

Time-frequency Analysis and Convolutional Neural Network Based Fuze Jamming Signal Recognition

Jikai Yang¹, Zhiqian Bai^{1,*}, Jiacheng Hu¹, Yingchao Yang¹, Zhaoxia Xian¹, Xinhong Hao², KyungSup Kwak³

¹Shandong Provincial Key Lab. of Wireless Communication Technologies,

School of Information Science and Engineering, Shandong University, Qingdao 266237, Shandong, China

²School of Mechatronical Engineering, Beijing Institute of Technology, Beijing 100081, China

³Graduate School of Information Technology and Telecommunications, INHA University, Incheon 22212, Korea

Email: yjk1425@163.com, zqbai@sdu.edu.cn*, 906603100@qq.com, yangyingchao1991@hotmail.com, xianzhaoxia2000@163.com, haoxinhong@bit.edu.cn, kskwak@inha.ac.kr

Abstract—Fuze jamming signal recognition plays a critical role in the battlefield environment. To improve the performance of fuze jamming signals detection, we propose a fuze jamming signal detector based on time-frequency analysis (TFA) and convolutional neural network (CNN), called TFA-CNN, in this paper. The detailed recognition process of the proposed TFA-CNN detector is provided, where the short-time Fourier transform (STFT) is first employed to convert the original jammed fuze signals into the time-frequency images and then the TFA-CNN detector is built to train the recognition model. Simulation results verify that the TFA-CNN detector outperforms the typical existing recognition detectors, such as LeNet, time-frequency images and convolutional neural network (TFI-CNN) and deep neural network (DNN), in the detection performance with a slightly higher time complexity. Specially, the average recognition accuracy of the proposed detector achieves 99.8% even at a low signal-to-interference-plus-noise ratio (SINR).

Index Terms—fuze, CNN, STFT, image, accuracy

I. INTRODUCTION

It is known that fuze jamming signal recognition is a prerequisite for realizing the intelligent fuze anti-jamming. Accurate recognition of the fuze jamming signals is conducive to subsequent anti-jamming decisions and is of significant importance to improve the fuze anti-jamming capability.

Traditional fuze jamming recognition schemes usually accomplish the recognition by manually extracting the signal features in the time or frequency domain. A signal singularity orientation method based on wavelet transform was proposed in [1], which can effectively identify the jamming signal and achieve the precise singularity location of the radio fuze signal. A fractional Fourier domain (FFD) based digital radio frequency memory (DRFM) anti-repeat jamming method was presented in [2] to effectively recognize the jamming signal and perform anti-jamming. Y. Huang *et al.* proposed a frequency modulation (FM) fuze signal recognition based on Shannon entropy and singular spectral entropy for amplitude modulated swept jamming signals, and support vector machine (SVM) was used for classification [3]. An adaptive sparse time-frequency analysis (ASTFA) scheme was proposed in [4] to distinguish electromagnetic interference (EMI) signals in the time domain and recognize the interference type. However, the accuracy achieved by traditional recognition methods is

limited. Moreover, multiple jamming signals may coexist in the modern battlefield environment, and some of the jamming sources intendedly operate at similar frequency of the fuze signal. Extracting the features of the fuze jamming signals by traditional methods becomes more and more complicated and is hard to be practically implemented.

The continuous development of deep learning (DL) is gradually being applied to many fields, including jamming signal recognition. [5] proposed a K-nearest neighbors (KN-N) based radio fuze anti-jamming method by extracting the frequency exponential entropy and normative entropy features of the fuze signal, and the classifier performed effectively. A convolutional neural network (CNN) based jamming detection and classification for synthetic aperture radar was proposed in [6], where the jamming signal can be effectively classified by a visual geometry group (VGG) trained by frequency domain signals. S. J. Hong *et al.* proposed a classification for radar signals based on CNN to improve the classification accuracy by extracting two radar signal parameters, carrier radio frequency and signal pulse repetition interval, as the input of the CNN [7].

