AUTOMATIC RADAR WAVEFORM RECOGNITION BASED ON TIME-FREQUENCY ANALYSIS AND CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

In this paper, we apply the idea of deep learning to radar waveform recognition. Since the frequency variation with time is the most essential distinction among radar signals with different modulation types, we transform one-dimensional radar signals into time-frequency images (TFIs) using time-frequency analysis and design a convolutional neural network to recognize the frequency variation patterns exhibited in TFIs. Furthermore, we analyze the statistical characteristics of the noise in TFIs and introduce a naive approach to reduce its influence on the frequency variation patterns. Simulation results demonstrate the impressive recognition rate under very low SNR conditions and the strong generalization ability of our proposed recognition method.

***Index Terms*—** radar waveform recognition, deep learning, convolutional neural network, time-frequency image, noise reduction

1. INTRODUCTION

Automatic radar waveform recognition is one of the most fundamental techniques in electronic warfare (EW) applications such as cognitive radar, radar emitter recognition, and threat detection [1]. Lots of methods have been proposed to recognize radar signals with different modulation types, most of which are composed of two parts, i.e., feature extraction and classifier design. Though designing efficient classifier is indispensable, feature extraction plays the key role. In order to exhibit the distinctions among different radar signals, many signal processing methods are employed to handle single radar pulses. For example, Lunden [1], Zheng [2][3], Ren [4] and Konopko [5] derive features based on time-frequency analysis (TFA), Rigling [6] and Wang [7] exploit features based on auto-correlation functions, and Pu [8] and Gao [9] characterize the frequency change of radar signals based on instantaneous frequency analysis (IFA). In addition, high-order spectral analysis [10], principle component analysis [11] and entropy method [12] are also used to derive features. As for classifier design, many frequently-used machine learning methods are directly applied to classify the extracted features, such as clustering [4][11][13], support vector machine [9][10][14][15], artificial neural network [12], and probabilistic graphical model [7]. Additionally, some self-designed classifiers [1][2][3][8] are also employed.

Those aforementioned classical two-step recognition methods suffer two common weaknesses. First, in order to obtain discriminative features, too much attention have to be paid to discover efficient distinctions and to find ways to characterize them, but sometimes, some important features may be undiscovered, or the extracted features are not discriminative enough for recognition. For instance, Gao [9] extracts features based on IFA and Wang [7] extracts features based on ACF, and because IFA is very sensitive to the noise while ACF is relatively robust, the ACF-based algorithm outperforms the IFA-based algorithm. Second, seldom of these methods pave ways to tackle the influence of the noise. Konopko [5] intuitively designs a filter to handle the noise without any theoretical support, and just receives a slight performance improvement.

To overcome the first drawback, we apply the idea of deep learning to radar waveform recognition. Automatically learning the features of the input data is the core of deep learning methods. Their hierarchical deep network structures simulate the neural network of human brains and mathematically act as adaptive nonlinear kernel functions. Though feature extraction is not needed any more, different representations of radar signals as input may contribute to different results. In fact, the most essential distinction among radar waveforms with different modulation types is their frequency variation with time. TFA transforms one-dimensional signals into time-frequency images (TFI), which explicitly exhibit their frequency variation patterns. In our work, a convolutional neural network (CNN), which has shown significant results in facial recognition [16], vehicle recognition [17][18] and other recognition tasks is designed to recognize TFIs of radar signals, and we name this method as TFI-CNN. To cope with the second drawback, we first analyze the statistical characteristics of TFIs, and then design a naive filter based on the theoretical analysis to suppress the noise in TFIs.

