Feature Extraction Using Surrounding-Line Integral Bispectrum for Radar Emitter signal

Tao-wei Chen, Wei-dong Jin, and Jie Li

***Abstract*—In everchanging threat emitter environment, specific emitter identification (SEI) technology extracts subtle but persistent features from received pulse signal to create a fingerprint unique to a specific radar. Unlike conventional five parameters deinterleaving algorithm, which can be grossly ambiguous for radar emitter sorting, the SEI technology provides hardware specific identification. In this paper, we propose an approach for extracting unintentional phase modulation features caused by oscillator based on surrounding-line integral bispectrum. The quantitative features, i.e. bispectra entropy, waveform entropy and mean of surrounding-line integrated bispectra, is extracted using entropy-like function to reveal the subtle difference between emitters. Computer simulations show that how the phase-noise-induced signal changes analysis based on bispectrum approach can be used to determine which of emitters transmitted a pulse signal.**

I. INTRODUCTION

RADAR emitter signal deinterleaving plays an important role in electronic warfare. It is a crucial component in threat detection and analysis in electronic support measures (ESM) and electronic intelligence (ELINT). Conventional deinterleaving approaches, which separate the received pulse trains into individual emitter group, are usually based on the use of pulse parameters such as direction-of-arrival (DOA), radio frequency (RF), time-of-arrival (TOA), pulse width (PA), pulse repetition interval (PRI) [1]. They are efficient in simple emitter environment, i.e., emitters with fixed frequency and PRI from inter-pulse, low pulse density and simple waveform. However, in modern radar systems, the threat environment has changed dramatically and more sophisticated waveforms have been used. Inter-pulse information only may be difficult to separate those received pulse trains according to their originations. To sort radar emitters in high density and high interleaving environment, we need to explore the detailed structure inside each pulse, called intra-pulse information [2]. Both intentional and unintentional modulations in the radar signals provide important information to perform SEI. In recent years, SEI technology exploits unintentional modulations on pulse (UMOP) features, which are subtle but unavoidable to create a fingerprint unique, to match received pulse to a specific radar. Several intrapulse information based approaches have been proposed for SEI. In [2][3] extracted intrapulse information are used for recognizing a specific emitter. Clustering and determination of the number of emitters from a set of received pulse using intrapulses and information theoretic criterion has been studied in [4][5]. Moreover, ONR has invested in SEI technology for more than a decade [6].

The particular SEI application considered in this paper is that inrapulse features are extracted to identify unique unintentional phase modulation information generated by the oscillators of radar transmitter and receiver. Unintentional phase modulation is normally referred to as phase noise and phase jitter [7]. It is a major contribution to time-frequency domain distortion, frequency offset and drift of radar signal. In order to analysis the characteristics of oscillators phase noise, we present an approach for UMOP features extraction of radar emitter signal based on surrounding-line integral bispectrum. The paper is organized as follows. In section II, we discuss the phase noise in oscillator and phase noise power spectrum. In section III, we review the bispectrum and define surrounding-line integral bispectrum. The entropy-like function [20] is introduced to further quantitatively extract features from surrounding-line bispectrum and bispectra. In section IV, computer simulations are used to demonstrate the feasibility and effectiveness of the approach.

II. PHASE NOISE IN OSCILLATOR

A. Sideband in The Spectrum of Oscillator

Assume that an ideal sinusoidal oscillator would have an output voltage expressed as $V_{out}(t) = A\sin(\omega_0 t + \varphi_0)$, where A is the amplitude, ω_0 is the frequency and φ_0 is arbitrary, fixed phase reference. The spectrum of an ideal oscillator with no random fluctuations is a pair of impulses at $\pm\omega_0$. In a practical oscillator, however, the output is more generally given by [8]

$$V_{out}(t) = A(t)\sin(\omega_0 t + \varphi(t)) \tag{1}$$

Where $\varphi(t)$ is phase in the oscillation and may vary with time, $A(t)$ is amplitude of fluctuation. In most system, the variation in $A(t)$ can be sufficiently suppress. Therefore, the present of amplitude and phase fluctuations cause sideband in

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Tao-wei Chen is with the School of Information Science & Technology, Southwest Jiaotong University, Chendu, Sichuan, 610031, China. He is now a Ph.D student. (mobile phone: 8613438837323; e-mail: cctw33@ sina.com).

