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

Mingzhe Zhu, Xinliang Zhang, Yue Qi, Hongbing Ji

School of Electronic Engineering, Xidian University, Xi'an 710071, China

Motivation: Civil Flights Recognition

Challenges:

- Traditional Specific Emitter Identification (SEI) features prone to work ineffectively and has low physical representation.
- Feature extraction and optimization algorithms need to be more simplified and applicable to engineering realization.
- In bad whether, low visibility situation or signals are interfered,there is a special need for control tower to recognize the coming flights.
- Limited SEI databases.

Innovative Points:

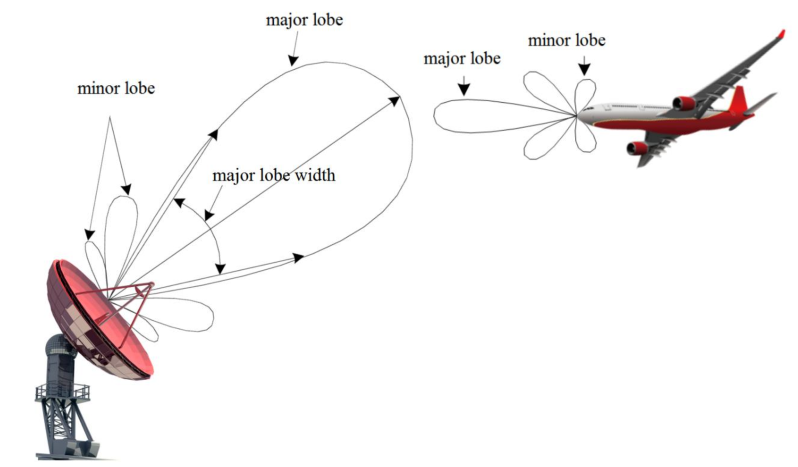
- Applying **signal reconstruction approach** to **feature extraction** method.
- Using **compressed sensing** theory extracts **CS-mask** from **ambiguity** domain.
- **Feature optimization** methods based on signals and energy are suitable for **engineering realization**.
- Create, collect and build **12** big **databases** for **SEI**.

Advantages:

Inspired by ambiguity-function representative slice feature, we propose a compressed sensing mask feature in ambiguity domain which can:

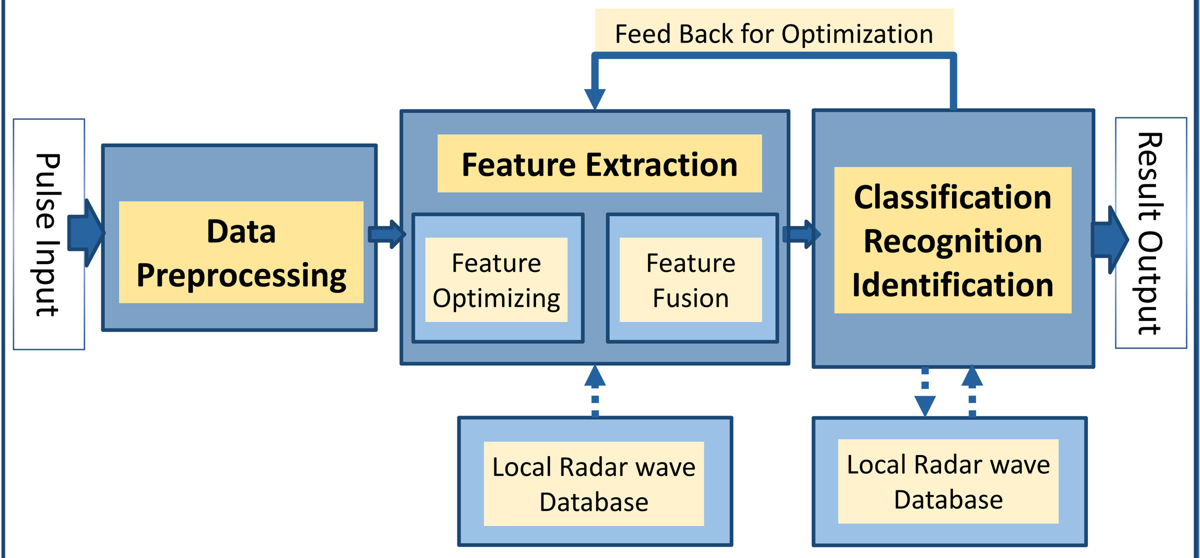
- **improves the recognition rate of civil flight radar emitters.**
- **represents physical characteristics of measured radar signals.**
- **contains more time varying information.**
- **alleviates the computational costs and data size.**