In this paper, we propose a fuze jamming signal detector based on time-frequency analysis and convolutional neural network (TFA-CNN). First, the original jammed fuze signal is converted into a time-frequency image by pre-processing, and the jamming signal features can be extracted in the time and frequency domains jointly. Then, the time-frequency image is input to the TFA-CNN detector for jamming signal recognition. It is shown that the proposed detector can effectively recognize a variety of single or mixed jamming signals.

The rest of this paper is as follows. In Section II, we introduce the system model, the pre-processing approach, and the network structure of the TFA-CNN detector. Section III describes the dataset generation and offline training. Simulation results and analysis are provided in Section IV. Finally, Section V draws the conclusion.

II. JAMMING SIGNAL RECOGNITION WITH CNN

A. System Model

We consider the FM radio fuze jamming signal recognition system shown in Fig. 1, including the target detector, the

jamming source, and the jamming signal recognition module. The target detector sends the fuze signal by FM expressed as

$$u_{on}(t) = U_{on} \cos \left(\omega_0 t + \frac{\Delta\omega}{\Omega_m} \sin \Omega_m t \right) \quad (1)$$

where U_{on} is the transmit fuze signal amplitude, ω_0 is the carrier angle frequency, $\Delta\omega$ is the maximum carrier angle frequency shift, and Ω_m is the modulated fuze signal frequency. Then, the transmitted fuze signal reaches the target. After the target reflection, the fuze echo signal is formed and expressed as

$$u_c(t) = U_c \cos \left[\omega_0(t - \tau) + \frac{\Delta\omega}{\Omega_m} \sin \Omega_m(t - \tau) \right] \quad (2)$$

where U_c is the fuze echo signal amplitude, $\tau = \frac{2r}{c}$ is the delay time, r is the distance between the fuze and the target, and c is the light speed.

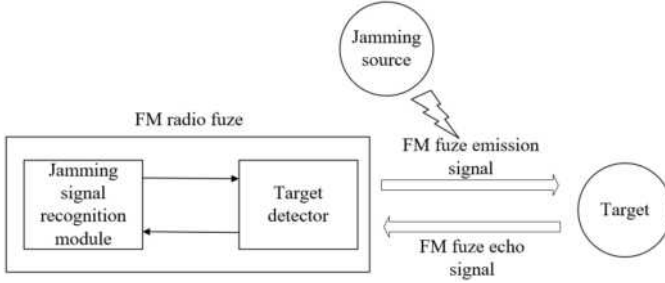


Fig. 1. FM radio fuze jamming signal recognition system.

After being interfered by the jamming sources, the signal obtained at the target detector receiver can be written as

$$u(t) = u_c(t) + j(t) + n(t) \quad (3)$$

where $j(t)$ is the jamming signal and $n(t)$ is the additive Gaussian white noise (AWGN). The received signal is further mixed with the local oscillator signal that matches the carrier signal and enters the jamming signal recognition module. The jamming signal recognition module consists of two parts: the TFA module and the CNN detector, as shown in Fig. 2. The CNN detector extracts time-frequency images features and recognizes the jamming signals correctly.

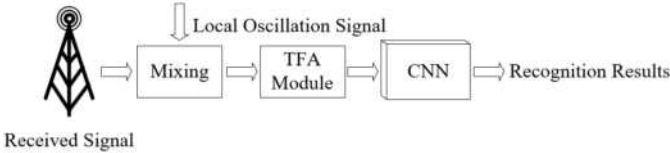


Fig. 2. Jamming signal recognition module.

