Method for Feature Extraction of Radar Full Pulses Based on EMD and Chaos Detection

Qiang Guo and Pulong Nan

Abstract: **A novel method for extracting frequency slippage signal from radar full pulse sequence is presented. For the radar full pulse sequence received by radar interception receiver, radio frequency (RF) and time of arrival (TOA) of all pulses constitute a two-dimensional information sequence. In a complex and intensive electromagnetic environment, the TOA of pulses is distributed unevenly, randomly, and in a nonstationary manner, preventing existing methods from directly analyzing such time series and effectively extracting certain signal features. This work applies Gaussian noise insertion and structure function to the TOA-RF information sequence respectively such that the equalization of time intervals and correlation processing are accomplished. The components with different frequencies in structure function series are separated using empirical mode decomposition. Additionally, a chaos detection model based on the Duffing equation is introduced to determine the useful component and extract the changing features of RF. Experimental results indicate that the proposed methodology can successfully extract the slippage signal effectively in the case that multiple radar pulse sequences overlap.**

Index Terms: **Duffing equation, empirical mode decomposition, feature extraction, Gaussian noise insertion, structure function.**

I. INTRODUCTION

In a complex and dense signal environment, radar signal sorting is the core technology of radar signal detection system. This technology involves feature extraction of radar signals. Traditional sorting methods usually depend on feature parameters, such as time of arrival (TOA), radio frequency (RF), pulse width (PW), angle of arrival (AOA) and pulse amplitude (PA) [1], [2]. However, with the rapid development of radar technology, the number of emitters increases considerably, resulting in signals overlapping more severely and the modulation forms of signals becoming more complicated. Many new radar systems are simultaneously provided with slippage, transition and random agility of different parameters (including RF, PW, and pulse repetition interval). Additionally, the between-class boundaries of signals described by conventional feature parameters overlap severely. For frequency slippage signals whose frequency changes periodically with time, no traditional five-parameter sorting method can realize signal extraction effectively. Therefore, the radar signal sorting based on five traditional parameters is no longer applicable in a modern electronic battlefield.

Recent methods for extracting feature parameters of radar signals include atom decomposition [3]–[6], fuzzy function [7], [8], relative non-ambiguity phase restoral [9], [10], support vector machine (SVM) classification [11]–[13] and difference autocorrelation feature extraction [14]. Atom decomposition linearly represents the optimal form of received signal using several functions in atom decomposition dictionary. For fuzzy function sorting methods, the extracted characteristic vector of main ridge slice is constituted by the direction of main ridge, slice barycenter and radius of inertia. The vector can excellently reflects waveform structures of different signals. The approach using the relative non-ambiguity phase restoral implements non-ambiguity of signal phase and differential operation. A further intra-pulse modulation pattern is recognized on the basis of the analysis of frequency behavior. In sorting methods based on SVM, SVM is employed as a classifier to automatically distinguish different signals and has proven to be capable of achieving a high correct recognition rate. Difference autocorrelation feature extraction methods implement the correlation process of a difference operation of radar emitter signals. The optimal separable feature vector used to classify signals is obtained according to the envelope characteristics of the autocorrelation function. The above methods, however, cannot directly analyze the pulse sequence intercepted by a radar signal receiver because intervals between pulses are not equivalent, which leads to great difficulty when extracting a slippage signal. Aiming at resolving the dilemma, this work converts the feature extraction of slippage signal to the problem of extracting a periodic signal in the case of low SNR. An approach based on empirical mode decomposition (EMD) and chaos detection model is presented to extract slippage signal in radar full-pulse sequence. In this paper, a structure function series with equal intervals can be achieved first by preprocessing. Next, the obtained structure function series is decomposed to several intrinsic mode functions (IMFs) by adopting EMD. Then, an attempt is made to apply a chaos detection model based on the Duffing equation to each IMF. If the phase track of one IMF has a periodic status, then we can determine that the IMF with the most significant periodicity corresponds to the frequency feature of the slippage signal. The slippage signal is finally extracted. Simulation results validate the effectiveness of the approach.

