COMPRESSED SENSING MASK FEATURE IN TIME-FREQUENCY DOMAIN FOR CIVIL FLIGHT RADAR EMITTER RECOGNITION

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ABSTRACT

Specific emitter identification (SEI) is gaining popularity since it can distinguish different individuals in same type of radar emitter under complex electromagnetic environment. However, classification of signals is still a challenging task when the feature has low physical representation. In this work, we propose a compressed sensing mask feature in ambiguity domain, which can significantly improve the recognition rate of civil flight radar emitters. Furthermore, it not only represents physical characteristics of measured radar signals but also contains more time varying information and alleviates the computational costs. The physical significance and effectiveness of the proposed feature can be verified by reconstructing Wigner-Ville distribution (WVD) from the sparsest ambiguity function. Experimental results corroborate the highly accuracy and stability of the proposed approach.

***Index Terms*—**compressed sensing, time-frequency analysis, feature extraction, radar emitter recognition

1. INTRODUCTION

Radar emitter recognition has become increasingly popular under the complex electromagnetic environment. It can be beneficial to both military and civilian. In general, the analysis framework of radar emitter recognition system is illustrated as Fig.1. The key step is to extract representative features. Traditional SEI features consist of radio frequency, pulse width, spectrum, instantaneous phase [1], wavelet [2], ambiguity function, ambiguity function representative-slice [3], three-dimensional distribution [4], etc. However, when it comes to current complex conditions, such methods prone to work ineffectively.

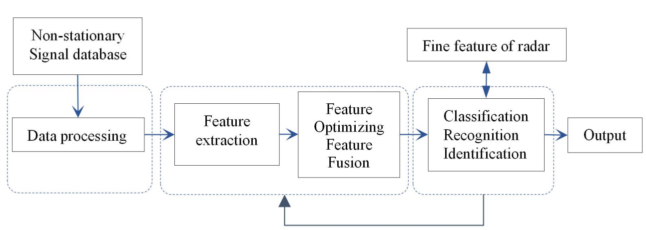


Fig.1. The Emitter Recognition System

Ambiguity function representative-slice [3] is proposed to efficiently eliminate the cost in time and memory since it uses a slice of the whole time-frequency plain. However, it has some drawbacks in certain circumstances:

(1) This method cannot cover all situations, because representative-slice derives from posteriority. And it focuses on frequency resolution of signals, but it ignores time varying information including modulation types and subtle characteristics signals emitted.

(2) The representative-slice subjects to specific emitter types. It performs inaccurately and sometimes unstably. Also, it cannot optimize instantly since additional samples may change the position of representative-slice then resulting in recalculation of whole feature set.

In order to surmount these limitations, it is appreciable to construct a more meaningful feature to classify, recognize and identify specific emitters. Therefore, we extract a compressed sensing mask (CS-mask) feature from ambiguity function (AF). The compressed sensing (CS) can reduce the redundancy of data for one-dimensional time series as well as two-dimensional images. Mathematically, CS is based on l_1-norm optimization. The K sparse N point signal in a specific domain can be characterized by M measurements (M>K, M<<N). It is worth emphasizing that CS may transform a non-stationary signal into a sparse domain. In particular, Patrick Flandrin and Pierre Borgnat developed the time-frequency localization by exploiting sparsity constraints and compressed sensing [5]. It is noticed that the goal is to improve the time-frequency signal resolution and inhibit cross-terms. In this paper, compressed sensing is inspired as the sparse ambiguity function feature for large sets of civil flight radar emitter recognition. It can effectively enhance the recognition rate with less computational cost. Moreover, this feature extraction approach contains both time and frequency details compared with the traditional methods.

