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RESEARCH ARTICLE

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A feature extraction method for the signal sorting of interleaved radar pulse serial

Abstract In this paper, a new feature extraction method for radar pulse sequences is presented based on structure function and empirical mode decomposition. In this method, 2-D feature information was constituted by using radio frequency and time-of-arrival, which analyzed the feature of radar pulse sequences for the very first time by employing structure function and empirical mode decomposition. The experiment shows that the method can efficiently extract the frequency of a period-change radio frequency signal in a complex pulses environment and reveals a new feature for the signal sorting of interleaved radar pulse serial. This paper provides a novel way for extracting the new sorting feature of radar signals.

Keywords signal sorting, structure function, empirical mode decomposition, feature extraction

1 Introduction

Radar signal sorting is a vital part of electronic intelligence system (ELINT) and electronic support measures (ESM) processing. We can analyze and extract the parameters of radar emitter signals based only on sorting. The current low-efficiency methods (e.g. histogram [1–3], clustering [4,5], etc.) are based on five parameters which include time-of-arrival (TOA), radio frequency (RF), pulse width (PW), direction of arrival (DOA) and pulse amplitude (PA).They cannot adapt to the complex-variety and high-density pulses environment in modern electronic warfare. According to variant characteristics of instantaneous pulse parameters for radar emitter signals, a method of feature extraction for the radar pulse serial signal based on structure function and empirical mode decomposition (EMD) is presented. A new method of feature extraction of signal sorting is shown in this part by using RF and TOA 2-dimension feature information. The steps of the method are: first, preprocessing by inserting noise on radar pulse sequences to develop an equal-interval time sequence; second, making a structure function sequence by correlation processing on the treated time sequence through using structure function; finally, decomposing the new structure function sequence into many intrinsic mode functions (IMF) by EMD. The frequency of the period-change RF parameter signal is extracted after getting rid of the high-frequency components among the IMFs. The validity of the feature extraction method is demonstrated by the simulation experiment.

2 Feature extraction method

2.1 Preprocessing

Theoretically, a 2-D information sequence can be constituted with the RF and TOA parameters of every pulse in radar pulse serial obtained from radar interception receiver. But the distribution of the pulse TOA in the group of obtained time sequence is uneven, random and non-stationary. Hence, it is difficult to make the time sequence analysis directly. We convert them into equal-interval time sequence with the help of noise-insertion method.

From the pulse RF data intercepted from real warfare environment, we conclude that the RF parameters approximately submit to Gaussian distribution. We insert Gaussian noise in the preprocessing, which does not affect the frequency feature of the period signal in the original data and reduces the noise power when zero is inserted.

The preprocessing is to let the given RF parameter of the preprocessing radar pulse sequences be the function of pulse sequence number n, shown as $f(n)$, $n \in [1, N]$. We write R_f for the maximum span of $f(n)$, $n \in [1, N]$, i.e.

$$R_f = \sup_{1<m,\, n<N} \left| f(m) - f(n) \right| \tag{1}$$

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We write $\overline{f}$ for the average value of RF parameter $f(n)$, i.e.

$$\overline{f} = \frac{1}{N}\sum_{n=1}^{N} f(n) \tag{2}$$

where N is the length of the radar pulse sequence.

The inserted noise submits to Gaussian distribution

$$X \sim N(\overline{f},\ (\frac{R_f}{6})^2) \tag{3}$$

where $\overline{f}$ is the expectation of Gaussian distribution, R_f is the confidence interval. The upper quantile of Gaussian distribution is 3σ, i.e. degree of confidence is 99.7% and the variance of Gaussian distribution $\sigma^2 = (R_f/6)^2$.

The envelope curve of time sequence obtained by the preprocessing can be considered as a random process $S_1(X)$ that may be approximately described as a fractal Brownian random process (FBRP) [6].