II. PREPROCESSING

A. Gaussian Noise Insertion

For a radar full-pulse sequence received by a radar interception receiver, the RF and TOA parameters constitute a two-

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dimensional information series. It is cumbersome to directly analyze such a time series because the distribution of the TOA in this series is uneven, random, and nonstationary. For this reason, we change the original time series into a new one that has equal time intervals by inserting Gaussian noise.

The specific procedures are as follows: suppose k_1 is the serial number of a pulse. The domain of k_1 is $[1, K_1]$, where K_1 represents the total number of pulses. The RF and TOA parameters of the received radar full pulse sequence are defined to be functions with respect to k_1, and denoted to be $f(k_1)$ and $T(k_1)$ respectively.

The mean RF of the sequence can be expressed as:

$$\bar{f} = \frac{1}{K_1}\sum_{k=1}^{K_1} f(k_1) \tag{1}$$

The maximum range of $f(k_1)$ acting on $[1, K_1]$ is defined as R_f:

$$R_f = \sup_{1<i,j<K_1} |f(i) - f(j)| \tag{2}$$

and the noise to be inserted follows a Gaussian distribution:

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

where $\bar{f}$ denotes the expectation of the Gaussian distribution, and R_f denotes the confidence interval. The upper percentile of the Gaussian distribution is 3δ (δ represents the standard deviation), i.e. the degree of confidence is 99.7%, so the variance of the Gaussian distribution is given by $\delta^2 = (\frac{R_f}{6})^2$.

To guarantee that the noise-inserted time series is equal-interval and as short as possible, we let the greatest common divisor G be the interval of the noise-inserted series:

$$G = \gcd[T(k_1) - T(k_1 - 1)] \quad ,1 < k_1 < K_1. \tag{4}$$

Hence, the RF of the new time series can be attained:

$$S_1(k_2) = \begin{cases} f(k_1) & , k_2 = T(k_1)/G \\ X & , \text{otherwise} \end{cases} \tag{5}$$

where $k_2 \le K_2 = T(k_1)/G$, k_2 and K_2 represent the serial number and total number of the noise-inserted time series, respectively.

B. Structure Function

The random process derived above, defined as $S_1(m)$ ($m = k_2 \times G$ is TOA), has significantly low SNR. Hereby, the structure function involved in fractal geometry is introduced to $S_1(m)$ so that the correlation processing reduces the noise and enhances the energy of weak periodic signal in random process [15]–[17].

Taking the incremental variance of random process $S_1(m)$ as a structure function $S_2(h)$ and employing the structure function to the theory of fractional Brownian motion (FBM) , we have

$$S_2(h) = \langle |S_1(x+h) - S_1(x)|^2 \rangle \sim |h|^{2(2-D)} \tag{6}$$

where $\langle \cdots \rangle$ denotes the mean of time, D is the fractal dimension, and h is the process increment. As a statistic of the random process, the structure function $S_2(h)$ represents the variance of the increment of $S_1(m)$. The structure function $S_2(n)$ of the noise-inserted random series $S_1(m)$ is defined to be

$$S_2(n) = \frac{1}{M}\sum_{i=1}^{M} |S_1(i+n) - S_1(i)|^2 \tag{7}$$

where $M = K_2 - n$. $n_{\max}$, the length of the structure function series $S_2(n)$, can be properly chosen as long as it satisfies $n_{\max} < K_2$. K_2 denotes the length of the random series $S_1(m)$.

The SNR of original series is very low. Additionally, there exists no impact on the frequency characteristics of the periodic signal in a random process after multiple times of correlation processing. Therefore, we can further calculate the structure function of $S_2(n)$ to improve the SNR.

To validate the effectiveness of the correlation processing involving the structure function, suppose a mixture of a sinusoidal signal $x = \sin(314t)$ and Gaussian white noise. Then we have $y = x + noise$ with SNR = $-10\ dB$, sampling at $Fs = 10^4\ Hz$, which is shown in Fig. 1. Fig. 2 shows the structure function after twice of two correlation processing procedures. Obviously, the structure function has an excellent denoising effect when the SNR is low and can highlight the periodicity of a useful signal submerged in noise.