This paper is developed as follows. Section 2 introduces the TFI-CNN method, analyzes the statistical characteristics of the noise in TFIs, and proposes a noise reduction approach. Section 3 illustrates the simulation results and

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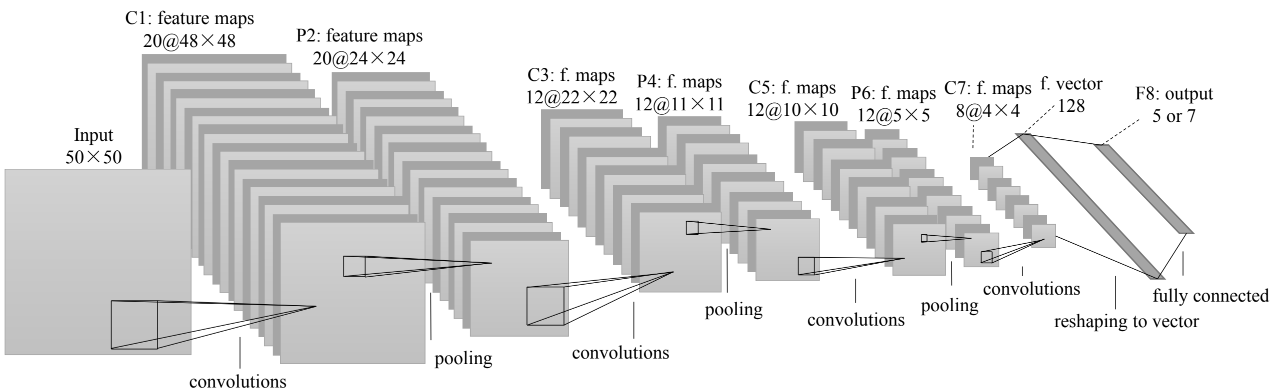

Fig. 1. The structure of the designed CNN with four convolutional layers, three pooling layers and one fully connected layer. The number of feature maps of each convolutional layers is 20, 12, 12, and 8, respectively. The kernel size of each convolutional layers is 3×3, 3×3, 2×2, and 2×2, respectively.

mainly discusses the generalization ability of our proposed method. Section 4 concludes this paper.

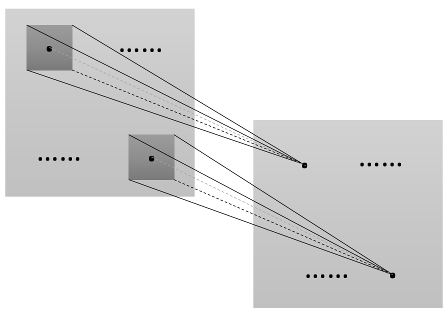

Fig. 2. The filtering process. Each point on the TFI is updated by averaging these points within the coverage of the square

2. CLASSIFIER DESIGN AND NOISE REDUCTION

2.1. TFI-CNN method

Suppose the intercepted noise-disturbed radar signal is

$$y(t) = x(t) + N(t), \tag{1}$$

where $x(t)$ denotes a radar signal and $N(t)$ is the additive Gaussian white noise with zero mean value and σ^2 variance. The most intrinsic difference among radar waveforms with different modulation types is their frequency variation with time. For instance, the frequency of a linear frequency modulation radar signal changes linearly with time and that of a frequency coding radar signal shifts with time. TFA transforms one-dimensional radar signals as TFIs, and the patterns in the images demonstrate the frequency evolution with time.

Now that TFIs are images, we can use a CNN to recognize them. CNN is consisted of multiple cascading layers, within which are feature maps. The deep network structure simulates the neural network of human brains and the hierarchical nonlinear combination of feature maps produces a highly complex and adaptive nonlinear kernel function. As depicted in Fig. 1, we design a CNN consisted of four convolutional layers, three pooling layers and one fully connected layer to recognize the TFIs of radar signals.