2. TIME-FREQUENCY FEATURE BASED ON COMPRESSED SENSING

Srdjan Stanković and Irena Orović reconstructed and restored signals by compressed sensing approach [6]. It is remarked that ambiguity domain can be used as the sparse optimization, followed by the l_1-*norm* minimization scheme in the sparsest time-frequency distribution:

$$A(\xi,\tau)=\int_{-\infty}^{+\infty}x(t+\frac{\tau}{2})x^{*}(t-\frac{\tau}{2})e^{j2\pi\xi t}dt \quad (1)$$
$$=\int_{-\infty}^{+\infty}WD(t,f)e^{-j2\pi(\xi t-f\tau)}dtdf$$

Where $A(\xi,\tau)$ is ambiguity function and $WD(t,f)$ is Wigner-Ville distribution, one of the common tools in time-frequency distribution, defined as:

$$WD(t,f)=\int_{-\infty}^{+\infty}x(t+\frac{\tau}{2})x^{*}(t-\frac{\tau}{2})e^{-j2\pi f\tau}d\tau \quad (2)$$

If considering WVD and ambiguity as finite length N points sequences, then the matrix correlation of them as follows, which are related by two-dimensional Fourier transform:

$$A_{f(N\times1)}=\Psi_{(N\times N)}\cdot W_{D(N\times1)} \quad (3)$$

Ψ is 2D Fourier transform matrix in a form of N×N. In order to reconstruct Wigner-Ville distribution with higher resolution and noise suppression from sparse ambiguity function, the measurement matrix Φ in a size of M×N using in the compressed sensing is defined to reduce measurements. M sparse measurement of ambiguity vector, or feature $A^{Mask}_{f(M\times1)}$ is obtained by (4):

$$A^{Mask}_{f(M\times1)}=\Phi_{M\times N}\cdot A_{f(N\times1)}=\Phi_{M\times N}\cdot\Psi_{(N\times N)}\cdot W_{D(N\times1)} \quad (4)$$

It is important to select proper samples in ambiguity domain, since with appropriate ambiguity function mask [6], a better and representative radar signal feature can be extracted to improve the rate of identification. Typically, the radar emitter identification via ambiguity representative-slice [3] proposed by L. Wang and H.B. Ji can indeed lower the computational costs and have a distinguished performance in moving radars and static emitters. Unfortunately, regarding slices of ambiguity function with shift frequency near zero as a major representative feature of radar emitter pulse might not make a full sense in physical. In addition, frequency mask is always used as a sparsity matrix to restore and reconstruct signal, which has never been used as a feature extraction approach in radar emitter identification. Hence, we proposed a robust and persuasive compressed time frequency sensing feature.

3. CS-MASK FOR EMITTER IDENTIFICATION

The ideal feature in sparsest ambiguity domain is noted as:

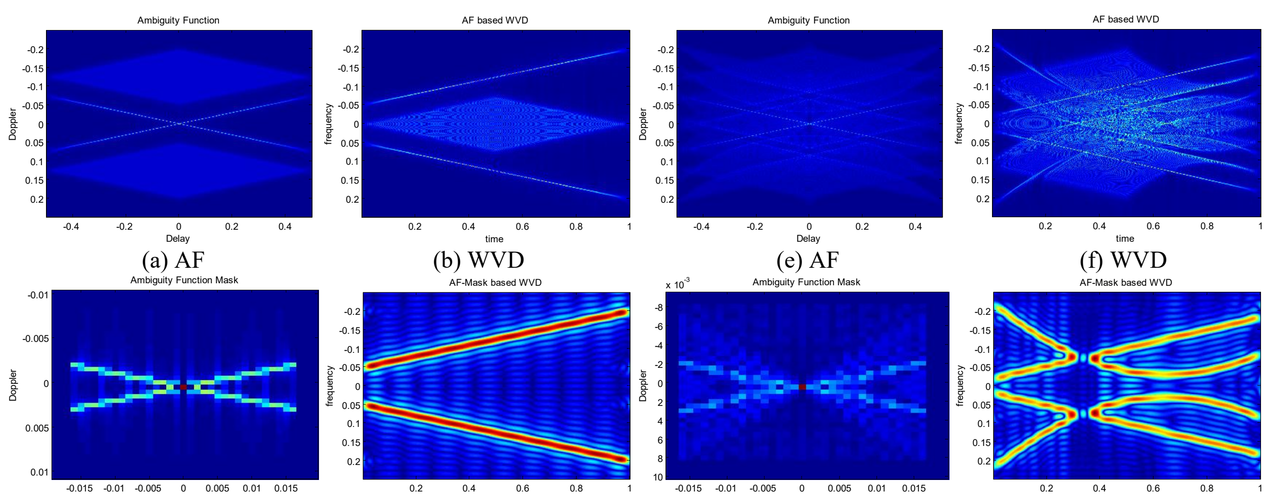
$$F^{A}_{ideal}=A_f(\xi,\tau)\Big|_{\xi,\tau\neq0} \quad (5)$$