2.2 Structure function

We define increment variance of the random process $S_1(X)$ as structure function $S_2(h)$. Applying the theory of fractional Brownian motion (FBM) with structure function, we get [6]

$$S_2(h) = <|S_1(x+h) - S_1(x)|^2> \sim |h|^{2(2-D)} \tag{4}$$

where $<\ldots>$ denotes time average, D represents the fractal dimension. As a statistic of the random process, the structure function $S_2(h)$ denotes the variance of process $S_1(X)$ increment.

During the correlation processing, we apply structure function instead of autocorrelation function [7]. Let us define the structure function of random sequence $S_1(n)$, after preprocessing, as $S_2(n)$,

$$S_2(n) = \frac{1}{M}\sum_{i=1}^{M} |\, S_1(i+n) - S_1(i)\,|^2 \tag{5}$$

where $M = N - n$, N is sequence length, $S_1(i)$ is the random sequence after preprocessing.

Through correlation processing, a proportion of noise can be removed and the energy of the period signal contained in random sequence can be increased. However, the signal-to-noise ratio (SNR) of the original signal sequence is so low that, after correlation processing, the structure function sequence is still a non-stationary process. We carry out EMD processing to decompose signal $S_2(n)$ into several IMF components, remove the high-frequency component and extract the low-frequency component with the period feature.

2.3 The empirical mode decomposition

The time-frequency analysis approach based on EMD consists of two steps. First, the time sequence data are decomposed by EMD into a group of IMF. Then, each IMF is transformed by Hilbert transformation (HT) and its time-frequency spectrum is analyzed [8]. EMD is the key to the approach. In fact, a signal is to be stationary-processed in the method. The result is that the various scales of fluctuations and trends of signals are decomposed step-by-step to make out a series of data sequences with various scales of features. Each sequence is an IMF component. Huang defined the function, meeting the following conditions, as IMF [8].

First, in the whole data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one.

Second, at any point, the mean value of the envelopes defined by the local maxima and the local minima is zero.

The essence of EMD is that the signal is decomposed into several IMF components. The various IMF components have different scales of features, which help to analyze the signals in particular.

We now present the empirical mode decomposition process of the structure function sequence $S_2(n)$, which is obtained from the radar pulse train data by preprocessing and correlation processing.

The decomposition method can simply use the envelopes $S_2(t)$, defined by the local maxima and minima of structure function sequence $S_2(n)$, separately. Once the extrema are identified, all the local maxima are connected by a cubic spline line as the upper envelope. The procedure is repeated for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them. Their mean is designated as m_1, and the difference between the data and m_1 is the first component, h_1, i.e.

$$S_2(t) - m_1 = h_1 \tag{6}$$

If h_1 does not meet the above two IMF conditions, a second sifting is to be made. In the second sifting process, h_1 is treated as the data, then

$$h_1 - m_{11} = h_{11}\,. \tag{7}$$

The sifting process serves two purposes: to eliminate riding waves and to make the wave-profiles more symmetric. Toward this end, the sifting process may have to be repeated for k times, until we get h_{1k} such that

$$h_{(k-1)} - m_{1k} = h_{1k} = \mathrm{IMF}_1 \tag{8}$$

the first IMF component from the data.

The sifting process achieves the second purpose by smoothening uneven amplitudes. Unfortunately, this effect, when carried to the extreme, could obliterate the physically meaningful amplitude fluctuations [8]. To guarantee that the IMF components retain enough physical sense of both amplitude and frequency modulations, we have to determine a criterion for the sifting process to stop. This can be accomplished by limiting the size of the standard deviation (SD), computed from the two consecutive sifting results as

$$\mathrm{SD}=\sum_{t=0}^{T}\left[\frac{\left|h_{1(k-1)}(t)-h_{1k}(t)\right|^{2}}{h_{1(k-1)}^{2}(t)}\right] \tag{9}$$

A typical value for SD can be set between 0.2 and 0.3 [8]. As a comparison, the two Fourier spectra, computed by shifting only five out of 1 024 points from the same data can have an equivalent SD of 0.2–0.3 calculated point-by-point. Therefore, a SD value of 0.2–0.3 for the sifting procedure is a very rigorous limitation for the difference between siftings.