2.2. Statistical analysis of TFI and noise reduction

Wigner-Ville Distribution (WVD) is one of the frequently-used TFA methods, and the cross WVD of two signals $g(t)$ and $h(t)$ can be obtained as

$$W_{g,h}(t,\omega) = \int_{-\infty}^{+\infty} g\left(t+\frac{\tau}{2}\right) h^{*}\left(t-\frac{\tau}{2}\right) e^{-j\omega\tau} d\tau \cdot \tag{2}$$

If $g(t)$ and $h(t)$ are equal, Eq. 2 is the auto WVD of $g(t)$. By combining Eq. 1 with Eq. 2, the WVD of a noise-disturbed radar signal can be represented as

$$W_y(t,\omega) = \underbrace{W_x(t,\omega)}_{I} + \underbrace{W_{x,N}(t,\omega)}_{II} + \underbrace{W_{N,x}(t,\omega)}_{III} + \underbrace{W_N(t,\omega)}_{IV}, \tag{3}$$

where (I) and (IV) are the auto WVDs of the radar signal and the noise, respectively, and (II) and (III) are their cross WVDs. Term (I) demonstrates the frequency variation of radar signals and terms (II), (III) and (IV) play the role of disturbing (I). Therefore, it is necessary to diminish their influence on (I).

To reduce the influence of the cross WVDs, the preferred option is using Cohen class, which is more suitable for the WVD of a signal composed of multiple single-frequency signals. However, the power spectrum of Gaussian white noise occupies the full-frequency band, indicating that Cohen class would not work at all. In addition, term (IV) is the auto WVD of $N(t)$, which cannot be suppressed by applying Cohen class. Therefore, we need to explore new ways to reduce the influence of (II), (III) and (IV). For (II) and (III), since they are linear transformations of $N(t)$, they comply with a zero-mean two-dimensional stationary Gaussian process. Their correlation function is

$$
\begin{aligned}
&E\left\{W_{x,N}\left(t_1,\omega_1\right)W_{x,N}{}^*\left(t_2,\omega_2\right)\right\} \\
&= E\left\{\int_{-\infty}^{\infty} x\left(t_1+\frac{\tau}{2}\right)N^*\left(t_1-\frac{\tau}{2}\right)e^{-j\omega_1\tau}d\tau\int_{-\infty}^{\infty} x^*\left(t_2+\frac{\mu}{2}\right)N\left(t_2-\frac{\mu}{2}\right)e^{j\omega_2\mu}d\mu\right\} \\
&= \int_{\tau=2(t_1-t_2)+\mu}\int_{-\infty}^{\infty} E\left\{N^*\left(t_1-\frac{\tau}{2}\right)N\left(t_2-\frac{\mu}{2}\right)\right\}x\left(t_1+\frac{\tau}{2}\right)x^*\left(t_2+\frac{\mu}{2}\right)e^{-j\omega_1\tau+j\omega_2\mu}d\tau d\mu \\
&+ \int_{\tau\_else}\int_{-\infty}^{\infty} E\left\{N^*\left(t_1-\frac{\tau}{2}\right)N\left(t_2-\frac{\mu}{2}\right)\right\}x\left(t_1+\frac{\tau}{2}\right)x^*\left(t_2+\frac{\mu}{2}\right)e^{-j\omega_1\tau+j\omega_2\mu}d\tau d\mu \\
&= \int_{-\infty}^{\infty} E\left\{N^*\left(t_2-\frac{\mu}{2}\right)N\left(t_2-\frac{\mu}{2}\right)\right\}x\left(2t_1-t_2+\frac{\mu}{2}\right)x^*\left(t_2+\frac{\mu}{2}\right)e^{-2j\omega_1(t_1-t_2)-j(\omega_1-\omega_2)\mu}d\mu \\
&= \sigma^2 e^{-2j\omega_1(t_1-t_2)}\int_{-\infty}^{\infty} x\left(2t_1-t_2+\frac{\mu}{2}\right)x^*\left(t_2+\frac{\mu}{2}\right)e^{-j(\omega_1-\omega_2)\mu}d\mu
\end{aligned}
\quad (4)
$$