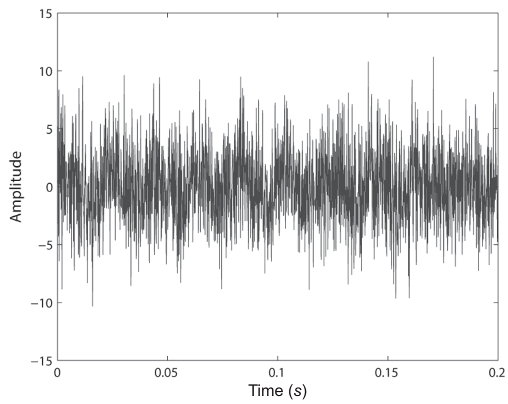

Fig. 1. Mixture of sinusoidal signal and Gaussian noise.

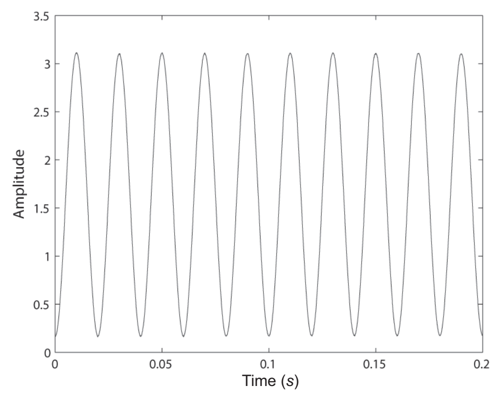

Fig. 2. Structure function after twice of correlation processing.

III. FEATURE EXTRACTION

A. Empirical Mode Decomposition

The structure function $S_2(n)$ is still a nonstationary process after preprocessing. In this method, EMD is adopted so as to decompose the structure function into IMF components, which contain high-frequency components and low-frequency components [18].

In fact, EMD is a process in which the components with different fluctuations or trends are separated by turn. The fact that scale features of different IMF components differ allows to analyze the signal particularly.

IMF components have to satisfy the following two conditions: in the entire data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one; at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero [18].

In the following, we specify the EMD process of the structure function series $S_2(n)$. This process involves the envelopes of local maxima and local minima of $S_2(n)$. Once all of the extrema are known, the cubic spline function connecting all the local maxima shapes the upper envelope. The lower envelope can be gained by repeating the same procedure for all the local minima. Define the mean value of the upper and lower envelopes as m_1. Subtracting m_1 from $S_2(n)$, we derive

$$S_2(n) - m_1 = h_1. \tag{8}$$

If h_1 does not satisfy two basic conditions of the IMF mentioned above, it must be *sifted* repetitively. Take h_1 as a data set, and let m_{11} be the mean of the envelope of h_1. This procedure can be expressed as

$$h_{11} = h_1 - m_{11}. \tag{9}$$

In order to remove the ride waves and make the data more symmetrical, we must repeat the *sifting* process until the kth equation of $h_{1k} = h_{1(k-1)} - m_{1k}$ meets two basic conditions of IMF. Additionally, define $IMF_1 = h_{1k}$, i.e., IMF_1 is the first IMF component separated from the structure function series $S_2(n)$.

We have to limit the stopping condition of the *sifting* process so that IMF is meaningful physically. The stopping condition can be defined to be the standard deviation SD of $h_{1(k-1)}$ and h_{1k}:

$$SD = \sum_{t=0}^{T} \frac{\left|h_{1(k-1)} - h_{1k}\right|^2}{h_{1(k-1)}^2}. \tag{10}$$

When SD is less than the set value, the *sifting* process will stop. According to [18], SD is set to be 0.25 in this work.