Background:



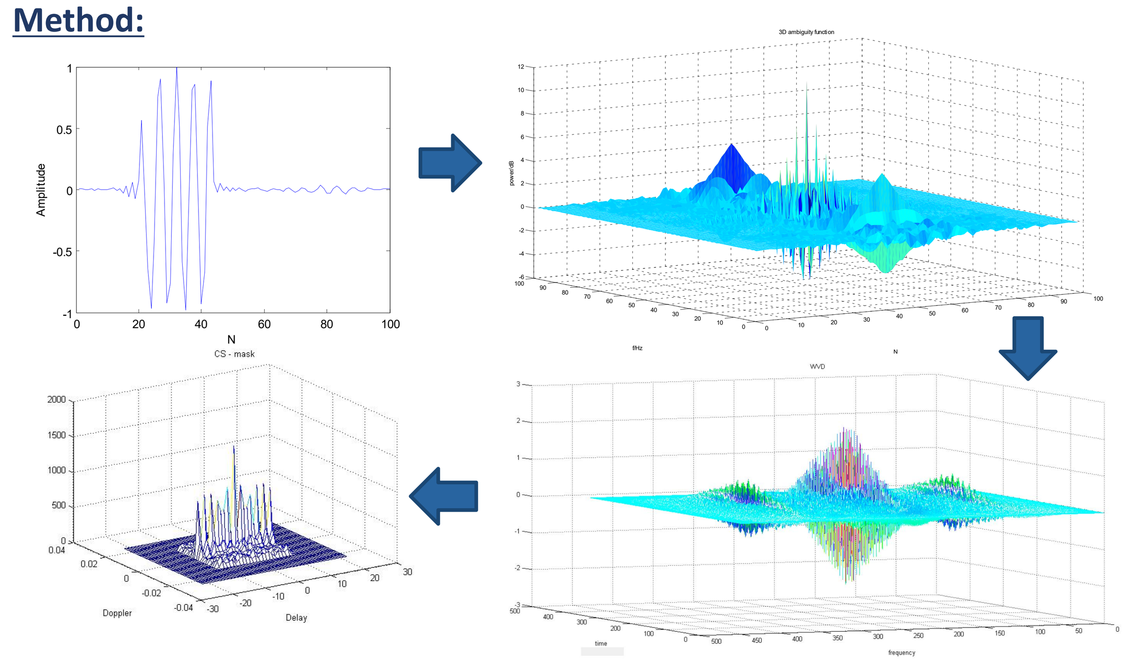
System Framework:

Recognition System Structure



Feature selection: a mask of ambiguity function

Method:



Mathematic Model:

Ambiguity function is defined as:

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

$$=\int_{-\infty}^{+\infty} WD(t,f)e^{-j2\pi(\xi t-f\tau)}dtdf \qquad (1)$$

If considering WVD and ambiguity as finite length N points sequences, then the matrix correlation of them as follows:

$$A_{f(N\times1)}=\Psi_{(N\times N)}\cdot W_{D(N\times1)} \qquad (2)$$

Ψ is 2D Fourier transform matrix. **Φ** is measurement matrix. CS-mask feature based on AF is defined as:

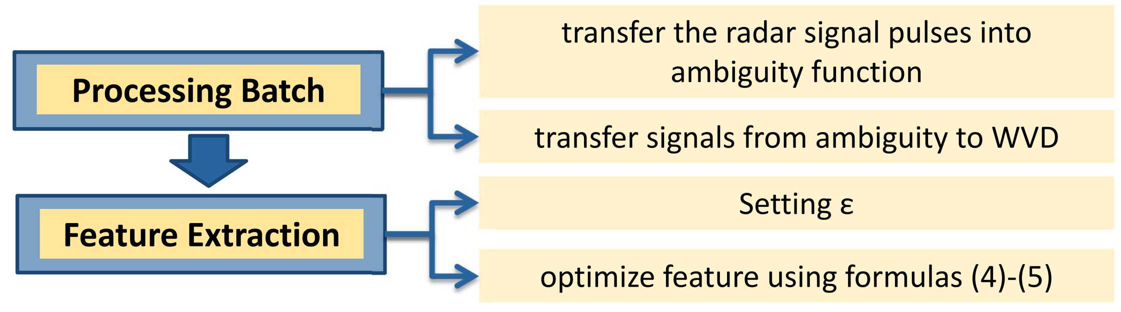
$$A_{f(M\times1)}^{Mask}=\Phi_{M\times N}\cdot A_{f(N\times1)}=\Phi_{M\times N}\cdot\Psi_{(N\times N)}\cdot W_{D(N\times1)} \qquad (3)$$

The sparse feature can be obtained according to CS theory, which can be optimized as:

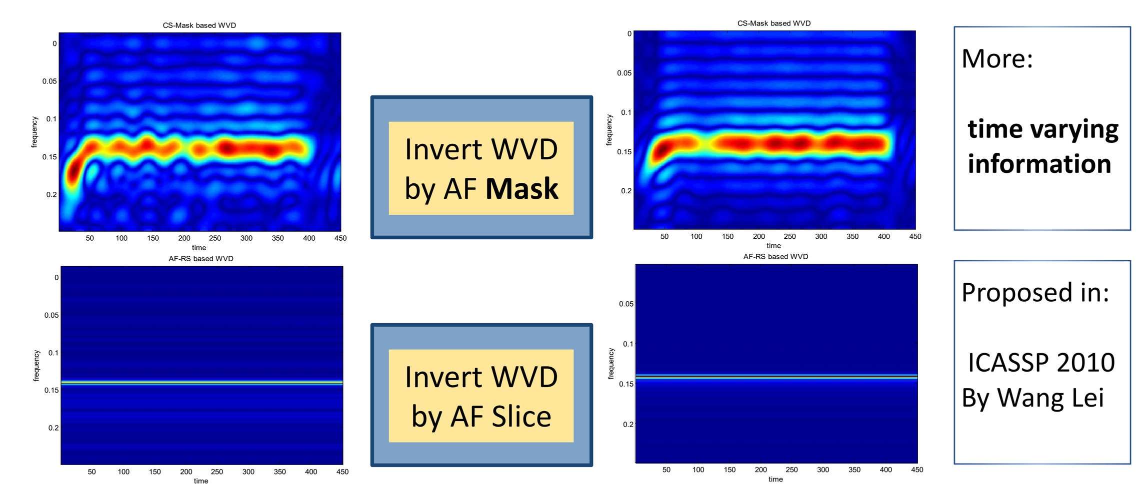
$$A_f^{Mask}=\min_A\left\|A_f\right\|_1 \qquad (4)$$

$$s.t.\sum_{k=1}^{N}\sum_{n=1}^{M}\frac{1}{N\cdot M}(\mathscr{F}_{2d}^{-1}\{A_f\}\text{-}W_D)\le\varepsilon\Big|_{(\xi,\tau)\in\Omega} \qquad (5)$$

Algorithm:



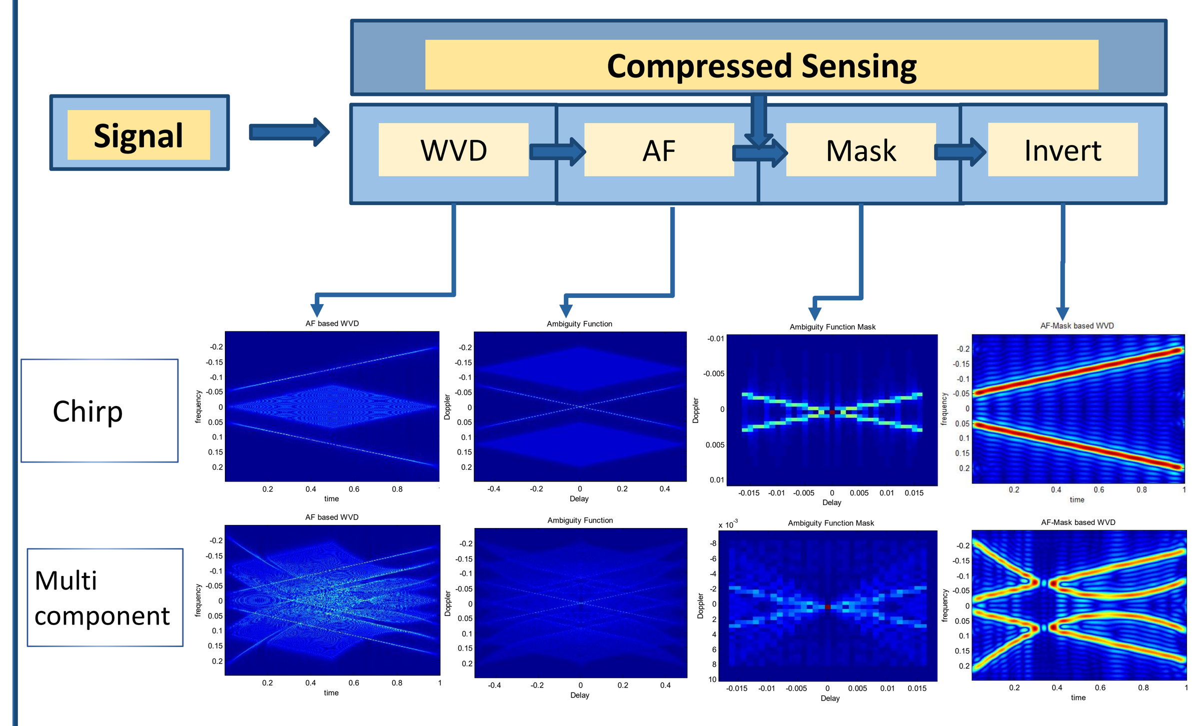
Mask or Slice?



Merits of CS-mask

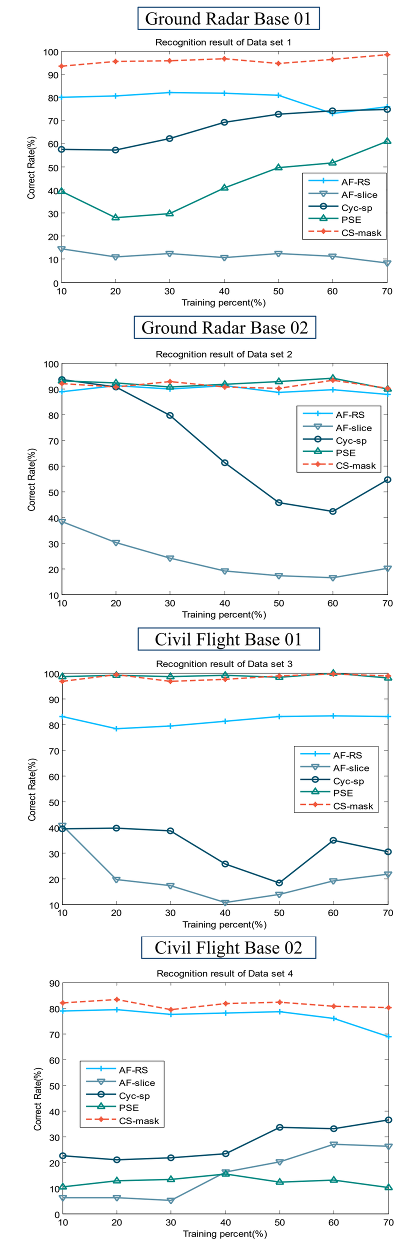
Information Representation:

Masked Ambiguity Function: Containing IF info



Identification accuracy:

Classification Result



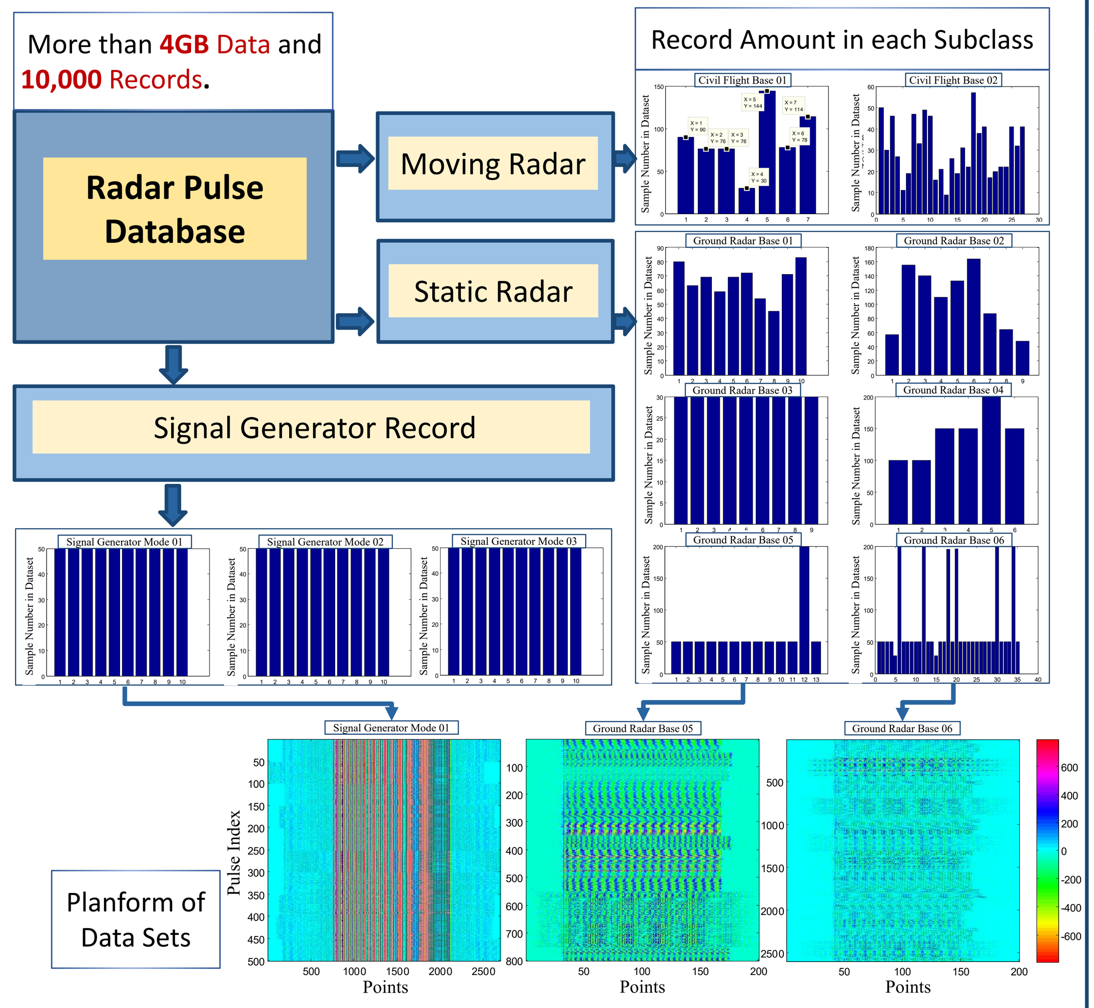
- Four databases including two ground radar bases and two civil flight bases.
- CS-mask owns higher accuracy and robustness in data sets I and IV.
- CS-mask and PSE both performs higher accuracy in data sets II and III.
- CS-mask preforms much more prevalent and stable in general.