Supposing the complex envelop of any radar pulse is $x(t) = g(t)\exp(j\varphi(t))$, where $g(t)$ is a window function with duration time equal to T, if t_1=t_2,

$$
E\left\{W_{x,N}\left(t_1,\omega_1\right)W_{x,N}{}^*\left(t_1,\omega_2\right)\right\} \propto e^{2j(\omega_1-\omega_2)t_1}\int_{-\infty}^{\infty} g(\mu)g^*(\mu)e^{-2j(\omega_1-\omega_2)\mu}d\mu, \quad (5)
$$

Considering T is relatively large, Eq. 5 approximately equals to the impulse function $\delta(\omega_1-\omega_2)$ especially when $g(t)$ is a rectangle function. When $t_1 \neq t_2$, Eq. 4 is complex. However, because radar waveforms change continuously, we could still regard Eq. 4 as $\delta(\omega_1-\omega_2)$ as long as t_1-t_2 is small. Therefore, if the distance of any two different points of (II) or (III) is not too far, they are nearly uncorrelated. As for (IV), it is still zero-mean white noise (shown in Appendix).

Note that (II) and (III) are short-distance uncorrelated and (IV) is the white noise, we could regard the three terms as white noise within local areas of the TFIs. Knowing the expectation of the white noise is equal to zero, we update each point in the TFIs by averaging points within the coverage of a square, illustrated in Fig. 2. However, the filtering process also inevitably exerts its influence on (I), which will be discussed in detail in Section 3.

3. SIMULATION RESULTS AND DISCUSSION

3.1. Simulation results of the TFI-CNN method

Linear frequency modulation radar signals (LFM), single carrier radar signals (SCR), phase coded radar signals with three-element Barker code (PCR3), frequency coded radar signals with five-element Costas code, and nonlinear frequency modulation radar signals (NLFM) are used to evaluate the TFI-CNN method. Meanwhile, we reevaluate the state-of-the-art radar waveform recognition method [7] (which is named as ACF-DGM in this paper) on its own dataset composed of three types of radar signals, i.e., LFM, SCR, and PCR3. In order to simulate real radar signals, we generate all the radar signals with different carrier frequency, LFM signals with different slope, and NLFM signals with different sweep-frequency range, and the three parameters comply with three different uniform distributions. Moreover, when radar signals are transformed into TFIs, generally they are too large, which is time-consuming to manipulate, so we down-sample them to 50×50. Simulation results are shown in Fig. 3. As illustrated, the TFI-CNN method shows a significant performance improvement compared with the ACF-DGM method, and notably, the recognition rate is still higher than 95% under -5dB SNR condition. Additionally, Zheng [2] tests his TFA-based method on dataset composed of five types of radar signals similar to ours, and only receives 90% recognition rate under -4dB SNR condition.

3.2. Diminishing the influence of noise

The TFIs are first smoothed by the designed filter, and then down-sampled to 50×50. We vary the filter size to test the performance of the noise-reduction approach. Simulation results are illustrated in Fig. 4, which shows that a smoothing filter of size 23 by 23 gives the best recognition rate improvement at around 8%.

In fact, the smoothing filter is a low-pass filter, so increasing the filter size decreases its low-pass bandwidth. To reduce the influence of the noise, filtering with larger size would be more efficient. However, when the filter size is too big, not only the short-distance uncorrelation property of the cross WVDs of radar signals is violated, but also too much high-frequency components of the frequency variation patterns are filtered out. In summary, the filtering process suppresses the influence of the noise as well as reduces the resolution of the frequency variation patterns.

3.3. Evaluating the generalization ability

While the TFI-CNN method exhibits its efficiency on the dataset composed of five types of radar signals, we wonder whether it would still work well on dataset consisted of more types of radar signals. To test its generalization ability, we add two more types of radar signals, i.e., phase coded radar signals with thirteen-element Barker code, frequency coded radar signals with ten-element Costas code, and evaluate our proposed method along with the ACF-DGM method on the same dataset composed of the seven types of radar signals. Simulation results are shown in Fig. 5. As illustrated, the TFI-CNN method still maintains outstanding performance in a broad range of SNR condition while the ACF-DGM method has lost its effectiveness. Additionally, Lunden [1] tests his WVD-based method on dataset consisted of eight types of radar signals and only achieves 98% recognition rate under +6dB SNR condition.