From the *sifting* process above, we see that IMF_1 includes the component with the smallest scale or shortest period in the structure function series $S_2(n)$. $S_2(n)$ minus IMF_1 is the remaining component r_1:

$$r_1 = S_2(n) - IMF_1. \tag{11}$$

Supposing that there still exist several long-periodic components in r_1, repeat the *sifting* process for r_1, which is considered as a new data set. Repeating the procedures above, we have

$$\begin{aligned} r_2 &= r_1 - IMF_2, \\ r_3 &= r_2 - IMF_3, \\ &\vdots \\ r_N &= r_{N-1} - IMF_N. \end{aligned} \tag{12}$$

The decomposition stops when r_N is monotonous in that it cannot be decomposed further. The last remaining component r_N is regarded as the trend component. Combining (11) and (12), $S_2(n)$ is expressed as:

$$S_2(n) = \sum_{j=1}^{N} IMF_j(n) + r_N(n). \tag{13}$$

Thus, the structure function series that is obtained by preprocessing the two-dimensional time series comprised of RF and TOA is decomposed into an IMF set and remaining component.

B. Chaos Detection of Periodic Signal

After EMD decomposition of structure function series $S_2(n)$, we take into account that it is difficult to precisely determine which IMF corresponds to the frequency feature of the slippage signal. Hence, to effectively detect the periodic signal, we introduce the chaos detection model of a periodic signal based on the Duffing equation [19], [20].

The original form of the Duffing equation is:

$$\ddot{x} + k\dot{x} + \alpha x + \beta x^3 = f(x,t) \tag{14}$$

where $k > 0$ represents the damping ratio, $\alpha x + \beta x^3$ represents the nonlinear restoring force, and $f(x,t)$ represents the periodic disturbing force. In general, the periodic disturbing force is set to be $f(x,t) = \gamma\cos(\omega t)$. $\gamma\cos(\omega t)$ is the built-in signal; γ denotes the amplitude of the built-in signal; ω, the frequency of the built-in signal, is equal to the frequency of the signal to be measured, which is usually unknown. Therefore, we let $f(x,t)$ be 0.

To suppress the chaotic motion of the Duffing chaotic oscillator, a weak periodic disturbance is added to the coefficient of x^3 in (14). Equation (14) becomes

$$\ddot{x} + k\dot{x} - x + b[1 + \eta\cos(\omega_1 t)]x^3 = 0 \tag{15}$$

where $\eta\cos(\omega_1 t)$ is the system perturbation. η $(\ll 1)$ and ω_1 denote the amplitude and frequency of the perturbation respectively.

In the case of $\eta = 0$, i.e., there is no perturbation, the system is in the strange attractor state. Once a periodic perturbation is added to the coefficient of the nonlinear cubic term x^3, the chaotic state is suppressed, and the system transitions from the chaotic state to the periodic state. Considering the sensitivity of the signal to be measured, as well as the stability of system, we add x^5 to the nonlinear term and simultaneously take the periodic disturbance factor as its coefficient. Because each IMF is discrete, the mathematical model of the detecting system is expressed as

$$\ddot{x} + k\dot{x} - x^3 + [1 + a\delta_T(n)]x^5 = 0 \tag{16}$$

where $a\delta_T(n)$ is the discrete periodic signal to be measured.

Represent the state equations of (16) as:

$$\begin{cases} \dot{x} = y, \\ \dot{y} = x^3 - [1 + a\delta_T(n)]x^5 - ky. \end{cases} \quad (17)$$

Then, (17) is used to detect each IMF. If, for one of the IMFs, the chaotic attractor appears in phase plane, we can confirm that this IMF corresponds to the slippage feature of slippage signal.

IV. EXPERIMENTS

A. Effectiveness Verification and Results Analysis

The efficiency and accuracy of the presented approach are evaluated based on experiments involving a set of radar pulse sequences. The sequence is comprised of four radar signals. In this set, the RF parameter of radar 1 changes according to sine regulation with a frequency of 70 Hz; the RF parameters of Radar 2 and Radar 4 are randomly agile, and that of Radar 3 switches randomly among 10 setting frequency points. The PRF jitter of the slippage signal is set to be 1%. Parameter information is listed in Table 1.

Table 1. Simulation data of radar full pulse sequence.