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

Big Radar Wave Database

Our Lab own a big Radar waveform database, include measured signals from different kinds of Radar emitter.

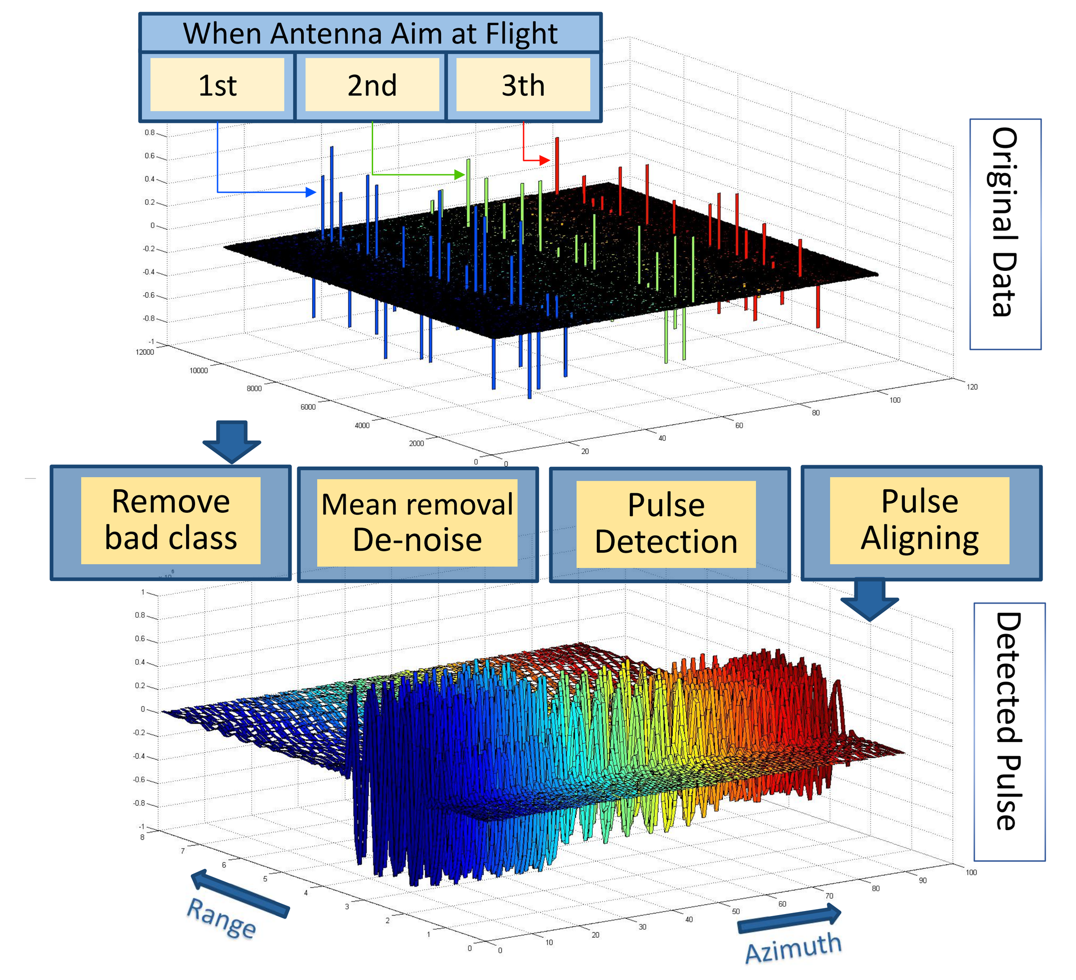
Radar Pulse Database



Building Civil Flights Database

Our Lab own a big Radar waveform database, include measured signals from different kinds of Radar emitter.