Wei-dong Jin is with the School of Electrical Engineering, Southwest Jiaotong University, Chendu, Sichuan, 610031, China.

Jie. Li is with the School of Information Science & Technology, Yunnan economy and finance university, Kunming, Yunnan, 650221, china.

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the spectrum of a practical oscillator. Fig. 1 shows the difference in the output spectrum of an ideal oscillator with that of an actual oscillator.

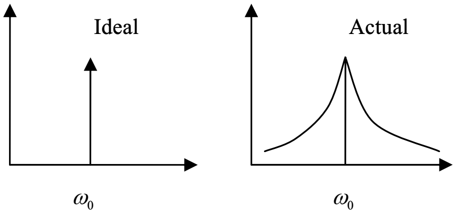

Fig. 1. The spectrum of an ideal and a practical oscillator.

B. Phase Noise

Phase noise $\varphi(t)$, generated at both transmitter and receiver oscillators, can be measured in the frequency domain, and is expressed as a ratio of signal power to noise power measured in a $1\ Hz$ bandwidth at a given offset $\triangle\omega$ from the center frequency ω_0. It is defined as follow [8]:

$$L_{total}\{\triangle\omega\} = 10\bullet\log\left[\frac{P_{sideband}(\omega_0+\triangle\omega, 1Hz)}{P_{carrier}}\right] \quad (2)$$

Where $P_{sideband}(\omega_0+\triangle\omega, 1Hz)$ represents single sideband (SSB) power at a frequency offset of $\triangle\omega$ from the carrier with a measurement bandwidth of $1Hz$. $P_{carrier}$ is the power at center frequency. The unit of phase noise is dBc/Hz (dB relative to center frequency). A typical phase noise plot of responses at various offset from the signal is usually comprised of three distinct slopes corresponding to three primary noise generating mechanisms in the oscillator, as shown in Fig. 2. [9]. The part A is called Flicker FM noise and its magnitude is determined primarily by the quality of the crystal. Noise in part B of Fig. 2, is called $1/f$ noise, caused by semiconductor activity. The horizontal part C is white noise or noise floor.

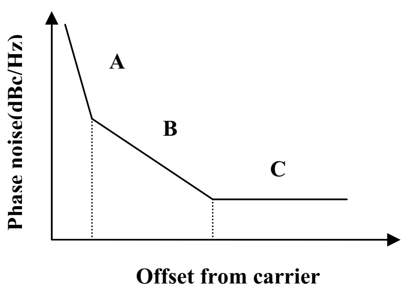

Fig. 2. Phase Noise

C. Phase Noise Spectrum

Let us assume that unintentional phase modulation $\varphi(t) = \beta\sin 2\pi f_m t$ .Where β is modulation index, f_m is offset frequency. Then we have [10]

$$V(t) = A\sin(2\pi f_0 t + \beta\sin 2\pi f_m t) \quad (3)$$

Using trigonometric identities, one drives

$$\begin{aligned} V(t) = {} & A\sin(2\pi f_0 t)\cos(\beta\sin(2\pi f_m t)) + \\ & A\cos(2\pi f_0 t)\sin(\beta\sin(2\pi f_m t)) \end{aligned} \quad (4)$$

And then

$$\begin{aligned} \cos(\beta\sin 2\pi f_m t) &= J_0(\beta) + 2[J_2(\beta)\cos 2\pi f_m t + \\ & \quad J_4(\beta)\cos 8\pi f_m t + \cdots] \\ \sin(\beta\sin 2\pi f_m t) &= 2[J_1(\beta)\sin 2\pi f_m t + \\ & \quad J_3(\beta)\sin 6\pi f_m t + \cdots] \end{aligned} \quad (5)$$