Radar number	Radio frequency (MHz)	Pulse repetition frequency (Hz)
1	$2300 + 50sin(2\pi \times 70t)$ (Slippage frequency)	$990 - 1010$ (PRF jitter)
2	$2550 - 2650$ (Agile frequency)	$300 - 400$ (PRF jitter)
3	$2050 - 2150$ (Agile frequency)	$800 - 1500$ (PRF stagger)
4	$2350 - 2550$ (Agile frequency)	$1000 - 1200$ (PRF jitter)

The original TOA-RF information sequence is shown in Fig. 3. Obviously, intervals between adjacent pulses are unequal and random. It is quite difficult for existing methods to directly analyze such a time series. To simplify the process of the series, we insert Gaussian noise into the original TOA-RF information sequence as shown in (5) and derive time series $S_1(m)$, which is shown in Fig. 4. From this figure, it can be seen that not only the equalization of the pulse intervals is accomplished, but the features of the original sequence are not affected.

The SNR of the noise-inserted pulse $S_1(m)$ is quite low and the useful periodic component is submerged to a great extent, so it is necessary to denoise the new time series. Here, we implement the correlation processing of $S_1(m)$ by calculating its structure function. Because multiple correlation processing has no influence on the frequency characteristic of the periodic component in the noise-inserted pulse sequence, the correlation processing of $S_1(m)$ can be repeated more than once to improve the denoising effect and highlight the low-energy periodic component is highlighted. Taking into account that excessive time consumption results from enormous computational burdens, we choose to repeat correlation processing three times as a result of cost-benefit analysis. The structure function series $S_2(n)$ after correlation processing is shown in Fig. 5.

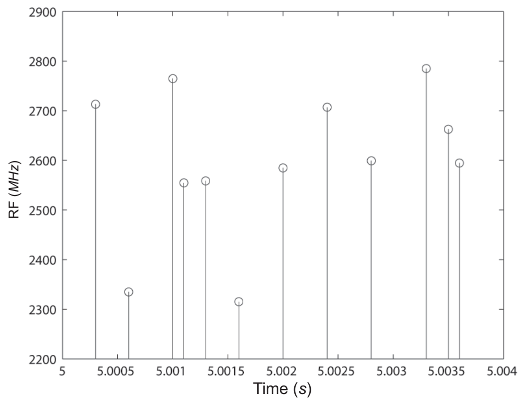

Fig. 3. Original pulse sequence.

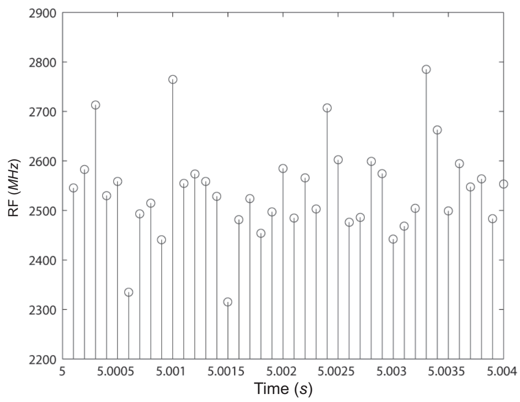

Fig. 4. Noise-inserted pulse sequence.

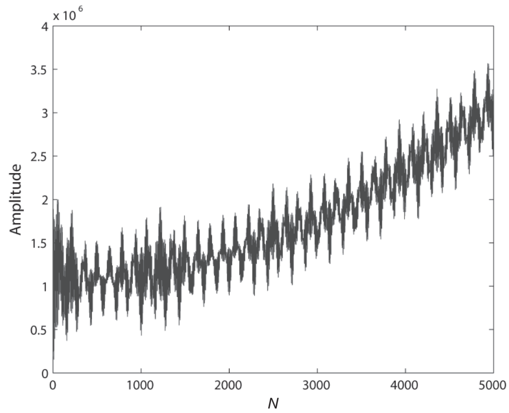

Fig. 5. Structure function $S_2(n)$ after repeating correlation processing three times.