Overall, IMF_1 should contain the component with the finest scale or the shortest period of the signal. We can separate IMF_1 from the rest of the data by

$$S_2(t)-\mathrm{IMF}_1=r_1 \tag{10}$$

Since the residue, r_1 still contains information of longer period components, it is treated as the new data and subjected to the same sifting process as described above. We get the result

$$r_1-\mathrm{IMF}_2=r_2, r_3,\ldots, r_{n-1}-\mathrm{IMF}_n=r_n \tag{11}$$

The sifting process, which can be stopped by any of the following predetermined criteria: the component IMF_n or the residue r_n, becomes so small that it is less than the predetermined value of substantial consequence, or the residue r_n, and becomes a monotonic function from which no more IMF can be extracted. Even though for data with zero mean, the final residue need not necessarily be zero, for data with a trend, the final residue should be that trend. By summing up Eqs. (10) and (11), we finally obtain

$$S_2(t)=\sum_{i=1}^{n}\mathrm{IMF}_i+r_n \tag{12}$$

Thus, we achieved a decomposition of the data—the structure function signals obtained from time sequences that consist of preprocessed and correlation processed RF and TOA 2-D information of radar pulse serial—into n-empirical modes, and a residue r_n, which can be either the mean trend or a constant. As discussed here, to apply the EMD method, a mean or zero reference is not required; EMD only needs the locations of the local extrema. The sifting process will generate the zero references for each component. Thus EMD eliminates the troublesome step of removing the mean values for the large DC term with non-zero mean, in the data; an unexpected benefit.

The noise (the high-frequency component) of the signal mainly concentrates on several initial IMF components. We can separate the IMF components from the signal $S_2(n)$ to remove the noise. The number of IMF removed is determined by various signals. The period-change RF signal, compared with the background of the complex RF change, is a low-frequency component. Therefore, we can treat this background as the noise and obtain the period-change signal by extracting the low-frequency component of EMD. On other occasions, for each IMF obtained by EMD, the local mean of the signal is calculated based on the upper and lower envelopes of the signal. All the local maxima and minima are connected by a cubic spline line as the upper and lower envelopes. In this procedure, the first and the second derivatives at both ends of the signal sequence must be treated as boundary conditions. If the information at both ends cannot be obtained from the data curve, the envelope line will swing widely at both ends of the data. This is the end issue of EMD.

It has to perform extrema envelope extending by the mirror periodic method (MPM) [9]. Then we can get reasonable IMF modes obtained by the EMD. According to the distribution feature of the signals, the extended signal is reflected as a period-ring signal without the ends, which avoids the end issue of EMD.

3 Simulation demonstration

In order to demonstrate algorithm, simulation data is provided in Table 1, where the RF parameter of radar 1 changes according to sine regulation and the changed frequency is 50 Hz, that of radar 3 is random jumping between the ten installed frequency points and the RF parameters of radar 2 and radar 4 are random agile.

We only choose the 2-D information that is RF and TOA to analyze. Applying the above approach, we can extract the period feature of emitter signal (radar 1) whose RF parameter changes according to period. The RF-TOA 2-D information sequence of the original signal is as Fig. 1.

According to Gaussian distribution in Eq. (3), the time sequence signal in Fig. 1 is preprocessed by the noise-insertion method and we can obtain the equal-interval time sequence S_1 (sample frequency f_s is 0.1 MHz). The signal S_1 is a correlation processed by Eq. (5) and we obtain the structure function sequence $S_2(n)$. The signal sequence, after

Table 1 Simulation data of radar parameters

Radar parameters	Radars			
	Radar 1	Radar 2	Radar 3	Radar 4
RF/MHz	2 500 + 100 sin (314t) (RF change according to sine regulation)	2 750–2 850 (agile frequency)	2 250–2 350 (jumping frequency on ten points)	2 550–2 750 (agile frequency)
PRF/Hz	1 000–1 010 (jittered PRF)	300–400 (jittered PRF)	800–1 000 (staggered PRF)	700–900 (jittered PRF)
The number of pulses	1 000	1 000	1 000	1 000