Where $J_n(\bullet)$ are the Bessel functions [11], which may be approximated as

$$J_0(\beta) \simeq 1 - \left(\frac{\beta}{2}\right)^2 \qquad J_n(\beta) \simeq \frac{1}{n!}\left(\frac{\beta}{2}\right)^n, n \ge 1 \quad (6)$$

When $\beta \ll 1$, $J_0(\beta) = 1; J_1 = \frac{\beta}{2}; J_n \approx 0, (n \ge 2)$, hence

$$\begin{aligned} V(t) \approx {} & A\sin(2\pi f_0 t) + \frac{\beta}{2}A\sin(2\pi(f_0 + f_m)t) - \\ & \frac{\beta}{2}A\sin(2\pi(f_0 - f_m)t) \end{aligned} \quad (7)$$

So phase modulation $\varphi(t)$ with a frequency f_m will cause two side tones $(f_0 \pm f_m)$ to appear at the $V(t)$ spectrum as shown in Fig.1.

III. SURROUNDING-LINE INTEGRAL BISPECTRUM AND ENTROPY-LIKE FUNCITON

A. Review of Bispectrum

As is well known, phase noise has provided important unintentional phase modulation information in radar emitter signals. The goal of this paper is to extract unique UMOP feature for SEI. In resent years, higher-order statistics (HOS) have received increasing interest, especially in the form of higher-order cumulants and spectra. It has been used in particular to extract information, and to detect and characterize non-linear properties in signals [12][13][14]. Furthermore, it has been found that the third-order spectrum, called bispectrum, has the ability to hold the information both in phase and in amplitude. The literature [15] has proposed the approach based on the bispectra and radial basis function (RBF) for identifying different transmitters of the same model. In fact, Bispectrm is a particular example of high-order spectra, which is defined to be the Fourier transform of third-order cumulant sequence. A review of bispectra [16][17] is briefly made for emitter feature extraction. Let $\{x(n), n = 0, \pm1, \pm2, \cdots\}$ be determined discrete signal and $x(n) \in Z^2$ then its bispectrm is defined as

$$\begin{aligned} & B_x(\omega_1, \omega_2) = X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2) \\ & with \quad X(\omega) = \sum\nolimits_n x(n)e^{-j\omega n} \end{aligned} \quad (8)$$

Assume that $\{x(n), n = 0, \pm1, \pm2, \cdots\}$ be a periodic signal with period N, then its bispctrum is defined as

$$B_x(k_1,k_2)=\frac{1}{N}X(k_1)X(k_2)X^*(k_1+k_2)$$
$$with \quad X(k)=DFT(x(n)). \tag{9}$$

Moreover, if $x(n)$ is a stationary stochastic process, then the corresponding definition below should be

$$B_x(\omega_1,\omega_2)=E_x\{X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)\}$$
$$and \tag{10}$$
$$B_x(k_1,k_2)=E_x\{X(k_1)X(k_2)X^*(k_1+k_2)\}$$

Where $E\{\bullet\}$ means a mathematical expectation with respect to x. The superscript asterisk denotes a conjugate of x.

The definition of bispectrum comes from a high-order cumulant. It has many excellent properties, one of which are the ability to statistically suppress the noise characterized by probability density with a zero-mean and symmetric distribution, namely:

Assume that $y(n)=x(n)+w(n)$, with $w(n)$ being a zero-mean Gauss noise. And $x(n)$ being a signal, then $B_y(k_1,k_2)=B_x(k_1,k_2)$.

B. Surrounding-line Integral bispectrum

From the definition of bispectrum, it can be seen that Using bispectra directly involve complex computation due to two dimensions of data, which restricts its application in real-time target recognition [18]. In order to decrease the computational complexity, many methods have been developed to convert a bispectrum from two dimensions to one, Including radially integrated bispectrs(RIB), axially integrated bispectra(AIB) and circularly integrated bispectrum(CIB) [19]. Based on these approaches we define the surrounding-line integrated bispectra as one dimensional feature vector. It is obtained by integrating along with four sides of square as shown in Fig.3. Every point denotes a value of bispectra.