The structure function $S_2(n)$ in Fig. 5 remains a nonstationary series, although the SNR rises substantially. $S_2(n)$ is still a mixture of components with different frequencies. Therefore, the structure function series is to be decomposed by EMD, and the results are shown in Fig. 6. From Fig. 6, we can see that the structure function $S_2(n)$ is decomposed into four IMFs with different frequencies and a residue component r_5. Among these five components, the frequency of IMF_1 is the highest and that of IMF_4 is the lowest. Residue component r_5 is the trend term.

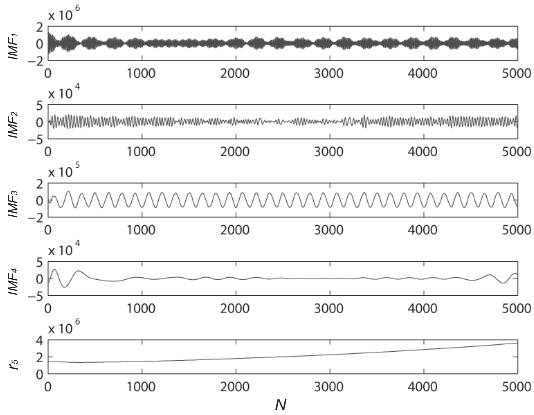

Fig. 6. All IMF components derived by the EMD process of $S_2(n)$.

To determine which IMF is periodic, we import all IMFs derived by EMD into the chaos detection model of a periodic signal (17) in turn. Before chaos detection, the initial system initial and the amplitude of the signal to be measured must be set properly: Let the initial system and amplitude be $x_0 = [0, 5]^{\mathrm{T}}$ and $a = 1$, respectively. The phase track of each IMF is shown in Fig. 7.

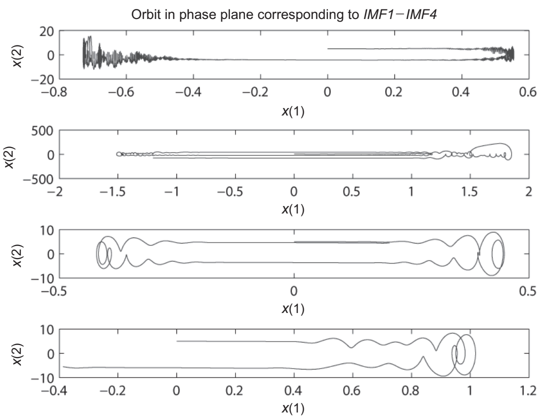

Fig. 7. Phase track of each IMF in phase plane.

From Fig. 7, only the trajectory of IMF_3 takes on periodic status in the phase plane, whereas the remaining three IMFs have chaotic trajectories. Thus, we conclude that IMF_3 is periodic and describes the frequency feature of the slippage signal.

To validate the accuracy of the detection results, we extract IMF_3 and transform it into the time-domain. The time-domain chart is shown in Fig. 8. Then, the spectrum of IMF_3 is obtained by means of the fast Fourier transform (FFT), which is shown in Fig. 9. Fig. 9 shows that the frequency of the signal corresponding to IMF_3 is 70 Hz. The results are consistent with the setting frequency.

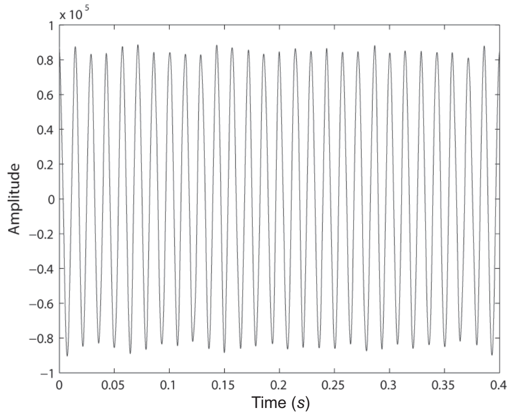

Fig. 8. Time-domain chart corresponding to IMF_3.