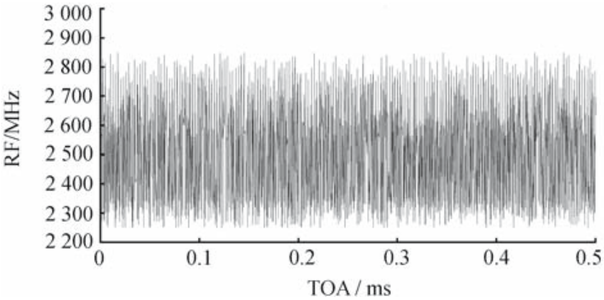

Fig. 1 The RF time sequence of original signal

preprocessing and correlation processing, is decomposed by EMD; the illustrations are passed over.

For the period-change emitter RF sequence, we can treat the random agile and jumping frequency sequences as the background noise. In the case of EMD, we remove the noise (the high-frequency component), that is, we combine several low-frequency IMF components (IMF_{12}–IMF_{15}) to get the structure function sequence $S(n)$ of the signal, after removing the noise, as Fig. 2 shows.

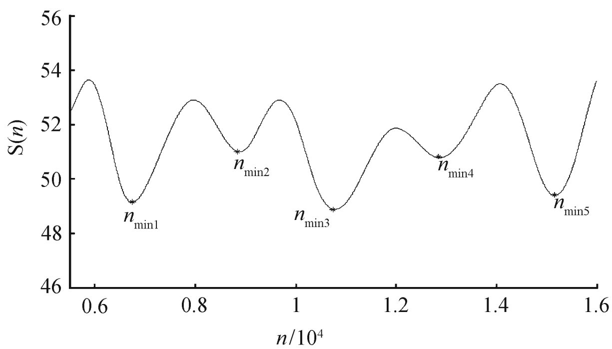

Fig. 2 The structure function after filtering noise

Based on the self-similar feature of period signal, from Eq. (5), we know that the structure function has the minima at the period points of period-signal. According to the feature, the period-signal frequency can be made out by Eq. (13) as soon as the adjacent minimum points (e.g. $n_{\min 1}$, $n_{\min 2}$, in Fig. 2) are found.

$$f_0 = \frac{1}{|n_{\min 1} - n_{\min 2}| T_s} \tag{13}$$

where $T_s = 1/f_s$, f_s is the sample frequency.

The period signal frequency was made out based on the adjacent minima in Fig. 2, as Table 2 shows.

Thus, the RF and TOA information of the original radar pulse serial were made up of a group of time sequence. First, we developed them to equal-interval random time sequence $S_1(n)$ by preprocessing; second, we developed a structure function sequence $S_2(n)$ through correlation processing on $S_1(n)$ by structure function; finally, we decomposed the structure function sequence $S_2(n)$ by EMD, removed the high-frequency component and got a new group of correlated sequence $S(n)$. Based on the self-similar feature of period signal, using any two adjacent minima values of correlated sequences $S(n)$ and sample frequency f_s, we extracted the frequency of the period-change RF signal in the original radar pulse sequence.

Table 2 Computation of the frequency of the period-change RF signal in the original radar pulse sequence

Co-adjacent minimum point	Sampling frequency f_s/MHz	Period signal frequency f_0/Hz
$n_{\min 1} = 6\,753$, $n_{\min 2} = 8\,852$	0.1	47.64
$n_{\min 2} = 8\,852$, $n_{\min 3} = 10\,803$	0.1	51.26
$n_{\min 3} = 10\,803$, $n_{\min 4} = 12\,851$	0.1	48.83

The mean of the calculated period signal frequency is $\overline{f_0} = 49.22$ Hz.

The simulation experiment proved that the period-change frequency of radar pulse serial RF sequence, extracted by the presented method, is the same as that of the emitter radar1 (relative error is −1.55%). Thus, through the above process, the period-change RF feature of radar pulse sequence was extracted successfully.

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