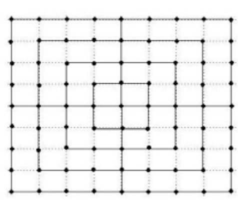

Fig.3. The bispectrum is integrated along with four sides of square

Compared with other integrated bispectrum described in [19], the surrounding-line integral bispectra can contain all information in the bispectrum and decrease the computational complexity.

C. Waveform and bispectrum Entropy-like Function

In order to further extract subtle difference between bispectra of radar emitter signals, waveform entropy-like fuction[20], mean of surrounding-line bispectrum and bispectra entropy-like function are introduced to distinct different emitters. Waveform and bispectrum entropy-like function is measurement of randomness and can quantitatively reveal power distribution of waveform and bispectrum matrix.

Suppose 1-D line spectrum sequence $W=\{w_1,w_2,\cdots,w_L\}$, let $\|W\|=\sum_{i=1}^{L}w_i, p_i=|w_i|/\|W\|$, and then the waveform entropy-like function defined as

$$En(W)=-\sum_{i=1}^{L}p_i\bullet\log p_i \tag{11}$$

Suppose row n and column n bispectrum matrix with $m(n,n)$, let $\|M\|=\sum_{i=1}^{n}\sum_{j=1}^{n}m(i,j), p_{ij}=|m(i,j)|/\|M\|$, and then the bispectra entropy-like function defined by

$$Eb(m)=-\sum_{i=1}^{n}\sum_{j=1}^{n}p_{ij}\bullet\log p_{ij} \tag{12}$$

Entropy is maximized when the power distribution are uniform, and entropy is minimized when the power concentrate in several component.

For now, summarizing the feature extraction algorithm described as follow:

1) Accumulate received signal from different emitters.
2) The bispectra of the signal is estimated using direct fast Fourier transform (FFT) method [13].
3) Calculate one dimensional surrounding-line bispectra by integrating alone with four sides of square as shown in Fig.3, and then normalize the surrounding-line bispetra.
4) Compute waveform entropy using Eqs.11, bispetra entropy using Eqs.12 and mean u of surrounding-line bispectra.
5) The quantitative features form three-dimensional eigenvector $V=[En,Eb,u]$.

IV. SIMULATION AND RESULT ANALYSIS

A. Bispectrum Feature Analysis of Pulse Signals

In this section, the numerical example involving unmodulated continuous wave (CW) radar signal is used to illustrate the difference of unintentional phase modulation caused by oscillators from three emitters. UMOP signal is generated according to phase noise theory. Its Frequency of each pulse signal is 70 MHz. Sampling frequency is 250 MHz and pulse width is 0.45 μs.

Fig.4 shows signal sideband phase noise to carrier ratio in $1Hz$ bandwidth (dBc). According to the phase noise power spectrum, we can simulate the CW radar pulse signal using phase noise theory described in section II. And then the bispectum estimation of signals received from three emitters can be obtained via direct FFT method. Fig. 5, 6 and 7 show that the bispectra of signals modulated by different phase noise power have obvious difference. These contour line in figures indicates that bispectrum retain the phase information and can be used to identify signals from different emitters.