Where $(\xi,\tau)\in\Omega$, according to [5], ideal feature should include as much as information while as sparse as data. The sparse feature can be obtained according to CS theory, which can be optimized as:

$$A^{Mask}_f=\min_A\left\|A_f\right\|_1 \quad (6)$$

$$s.t.\sum_{k=1}^{N}\sum_{n=1}^{M}\frac{1}{N\cdot M}(\mathscr{F}^{-1}_{2d}\{A_f\}\text{-}W_D)\leq\varepsilon\Big|_{(\xi,\tau)\in\Omega} \quad (7)$$

Where ε denotes user-specified bound, the 2D Fourier transform of ambiguity function is WVD, thus, the effectiveness and physical characteristics of sparsest ambiguity function can be examined by transformed WVD. The characteristics carried by compressed sensing mask from center ambiguity function are illustrated in Fig.2, The first group Fig.2(a-d) is an example of a chirp signal, Fig.2(e-g) analyze a multi-component signal form of chirp and secondary frequency modulation signals. Both signals in two groups own 1000 points. The ambiguity function and WVD are shown in formula (1). Take ε=0.2, we choose a mask at the center of ambiguity function with size 31*31 size up to 961 points, which satisfies (6-7). The 2D inverse Fourier transform of the masked ambiguity function is presented in Fig.2(d) and (h), which are WVDs.



(a) AF (b) WVD (e) AF (f) WVD

(c) CS-Mask (d) WVD (mask) (g) CS-Mask (h) WVD (mask)

Fig.2. The time-frequency distribution recovery of masked ambiguity function

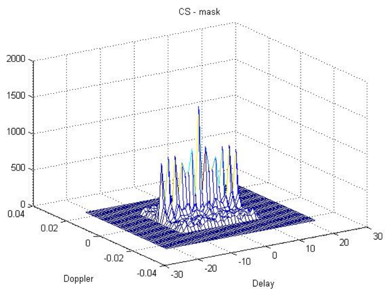


Fig.3. the CS-mask of a sample in *Data set* I

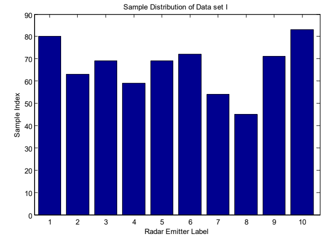
From Fig.2, the mask transformed from AF domain to WVD contains as many as signal's frequency details compared with original WVD. What's more, the cross-term has been restrained. The relative error of reconstruction reaches to $4.96*10^{-6}$, which can be accepted experimentally.

Fig.3 is the localization of 3-D compressed sensing mask feature from ambiguity function of the real measured radar signal pulse, in which x axis is time delay, y axis is Doppler frequency shift, and z label is amplitude of ambiguity. Most of the energy is concentrated in the center of the mask. Nonzero area is 23*23 while whole AF matrix contains 450*450 points. Verified by simulations, it is feasible that the feature can represent the whole ambiguity function mathematically. In addition, the algorithm of the program is demonstrated as follows:

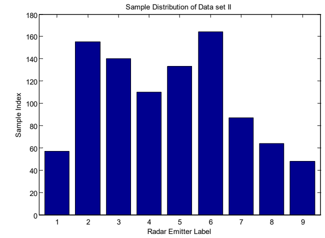
The algorithm of the program
1st . Pre-processing: 1.1 Radar pulses are demeaned, de-noised, normalized and aligned; 1.2 Remove the bad pulses and class which include missing data and insufficient data of class.
2nd. Feature extraction: 2.1. Batch process and transform the radar signal pulses into ambiguity function domain and generate the CS based ambiguity function mask feature. 2.2. optimize feature using formulas (6-7).
3rd. Classification & identification: With the AF mask feature, classification is performed by applying extreme learning machine (ELM) to the measured data.