Wave Records Pre-Processing



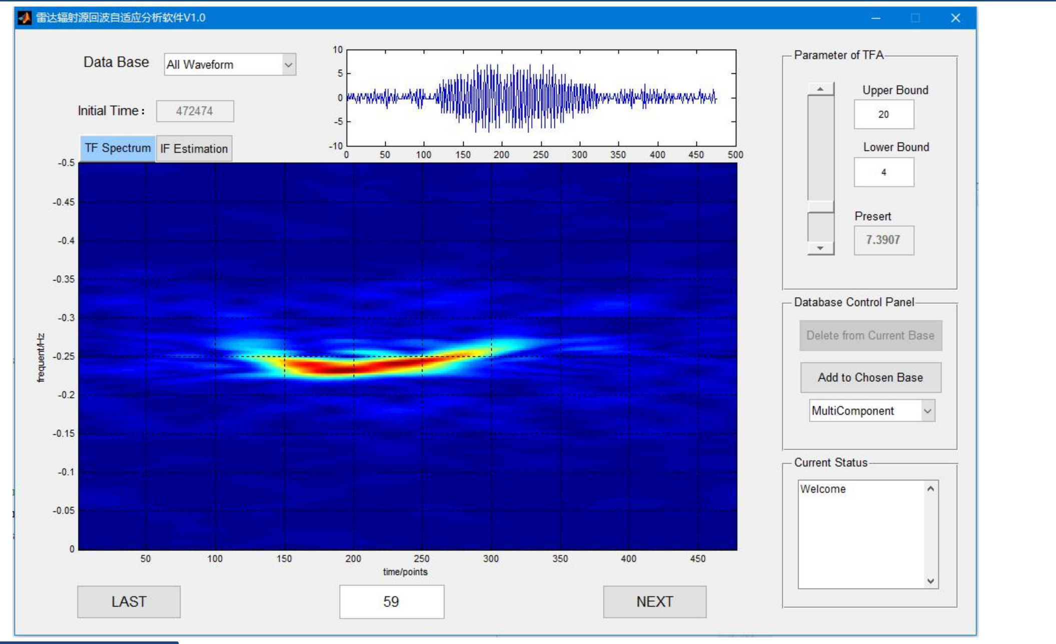
Conclusions

In this paper, a compressed sensing based feature ambiguity function mask is proposed to serve as a time-frequency feature for emitter recognition. The sparse CS-mask owns abundant time frequency information for radarprint feature extraction. This approach has some merits:

- Cover more time varying information of signals
- Avoid high dimension redundancy
- Possess better accuracy in civil flight meteorological radar identification
- own higher physical representation

Appendix

Radar Wave Viewing: TF domain



GUI function:

1. Time domain 2. TF domain 3. IF Estimation 4. Database operation

References

[1] X. H. Ru, Z. Liu, W. L. Jiang, Z. T. Huang, "Recog-nition performance analysis of instantaneous phase and its transformed features for radar emitter identification," *Radar, Sonar & Navigation*, IET, vol. 10, no. 5, pp. 945-952, 2016.

[2]L. Wang, H. B. Ji,Y. Shi, "Feature extraction and optimization of representative-slice in ambiguity function for moving radar emitter recognition," *ICASSP*, IEEE, Dallas, 2010.

[3] Z. Yang, W. Qiu, H. Sun, N. Arumugam, "Robust radar emitter recognition based on the three-dimensional distribution feature and transfer learning," *Sensors*, vol. 16, no. 3, 2016.

[4] S. Stankovic, I. Orovic, M. Amin, "Compressed sensing based robust time-frequency representation for signals in heavy-tailed noise," *ISSPA*, IEEE, Montreal, 2012.

Acknowledgement

This work is supported by the National Natural Science Foundation of China (No.61701374)

We gratitude to the anonymous reviewers whose valuable comments helped to improve the quality of this paper

Email: yueqi_xdu@Hotmail.com