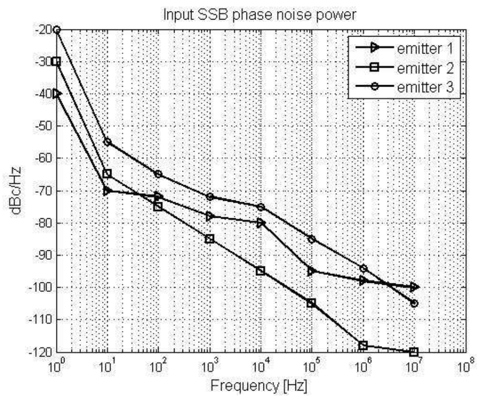

Fig.4. The illustration of oscillators' phase noise spectrum

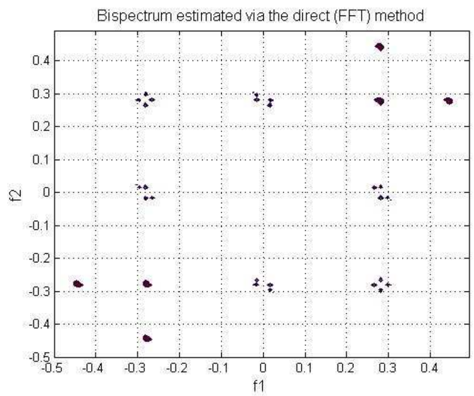

Fig.5. Contour line of the bispectrum for emitter 1 signal

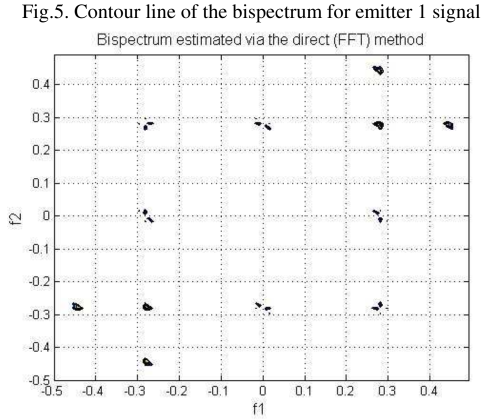

Fig.6. Contour line of the bispectrum for emitter 2 signal

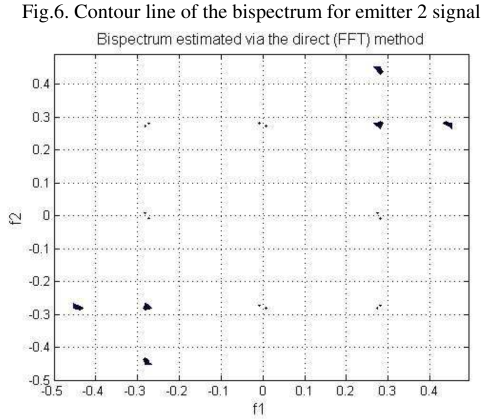

Fig.7. Contour line of the bispectrum for emitter 3 signal

B. Surrounding-line bispectrum and entropy features

In the experiment, classification and identification using bispectra directly will result in complex computation. Thus, surrounding-line integrated bispectrm is used to further extract one dimensional feature vectors from bispectra. According to the algorithm in section III, the feature vectors of three emitters signal is shown in Fig.8

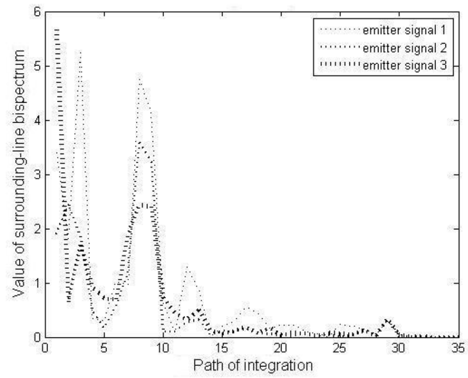

Fig.8. One dimensional surrounding-line integrated bispectrum for different emitter signal.

In order to analysis the deinterleaving performance of the feature vectors plotted in Fig.8 easily and intuitively, waveform and bispecta entropy-like function are used to obtain the quantitative feature from one dimensional surrounding-line bispectrum and bispectra, respectively. And then, the mean of surrounding-line bispectrum, waveform entropy and bispectra entropy form the three dimensional feature vectors. For 200 pulse signals from each emitter, 600 feature samples are generated and the distribution of all features is shown in Fig.9. It can be seen that the pulses from the same emitter separate themselves into different clusters.

