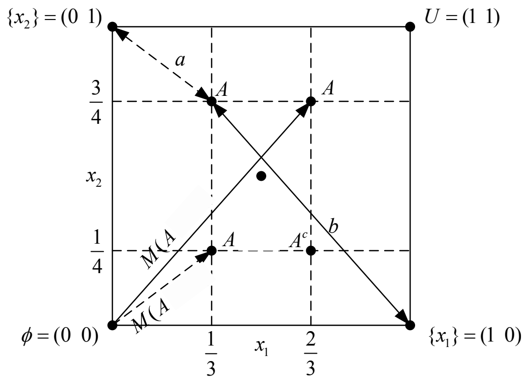

Figure 2 Fuzzy entropy geometry based on fuzzy set

In fact, the analysis mentioned above for $\forall A\in F(U)$, $F_{e_{Ko1}}(A)=F_{e_{Ko2}}(A)$ both is established and the proof process is in reference [9].

In addition, Parkash defines another fuzzy entropy of fuzzy set A as [10]:

$$F_e(A)=k\sum_{i=1}^{N}[f(\mu_A(x_i)] \tag{10}$$

Where $f(t)=-t\ln t-(1-t)\ln(1-t)$, $k>0$ is a normal number, $\mu_A(x_i)$ representing the membership function of fuzzy set A.

It is easy to prove that $f(t)$ is a symmetric function about $t=0.5$ strictly increasing monotonically within the interval $[0,0.5]$, strictly monotonically decreasing within the interval $[0.5,1]$, and obtaining the maximum value $\ln 2$ at that time $t=0.5$, as shown in Figure 3.

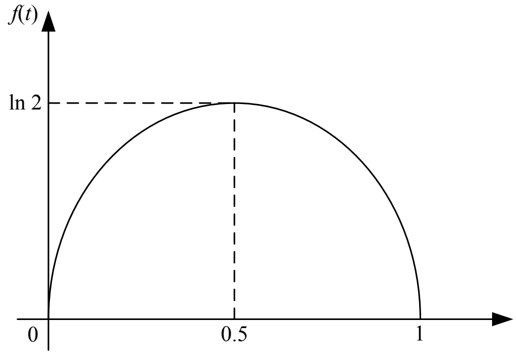

Figure 3 Schematic diagram of $f(t)$ function

It can be seen from equation (10) that if $\mu_A(x) \in \{0,1\}$, then $F_e(A) = 0$, if $\mu_A(x) \in \{1\}$, then $F_e(A)$ obtains the maximum value, so this paper takes $k^{-1} = N \ln 2$ as the normalization factor.

3 Fuzzy Entropy Feature Extraction Of Radar Signals

After many experiments, this chapter uses equation (10) as the fuzzy entropy calculation formula, using the sigmoid function [3] represented by equation (11) as the membership function:

$$\mu_A(x_i) = \begin{cases} 0, & x_i \le a; \\ (x_i - a)^2 / (b-a)(c-a), & a \le x_i \le b; \\ 1-(x_i - c)^2 / (c-b)(c-a), & b \le x_i \le c; \\ 1, & x_i \ge c \end{cases} \tag{11}$$

Where $b = (a+c)/2$, a and c determine the range of the fuzzy window width in the function, and change with the difference of the obtained fuzzy window. As a transition point of the function, the optimal parameter a, b, c can be obtained by obtaining the maximum entropy of the fuzzy set. That is, the parameters should satisfy the formula (12):

$$\max\{F_e(A), a, b, c \in x(n) \ \& \ a < b < c\} \tag{12}$$

Considering that the source signal contains a certain uncertainty, the fuzzy entropy can be used to measure the uncertainty of the signal. Assuming the resampled point is N, signal sequence is $x(n) = [x_1 \ x_2 \ ... \ x_N]$, A is the fuzzy subset corresponding to the sequence. Then if the optimal parameter a, b, c are determined, the membership degree of the signal sequence is obtained according to equation (11), consequently the fuzzy entropy of the signal sequence can be obtained according to equation (10).

To verify the validity of the entropy feature, the experiment is performed by selecting a signal as shown in the following equation.

$$f(t) = 3\sin(30\pi t) + \sin(150\pi t) + 5\cos(21.6\pi t) \tag{13}$$

The sampling frequency is 1000Hz, $t \in (0,1]$ is taken as the time.

Table 1 shows the mean and variance of the fuzzy entropy characteristics of the test signal at different SNR points. Ten experimental results are compared and analyzed.

Table 1 Mean and Variance of Fuzzy Entropy Characteristics of Test Signals

Experiment number	mean	variance
1	0.91598	1.5772×10^{-5}
2	0.91474	9.7685×10^{-6}
3	0.91624	2.2112×10^{-5}
4	0.91557	1.1918×10^{-5}
5	0.91636	2.5291×10^{-5}
6	0.91438	8.6436×10^{-6}
7	0.91517	1.0627×10^{-5}
8	0.91363	3.3000×10^{-5}
9	0.91598	1.1932×10^{-5}
10	0.91541	1.1081×10^{-5}

The mean of the test signal feature in table 1 reflects their central position in the feature space, and the magnitude of the variance value reflects the degree of aggregation of feature vectors at the center position. It can be seen that the characteristics of the test signal are concentrated at the center, and the fuzzy entropy feature is less affected by noise within a wide range of SNR.

4 Conclusion

Entropy represents the average uncertainty of the source in information theory. It can be used to measure the ambiguity of a fuzzy set in fuzzy subset theory. Therefore, the fuzzy entropy (FzzyEn) can be used to represent the uncertainty of the fuzzy set. On the basis of studying the entropy characteristics, this paper supplements the new characteristic parameters other than the conventional five parameters, and proposes the fuzzy entropy as the new feature of the radiation source signal. The entropy parameter is used to describe the uncertainty of the radiation source signal. The simulation of the test signal shows that its feature is highly concentrated at the center, and the fuzzy entropy feature is less affected by noise in a wide range of SNR.

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