B. Data Pre-processing

In order to extract more features from a one-dimensional time-series signal, we adopt the TFA method, where the short-time Fourier transform (STFT) is designed to acquire the time

and frequency domain characteristics of signals simultaneously [8]. The STFT of the discrete signal $x(n)$ can be written as

$$STFT(n, \omega) = \sum_m x(m)g(m-n)e^{j\omega m} \quad (4)$$

where $g(n)$ is the window function. Since the time-frequency image is obtained by transforming the signal processed by the STFT sliding window function, the time and frequency domain resolutions are not available at the same time. To avoid the serious distortion, we choose Hann window and set the length of the window function to be 256. Moreover, we set the overlap part of the window function as half length of the window function and convert the STFT-processed signal to an image with a size of 128×128 .

C. Structure of TFA-CNN Detector

To recognize the fuze jamming signals accurately, we propose the TFA-CNN detector. As shown in Fig. 3, the TFA-CNN detector consists of four convolutional layers, two pooling layers, and two fully connected layers. The dimension of the input layer of the TFA-CNN detector is $64 \times 64 \times 3$. The detailed configurations of the convolutional and pooling layers are shown in TABLE I. We perform the padding operation in the convolution layer to learn the edge features of the time-frequency image and maintain the image size better. The pooling layer utilized a maximum pooling operation for downsampling. We also perform successive convolution operations after the first pooling layer to learn more features. To reduce the complexity of the proposed detector, we use 1×1 convolution between convolution layer 2 and 4 and reduce the number of feature channels to limit the training parameters. A pooling layer follow the last convolutional layer in order to filter the learned features. The first fully connected layer has 512 neurons, and the second fully connected layer as the output layer has 15 neurons, representing 15 jamming signals. All the layers use the ReLU activation function except for the second fully connected layer that takes the Softmax activation function. To prevent the occurrence of the network overfitting, we apply Dropout process after the two pooling layers and the first fully connected layer. The Dropout rates are set as 0.2, 0.25, and 0.5, respectively.

TABLE I
DETAILED CONFIGURATIONS OF THE CONVOLUTION AND POOLING LAYERS

Connection layer	Number of filters	Kernel size	Pooling areas	Stride
Conv1	32	3×3	-	1
Pooling1	-	-	2×2	2
Conv2	64	3×3	-	1
Conv3	32	1×1	-	1
Conv4	64	3×3	-	1
Pooling2	-	-	2×2	2

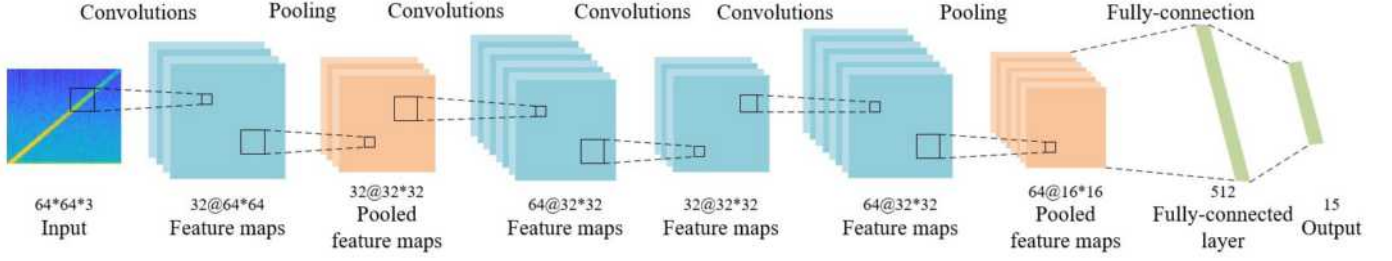


Fig. 3. Structure of TFA-CNN detector.