Since the ACF-DGM method extracts features based on the ACFs, any radar signals with similar ACFs will be difficult to discriminate. Unfortunately, the ACFs of LFM and NLFM radar signals are extremely similar to each other, which contributes to the radical performance decline of the ACF-DGM method. In fact, the frequency variation is the most intrinsic distinction among different radar waveforms,

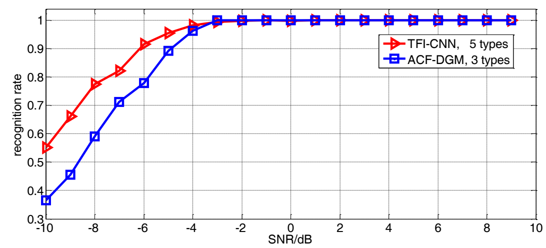

Fig. 3. Simulation results of the TFI-CNN method along with the ACF-DGM method

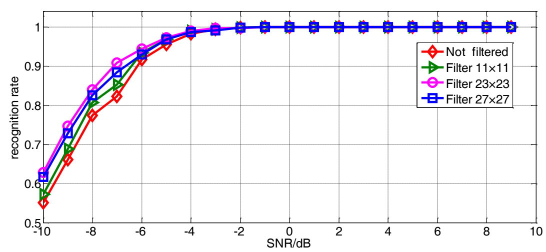

Fig. 4. Simulation results of the TFI-CNN method applied to the noise-suppressed TFIs. The performance is tested using filters with different sizes, i.e. 11×11, 23×23, and 27×27

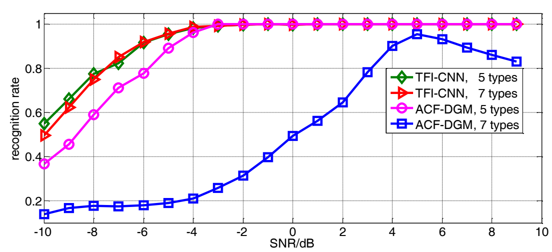

Fig. 5. Simulation results of evaluating the generalization ability of TFI-CNN method along with the ACF-DGM method

which further results in the differences of ACFs, high-order spectrums, entropy, principle components, and other characteristics. Most of the existing algorithms derive features based on these differences, but once some types of radar signals show similar properties on some characteristic, the corresponding difference would not be distinguishing enough for recognition. The TFI-CNN method directly learns to characterize the most intrinsic difference, and therefore shows strong generalization ability.

4. CONCLUSION

We propose a novel method to recognize radar waveforms with different modulation types. In contrast to existing works, we apply deep learning to radar waveform recognition. A CNN is designed to recognize TFIs of radar signals, the statistical characteristics of the noise in TFIs are analyzed and a naive noise-reduction approach is introduced. Simulation results demonstrate the impressive performance of the TFI-CNN method and show the effectiveness of the proposed noise-reduction approach. With relatively strong generalization ability, the TFI-CNN method is more applicable for real application.

5. APPENDIX

In this appendix, we give the proof of the white noise property of the auto WVD of the Gaussian white noise $N(t)$.