4. EXPERIMENT RESULTS

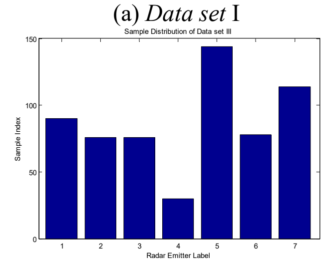
In experiments, the effectiveness of CS-mask feature is tested. All of the test signals are measured signals. Each sample containing one pulse has been detected from a long period record. For example, *Data set* I contains 10 classes of signal sampled from 10 static radars, and these radar emitters are of the same type with the same parameters. In addition, *Data set* I and II are static radars samples, while *Data set* III and IV are from moving emitters whose signals are from different civil flights' meteorological radars. The number of samples in each class is shown in Fig.4.



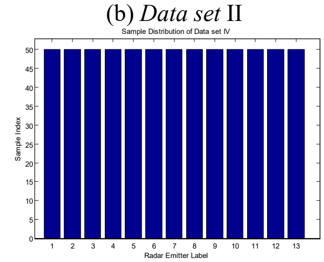
(a) *Data set* I



(b) *Data set* II



(c) *Data set* III

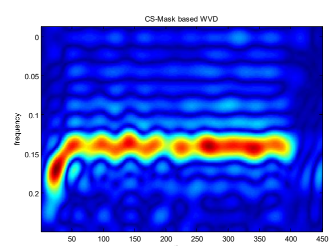


(d) *Data set* IV

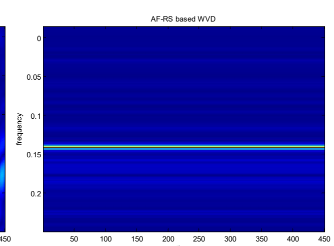
Fig.4. The sample distribution of three data sets

4.1. Experiment 1: information expression on CS-mask

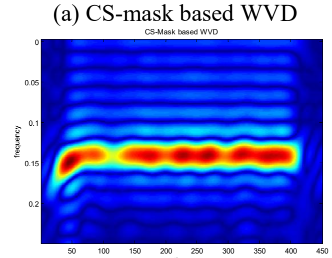
Experiment mainly contrasts the proposed method and ambiguity function representative-slice [3]. The first signal is the 1st in *Data set* I which belongs to class ONE, the WVDs of the two methods are shown in Fig.5(a-b). And Fig.5(c-d) illustrate the WVDs of the 335th sample whose label is class SIX. For the signal of 450 points, the CS-mask selects a central area with size 23*23 from which AF matrix includes 450*450 points. The radar signals in *Data set* I are approximately sinusoid with a frequency dropping at the beginning of the pulse. The WVD generated by CS-mask includes more time varying details of the signal compared with that generated by representative-slice of ambiguity function (AF-RS).



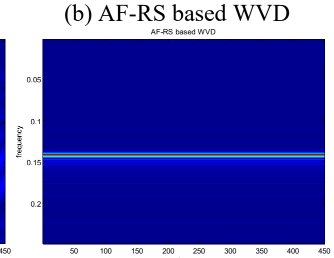
(a) CS-mask based WVD



(b) AF-RS based WVD



(c) CS-mask based WVD



(d) AF-RS based WVD

Fig.5. The comparison of recovered WVD using CS-mask and AF-RS features. (a-b) represent a sample in *Data set* I no.1, (c-d) represent a sample in *Data set* I no.353.