TABLE II
TYPES AND PARAMETERS OF JAMMING SIGNALS

Type	Variables of jamming	Value
Noise AM Jamming	Frequency	400MHz-600MHz
Noise FM Jamming	Chirp rate	800MHz
Sine-wave AM jamming	Frequency	400MHz-600MHz
Sine-wave FM jamming	Chirp rate	500MHz
Square-wave AM jamming	Frequency	400MHz-600MHz

III. DATASET GENERATION AND OFFLINE TRAINING

A. Dataset Generation

As shown in TABLE II, five fuze jamming signals are considered in our experiments. Typically, since more than one jamming signal may exist in the real environment, we obtain 10 mixed jamming signals by superimposing any two different signals of the five jamming signals mentioned above. The mixed jamming signals and the five single jamming signals make up a total of 15 jamming signals. The dataset is generated by MATLAB simulation, and the parameters are randomly selected according to TABLE II. Considering the high jamming power in the real environment, we generate 1,000 jammed fuze signals data every 5 dB intervals from -20 dB to 0 dB for each jamming signal. There are 5,000 jammed fuze signals data for each jamming signal and a total of 75,000 data for 15 jamming signals. The simulation data of the 15 jamming signals are then converted into the time-frequency images by STFT, where 75% of them are used for training and the remaining 25% are for verification. Moreover, 2,500 jammed fuze signals data of each jamming signal are generated for testing as described above.

B. Offline training

The dataset is composed of time-frequency images converted by STFT from the original jammed fuze signals data, and the corresponding labels of the time-frequency images are obtained by one-hot coding. In order to evaluate our detector accurately, the accuracy rate is chosen as the measure. Meanwhile, the classification cross-entropy loss function is

TABLE III
HYPER-PARAMETERS OF TFA-CNN

Training parameters	Value
Epoch	30
Learning rate	0.001
Optimizer	SGD
Batch size	64

adopted to improve the accuracy rate. The network model hyper-parameters are shown in TABLE III.

IV. SIMULATION RESULTS AND ANALYSIS

The simulation results of the proposed TFA-CNN detector are provided in this section. We select the Keras DL framework to build and train the TFA-CNN detector, and the hardware platform is AMD Ryzen 7 5800 CPU and RTX3070 GPU. And all comparative simulations are implemented on this hardware platform.

A. Recognition Performance

The recognition performance of the TFA-CNN detector considering the trained dataset with different overlap ratio is shown in Fig. 4. It is observed that the accuracy of the proposed model achieves the highest when the overlap ratio is about 50%. Meanwhile, the recognition performance becomes the worst with a 40% overlap ratio. This phenomenon happens since the time and frequency domain resolutions after STFT pre-processing cannot be achieved simultaneously. Moreover, the overlap ratio affects the quality of the generated images, influencing the model performance directly. In order to achieve a balance between the time and frequency domain resolutions of the generated images and the model recognition performance, we choose the overlap ratio as 50%.

The recognition performance the proposed STFT-based and conventional Wigner-Ville distribution-based (WVD-based) [9] methods is illustrated in Fig. 5. WVD method performs FFT on the instantaneous correlation function of the signal, which has many advantages, such as no added windows, no correlation between time and frequency, and high resolutions. We can see that the recognition accuracy by STFT pre-processing is significantly higher than that of WVD pre-processing because the cross-term interference occurs inevitably in WVD, leading to a low recognition accuracy. In

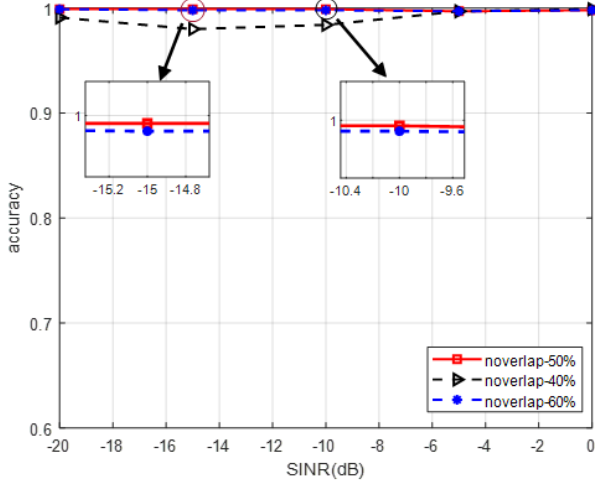


Fig. 4. Performance comparison with different overlap ratios.