The auto WVD of $N(t)$ is a two-dimensional stochastic process, and the correlation function is

$$E\left[W_N(t_1,\omega_1)W_N^*(t_2,\omega_2)\right] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} E\left\{N\left(t_1+\frac{\tau}{2}\right)N^*\left(t_1-\frac{\tau}{2}\right)N^*\left(t_2+\frac{\mu}{2}\right)N\left(t_2-\frac{\mu}{2}\right)\right\}e^{-j\omega_1\tau}e^{j\omega_2\mu}d\mu d\tau \quad \text{(A)}$$

To obtain the final result of Eq. A, we first introduce a conclusion of high-order cumulants of Gaussian stochastic process. It says that for a Gaussian stochastic process $g(t)$, its high-order cumulants can be expressed by two-order movements, and when the order equals to four,

$$\begin{aligned} &Cum\left(g(t_1),g(t_2),g(t_3),g(t_4)\right) \\ &= E\left[\left(g(t_1)g(t_2)g(t_3)g(t_4)\right)\right] - E\left[g(t_1)g(t_2)\right] - E\left[g(t_3)g(t_4)\right] \\ &- E\left[g(t_1)g(t_3)\right]E\left[g(t_2)g(t_4)\right] - E\left[g(t_1)g(t_4)\right]E\left[g(t_2)g(t_3)\right] \\ &= 0 \end{aligned}, \quad \text{(B)}$$

where t_1,t_2,t_3,t_4 could equal to each other.

As for the expectation within the integration in Eq. A, for brevity, we denote it as

$$E\left[N\left(t_1+\frac{\tau}{2}\right)N^*\left(t_1-\frac{\tau}{2}\right)N^*\left(t_2+\frac{\mu}{2}\right)N\left(t_2-\frac{\mu}{2}\right)\right] = E\left[n_1 n_2^* n_3^* n_4\right]. \quad \text{(C)}$$

By applying the introduced conclusion of high-order cumulants, when $t_1 \neq t_2$, the expectation can be obtained as

$$E\left[n_1 n_2^* n_3^* n_4\right] = \begin{cases} E\left[n_1 n_1^* n_1^* n_4\right] = \sigma^2 & \tau = 0, \mu = \pm(t_2-t_1) \\ E\left[n_1 n_4^* n_4^* n_4\right] = \sigma^2 & \mu = 0, \tau = \pm(t_2-t_1) \\ E\left[n_1 n_1^* n_4^* n_4\right] = 2\sigma^2 & \tau = 0, \mu = 0 \\ E\left[n_1 n_2^* n_2^* n_4\right] = 0 & \tau\mu \neq 0, \mu = \pm\left[2(t_2-t_1)-\tau\right] \\ E\left[n_1 n_2^* n_1^* n_4\right] = 0 & \tau\mu \neq 0, \mu = 2(t_2-t_1)+\tau \\ E\left[n_1 n_2^* n_3^* n_4\right] = 0 & elsewise \end{cases}. \quad \text{(D)}$$

and when $t_1 = t_2$, the expectation can be obtained as

$$E\left[n_1 n_2^* n_3^* n_4\right] = \begin{cases} E\left[n_1 n_1^* n_1^* n_1\right] = 2\left(\sigma^2+\sigma^4\right) & \tau = \mu = 0 \\ E\left[n_1 n_1^* n_2^* n_2\right] = 2\sigma^2 & \tau = \mu \neq 0 \\ E\left[n_1 n_1^* n_3^* n_4\right] = 0 & \tau \neq \mu, \tau\mu = 0 \\ E\left[n_1 n_1^* n_3^* n_4\right] = 0 & elsewise \end{cases}. \quad \text{(E)}$$

Substitute Eq. D and Eq. E back to Eq. A, the final result can be obtained as

$$E\left[W_N(t_1,\omega_1)W_N^*(t_2,\omega_2)\right] = 2\sigma^2\delta\left(\omega_1-\omega_2, t_1-t_2\right). \quad \text{(F)}$$

Therefore, the auto WVD of the Gaussian white noise process is still a white noise stochastic process.

6. REFERENCES

[1] J. Lunden and V. Koivunen, "Automatic Radar Waveform Recognition," in IEEE Journal of Selected Topics in Signal Processing, vol. 1, no. 1, pp. 124-136, June 2007.