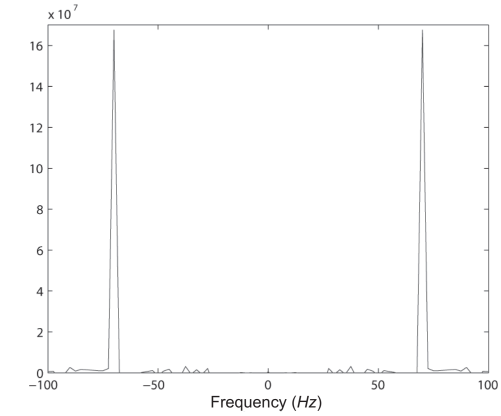

Fig. 9. Frequency spectrum of the signal corresponding to IMF_3.

The simulation results validate the effectiveness and accuracy of the presented feature extraction approach. Although the slippage signal is almost submerged in the TOA-RF information sequence completely, this method based on EMD and chaos detection not only succeeds in extracting the slippage signal, but calculates the slippage frequency. In addition, it remains effective in the case of lost pulses. Inspired by the proposed method, we can implement feature extraction with a two-dimensional information sequence comprised of TOA and one of other feature parameters.

B. Performance When Pulse Repetition Frequency (PRF) Jitters

In a complex electromagnetic environment, the TOA parameter of radar pulses is influenced by various sources of interderence. Because the TOA and PRF has the following relationship, it can be concluded that the instability of PRF inevitably deteriorates the performance of the proposed method.

$$TOA_n = TOA_{n-1} + 1/PRF \tag{18}$$

In this section, we examine the performance of the proposed method in the case that the PRF jitters by calculating and analyzing the success rates. Assume that the PRF of the frequency slippage signal jitters from 0% to 20%. The simulation experiment given by Section 4.1 is independently repeated 200 times for each jitter case. Then, the success rates are calculated and shown Fig. 10.

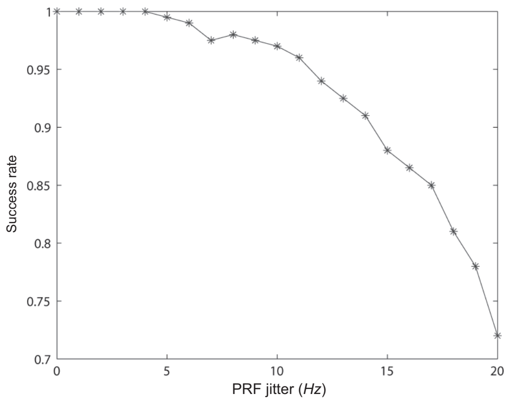

Fig. 10. Success rates in case of varying PRF jitter.

In Fig. 10, the success rate remains above 0.9 when the PRF jitter is not greater than 14%, whereas the success rate descends drastically and remains below 0.8 when the PRF jitter is greater than 18%. According to the results, we conclude that the proposed methods can reach the expected degree in the case that the PRF jitters within 15%, which is adaptive to general situation.

V. CONCLUSION

Signal sorting is a key technology in the field of electronic countermeasures, and is also the premise of identification and analysis of radar emitter signals. Along with the continuous increase in signal density and rapid augmentation of the number of radars, different radar signals overlap more severely, and the characteristics of intercepted radar emitter signals are unknown. As a result, the traditional methods work quite inefficiently. In the case that the parameters overlap too severely in a certain range, even clustering methods are inefficient. Combining EMD and chaos detection for the first time, this work extracts the frequency slippage signal in dense and complex full-pulse sequences. Simultaneously, the slippage frequency of a slippage periodic signal, which is an important sorting feature hidden in full-pulse sequences, is extracted. This method can also be adapted to analyze the two-dimensional information constituted by other sorting parameters and TOA, not just RF and TOA.

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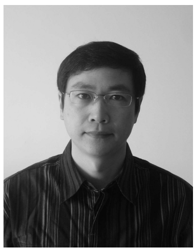

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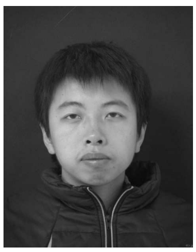

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