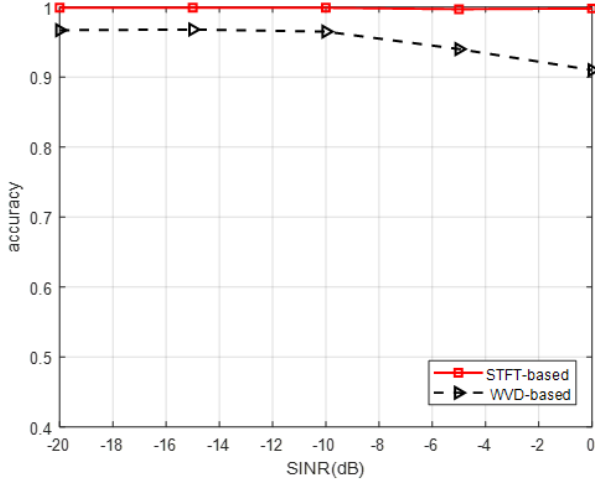


Fig. 5. Performance comparison under different pre-processing methods.

particular, the cross-term interference is more severe in the high SINR region, which causes a decrease in the recognition accuracy. Although STFT requires the addition of windows, which leads to the interconnection of the time and frequency domain resolutions, a high accuracy can be achieved through the selection of the appropriate window functions and parameters.

Fig. 6 demonstrates the recognition performance of the proposed TFA-CNN and typical LeNet [10], TFI-CNN [11], and DNN [12] detectors. It is noticed that the recognition accuracy of the proposed TFA-CNN detector is obviously better than that of the other detectors, especially in the low SINR region. For 15 jamming types, the TFA-CNN detector can achieve an average recognition accuracy of 99.8% in all the SINR regions. The average recognition accuracy of the DNN detector gets the lowest since the DNN detector mainly performs global feature extraction at each layer during the training

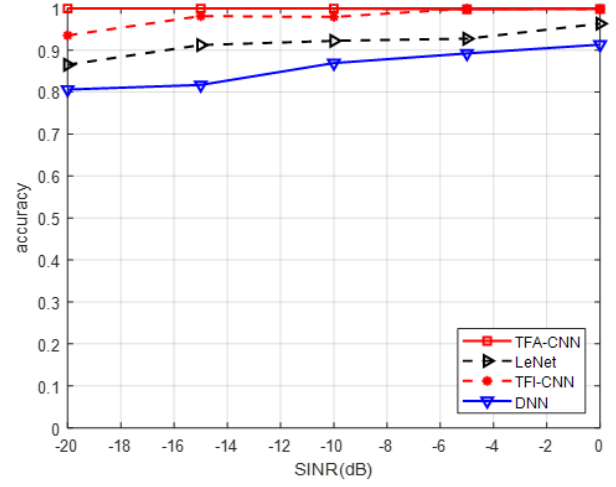


Fig. 6. Accuracy comparison of different jamming signal recognition models.

process and does not consider the structural characteristics of the images. In contrast, the CNN detector considers the contextual information of the features within each convolution, and the integration of features occurs slowly and orderly. Therefore, the CNN detector achieves an advantage over the DNN detector in image processing. The LeNet and TFI-CNN detectors perform poorly in the low SINR region because the structure of these two detectors is not sufficient to learn the features of all jamming signals, which degrades the average recognition accuracy.

B. Model Complexity

To give a comprehensive comparison based on the analysis of the recognition performance of the proposed detector, we also further analyzed the complexity of the proposed and existing detectors. It is described in TABLE IV regarding the complexity of the proposed and existing detectors. Here, the running time is chosen to measure the complexity, and 500 images from the test dataset are randomly selected for testing. We can see from TABLE IV that the TFA-CNN detector has a shorter running time than the TFI-CNN detector. Although the running time of the LeNet and DNN detectors is slightly shorter than that of the TFA-CNN detector, their recognition accuracy is obviously poor.