[2] D. Zeng, X. Zeng, H. Cheng and B. Tang, "Automatic modulation classification of radar signals using the Rihaczek distribution and hough transform," in IET Radar, Sonar & Navigation, vol. 6, no. 5, pp. 322-331, June 2012.

[3] D. Zeng, X. Zeng, G. Lu and B. Tang, "Automatic modulation classification of radar signals using the generalised time-frequency representation of Zhao, Atlas and Marks," in IET Radar, Sonar & Navigation, vol. 5, no. 4, pp. 507-516, April 2011.

[4] R. Mingqiu, C. Jinyan and Z. Yuanqing, "Classification of radar signals using time-frequency transforms and fuzzy clustering,"Microwave and Millimeter Wave Technology (ICMMT), 2010 International Conference on, Chengdu, 2010, pp. 2067-2070.

[5] K. Konopko, Y. P. Grishin and D. Jańczak, "Radar signal recognition based on time-frequency representations and multidimensional probability density function estimator," Signal Processing Symposium (SPSympo), 2015, Debe, 2015, pp. 1-6.

[6] B. D. Rigling and C. Roush, "ACF-based classification of phase modulated waveforms," 2010 IEEE Radar Conference, Washington, DC, 2010, pp. 287-291.

[7] Chao Wang, Hao Gao and Xu-Dong Zhang, "Radar Signal Classification Based on Auto-correlation Function and Directed Graphical Model," 6th International Conference on Signal Processing, Communications and Computing (ICSPCC), Hong Kong, August 2016.

[8] Y. Pu, W. Jin, M. Zhu and L. Hu, "Classification of Radar Emitter Signals Using Cascade Feature Extractions and Hierarchical Decision Technique," 2006 8th international Conference on Signal Processing, Beijing, 2006.

[9] Hao Gao and Xu-Dong Zhang. "Automatic Radar Waveform Recognition Using SVM." Applied Mechanics and Materials 229 (2012): 2348-2351.

[10] R. Mingqiu, C. Jinyan, Z. Yuanqing and H. Jun, "Radar signal feature extraction based on wavelet ridge and high order spectra analysis," Radar Conference, 2009 IET International, Guilin, 2009, pp. 1-5.

[11] Z. Yu, C. Chen and W. Jin, "Radar Signal Automatic Classification Based on PCA," 2009 WRI Global Congress on Intelligent Systems, Xiamen, 2009, pp. 216-220.

[12] J. Li and Y. Ying, "Radar signal recognition algorithm based on entropy theory," Systems and Informatics (ICSAI), 2014 2nd International Conference on, Shanghai, 2014, pp. 718-723.

[13] Ming Zhu, Wei-Dong Jin, Yun-Wei Pu and Lai-Zhao Hu, "Classification of radar emitter signals based on the feature of time-frequency atoms," 2007 International Conference on Wavelet Analysis and Pattern Recognition, Beijing, 2007, pp. 1232-1236.

[14] Mingqiu Ren, Jinyan Cai, Yuanqing Zhu and Minghao He, "Radar emitter signal classification based on mutual information and fuzzy support vector machines," 2008 9th International Conference on Signal Processing, Beijing, 2008, pp. 1641-1646.

[15] Ming-Qiu Ren, Yuan-Qing Zhu, Yan Mao and Jun Han, "Radar emitter signals classification using kernel principle component analysis and fuzzy support vector machines," 2007 International Conference on Wavelet Analysis and Pattern Recognition, Beijing, 2007, pp. 1442-1446.

[16] Li, H., Lin, Z., Shen, X., Brandt, J. and Hua, G., "A convolutional neural network cascade for face detection," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 5325-5334, 2015.

[17] R. Girshick, "Fast R-CNN," 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, 2015, pp. 1440-1448.

[18] Chen, X., Kundu, K., Zhu, Y., Berneshawi, A. G., Ma, H., Fidler, S., and Urtasun, R, "3d object proposals for accurate object class detection," in Advances in Neural Information Processing Systems, pp. 424-432, 2015.