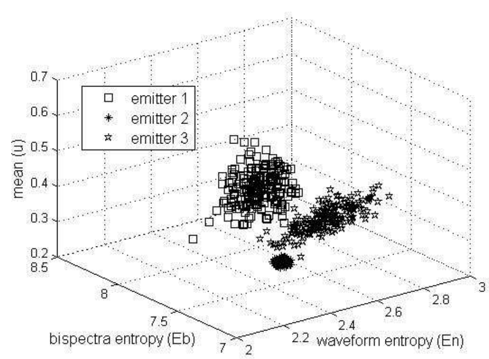

Fig.9. Feature distribution of radar signals from three emitters

Moreover, a consideration of measurement of phase noise is the Gaussian white noise accompanying radar signal. Fig.10 and 11 show that the clustering performance of pulse when the SNR is 20 and 15 dB. As can be seen in Fig.10, pulse signals from three emitters are slightly dispersed but obviously separable and hardly any overlapping when SNR is 20dB. However, in Fig.11, There exist overlapping when SNR is 15dB. We then applied fuzzy C-means (FCM) clustering technique to obtain the correct clustering rate for SNR=15dB. The clustering result is 80 percent for emitter 1, 85 percent for emitter 2 and 92.5 percent for emitter 3.

Finally, we compute the average values and variance values of three features within different SNR. The results presented in Table I show that the mean and variance of features of radar signals from three emitters. In Table I, the mean of features of radar emitter signals reflect the center point of clustering. Small variance indicates that the three-dimension feature has better clustering performance when the SNR is above 20dB. When the SNR becomes below 15dB, the boundaries between clusters become ambiguous, and some of clusters are no longer separable, making the deinterleaving difficult.

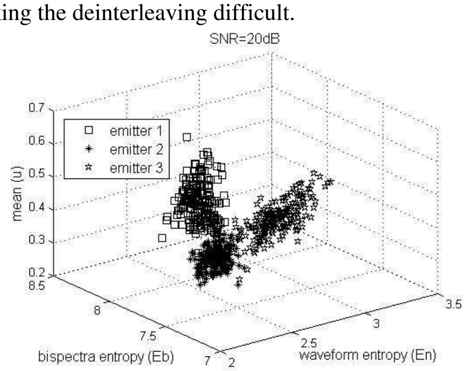

Fig.10. Feature distribution of radar signals from three emitters when SNR=20dB.

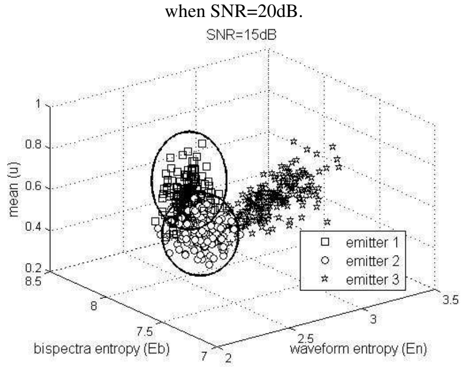

Fig.11. Feature distribution of radar signals from three emitter when SNR=15dB

TABLE I
MEAN AND VARIANCE OF FEATURES OF RADAR EMITTER SIGNALS

emitter	mean			variance		
	En	Eb	u	En	Eb	u
1	2.5039	7.8113	0.4173	0.0101	0.0152	0.0034
2	2.4230	7.4552	0.2722	2.24e-4	7.99e-4	2.37e-5
3	2.6867	7.6264	0.3175	0.0080	0.0116	8.75e-4
	mean (SNR=20dB)			variance (SNR=20dB)		
1	2.5516	7.9084	0.4599	0.0130	0.0229	0.0047
2	2.4698	7.6502	0.3332	0.0072	0.0115	0.0015
3	2.8854	7.7639	0.3688	0.0242	0.0169	0.0024
	mean (SNR=15dB)			variance (SNR=15dB)		
1	2.5846	8.0137	0.5654	0.0145	0.0190	0.0078
2	2.5622	7.8765	0.4443	0.0153	0.0210	0.0049
3	3.0455	7.9202	0.4868	0.222	0.0203	0.0076

V. CONCLUSION

In this paper, we focus on the SEI technique and present bispectrum approach for extracting unintentional phase modulation features, that is, phase noise in oscillator, which are unavoidable and unique to individual emitters. Computer simulations are used to demonstrate the feasibility and effectiveness of proposed approach. The simulation results show that the extracted features can provide satisfactory performance and stability under modest SNR.

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