TABLE IV
DIFFERENT JAMMING SIGNAL RECOGNITION MODEL RUNNING TIME

Model	Average running time (ms/per image)
TFA-CNN	5.59
TFI-CNN	6.22
LeNet	4.57
DNN	3.12

V. CONCLUSION

In this paper, we have proposed a TFA-CNN based fuze jamming signal detector. The detailed system design and

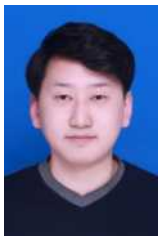
recognition process have been provided. Simulation results have shown that the proposed detector can achieve excellent recognition accuracy in both low and high SINR regions. Moreover, the proposed detector outperforms the existing TFI-CNN, LeNet, and DNN detectors and achieves a better balance between recognition accuracy and model complexity.

ACKNOWLEDGEMENT

This work was supported in part by the Innovation and Development Joint Foundation of Shandong Provincial Natural Science Foundation under Grant ZR2021LZH003, in part by the Natural Science Foundation of China under Grant 61771291 and 61871414, in part by the National Defense Preliminary Research Project under Grant 90903030202, and in part by the National Research Foundation of Korea-Grant Funded by the Korean Government (MSIT-NRF-2020R1A2B5B02002478). (Corresponding author: Zhiquan Bai.)

REFERENCES

- [1] Y. Q. Li, P. Li, X. P. Yan, and H. Chen, "Application of wavelet transform to radio fuze jamming identification," in *Proc. ICWCNMC*, Dalian, China, Oct. 2008, pp. 1-4.
- [2] S. Cheng, X. Luo, C. Dai, and X. Hao, "A novel anti-repeat jamming approach for frequency modulation fuze," in *Proc. IEEE ICUS*, Beijing, China, Oct. 2019, pp. 233-238.
- [3] Y. Huang, X. H. Hao, Z. J. Kong, and B. Zhang, "Recognition of target and jamming signal for FM fuze based on entropy features," *Acta Armamentarii*, vol. 38, pp. 254-260, Feb. 2017.
- [4] P. Li, Z. Zhou, and M. Sheng, "Identification of electromagnetic interferences based on adaptive sparsest time-frequency analysis," in *Proc. IEEE EMC/APEMC*, Suntec City, Singapore, May 2018, pp. 761-765.
- [5] B. Liu, X. Hao and J. Yang, "Anti-jamming method of radio fuze based on KNN," in *Proc. ICMSP*, Hangzhou, China, Jul. 2022, pp. 816-820.
- [6] J. F. Yu, J. W. Li, B. Sun, and Y. M. Jiang, "Barrage jamming detection and classification based on convolutional neural network for synthetic aperture radar," in *Proc. IEEE IGARSS*, Valencia, Spain, Jul. 2018, pp. 4583-4586.
- [7] S. J. Hong, Y. G. Yi, J. Jo, and B. S. Seo, "Classification of radar signals with convolutional neural networks," in *Proc. ICUFN*, Prague, Czech Republic, Jul. 2018, pp. 894-896.
- [8] S. G. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries," *IEEE Trans. Signal Process.*, vol. 41, no. 12, pp. 3397-3415, Dec. 1993.
- [9] A. A. Ahmad, A. Muhammad Lawan, M. Ajiya, and Z. Y. Yusuf, "Sorting of Low Probability of Intercept Radar Signals Based on Frequency Modulation Constancy Using Wigner-Ville Distribution," in *Proc. IEEE APACE*, Melacca, Malaysia, Nov. 2019, pp. 1-5.
- [10] W. Zhang, M. Krunz, and G. Ditzler, "Intelligent jamming of deep neural network based signal classification for shared spectrum," in *Proc. IEEE MILCOM*, San Diego, CA, USA, Nov. 2021, pp. 987-992.
- [11] C. Wang, J. Wang, and X. Zhang, "Automatic radar waveform recognition based on time-frequency analysis and convolutional neural network," in *Proc. IEEE ICASSP*, New Orleans, LA, USA, Mar. 2017, pp. 2437-2441.
- [12] S. Tang, M. Tao, X. Zhang, Y. Fan, J. Su, and L. Wang, "Adversarial deception on deep-learning based radio waveforms classification," in *Proc. URSI GASS*, Rome, Italy, Aug. 2021, pp. 1-4.