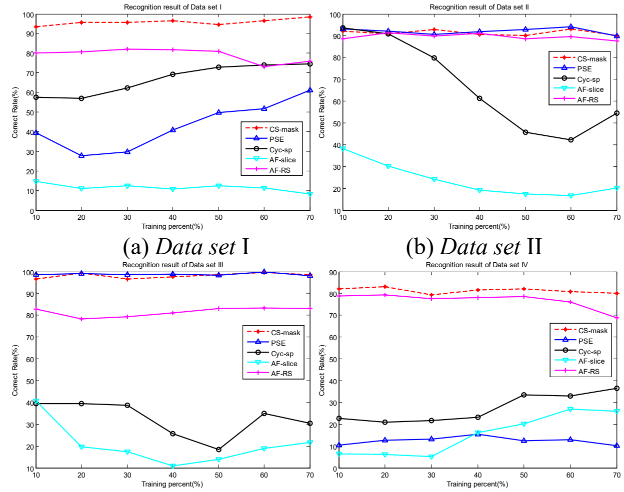
Moreover, it indicates the appearance moment of pulse. Although the AF-RS owns a good estimation of carrier frequency, the CS-mask contains more instantaneous frequency information especially when the emitter is LFM or other complicated modulation type.

4.2. Experiment 2: identification based on CS-mask

We extract feature from three data sets. Then randomly choose samples from each class under a training percentage rate ranging from 10% to 70%, and the remaining samples are used for testing the accuracy of classification. The classifier is ELM, a mono-layer random neural network, owing less time consuming and parameter-free. Results are shown in Fig.6. The proposed method is represented in red dashed line. From the result, the CS-mask owns better performance in accuracy and robustness in the first and fourth sets, compared with power spectrum estimation (PSE), cyclic spectrum (Cyc-sp), the zero slice of ambiguity function (AF-slice), and AF-RS. Particularly, in the second and third data sets, the feature PSE performs almost equally or sometimes better than proposed method, which means PSE feature is indeed suitable for *Data set* II and III than other two sets. However, CS-mask feature is much more prevalent and stable than other features, no matter what kind of data sets. The details of recognition accuracy are demonstrated in Table.1.

Table.1. The performance of classification

	Training rate	10%	20%	30%	40%	50%	60%	70%
I	CS-mask	**93.42**	**95.59**	**95.64**	**96.62**	**94.64**	**96.48**	**98.33**
	PSE	39.34	27.82	29.73	40.78	49.62	51.57	61.08
	Cyc-sp	56.14	53.79	66.57	69.09	69.52	69.91	71.75
	AF-RS	80.10	80.62	82.10	81.82	80.86	73.01	76.00
II	CS-mask	92.01	90.75	**92.87**	90.57	90.03	93.17	**90.16**
	PSE	**93.10**	**92.18**	90.61	**91.78**	**92.80**	**94.01**	89.84
	Cyc-sp	92.25	83.82	85.15	66.35	63.93	56.80	51.02
	AF-RS	88.69	91.27	89.96	91.06	88.59	89.58	87.70
III	CS-mask	96.74	**99.39**	96.67	97.54	**98.72**	99.51	**98.72**
	PSE	**98.63**	99.10	**98.68**	**98.95**	98.28	**100.0**	98.11
	Cyc-sp	83.24	81.23	82.91	85.82	77.16	83.59	82.78
	AF-RS	82.91	78.20	79.28	81.09	83.13	83.25	83.02
IV	CS-mask	**82.07**	**83.22**	**79.41**	**81.61**	**82.13**	**80.74**	**80.10**
	PSE	10.45	12.64	13.18	15.49	12.30	12.98	10.24
	Cyc-sp	18.70	17.33	19.70	29.01	23.81	32.95	34.63
	AF-RS	78.83	79.44	77.53	78.07	78.50	75.97	68.78



(a) *Data set* I (b) *Data set* II

(c) *Data set* III (d) *Data set* IV

Fig.6. The correct rate of recognition

5. CONCLUSIONS

In this paper, a compressed sensing based feature ambiguity function mask is proposed to serve as a time-frequency feature for emitter recognition. The central mask of ambiguity function can bring frequency information just using same length as signal. This approach can not only avoid high dimension feature brought by general time frequency domain but also cover more time varying information of signals.

Compared with other representative feature, the CS-mask method possesses no less accuracy in civil flight's meteorological radar identification, which owns low chirp rate. When facing signals emitted with more sophisticated modulation, the CS-mask can present more time varying detail and low feature dimension. The performance of CS-mask for FM signal is worth to be tested.

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