Jikai Yang is currently pursuing the M.S. degree in Electronic Information at the School of Information Science and Engineering, Shandong University, Qingdao, China. His research interests include deep learning, signal processing and signal recognition.



Zhiquan Bai received the M.Eng. degree in communication and information system from Shandong University, Jinan, China, in 2003, and the Ph.D. degree (Hons.) from INHA University, Incheon, South Korea, in 2007, under the Grant of Korean Government IT Scholarship. He held a postdoctoral position with INHA University, and was a Visiting Professor with The University of British Columbia, Canada. He is currently a Professor with the School of Information Science and Engineering, Shandong University. His research interests include cooperative technology and spatial modulation, orthogonal time frequency space modulation, MIMO technology, resource allocation and optimization, and deep-learningbased 5G wireless communications. He is a member of the editorial board of *Journal of Systems Engineering and Electronics* and also an associate editor of the *International Journal of Communication Systems*.



Jiacheng Hu received the B.S. degree from the School of Physical Science and Technology of Jinan University in Jinan, China. He is currently pursuing the M.S. degree in Electronic Information at the School of Information Science and Engineering, Shandong University, Qingdao, China. His research interests include OTFS, channel estimation, and deep learning.



Yingchao Yang is currently pursuing the Ph.D. degree in communication and information system from the School of Information Science and Engineering, Shandong University, Qingdao, China. His research interests include MIMO technology, spatial modulation, orthogonal time frequency space modulation, and cooperative communication.



Zhaoxia Xian received the B.S. degree from the School of Physical and Electronic Sciences at Shandong Normal University in Jinan, China. She is currently pursuing the M.S. degree in Electronic Information at the School of Information Science and Engineering, Shandong University, Qingdao, China. Her research interests include signal processing, signal recognition and deep learning.



Xinhong Hao received the B.S., M.S., and Ph.D. degrees in technical and electrical engineering from Beijing Institute of Technology University, Beijing, China, in 1996, 1999, and 2007, respectively. She is currently an Associate Professor with the Department of Technical and Electrical, Beijing Institute of Technology University.

Her research interests include intelligent detection and control, radio target detection and signal processing, and information perception and confrontation.



Kyung Sup Kwak received his BS degree from the Inha University, Incheon, Korea, in 1977 and his MS degree from the University of Southern California in 1981 and his PhD degree from the University of California at San Diego in 1988, under the Inha University Fellowship and the Korea Electric Association Abroad Scholarship Grants, respectively.

From 1988 to 1989, he was with Hughes Network Systems, San Diego, California. From 1989 to 1990, he was with the IBM Network Analysis Center, North Carolina. Since then, he has been with the School of Information and Communication Engineering, Inha University, Korea, as a professor. He is the director of UWB Wireless Communications Research Center (UWB-ITRC). Since 1994, he served as a member of the board of directors and the vice president and the president of Korean Institute of Communication Sciences (KICS) in 2006 and the president of Korea Institute of Intelligent Transport Systems (KITS) in 2009. He received many research awards, such as the award of research achievements in UWB radio from the Ministry of Information and Communication and Prime Ministry of Korea in 2005 and 2006, respectively. In 2008, he is elected as Inha Fellow Professor (IFP). In 2010, he received the Korean President official commendation for his contribution to ICT innovation and industrial promotion. He published more than 100 SCI journal papers, 300 conference/domestic papers, obtained 20 registered patents and 35 pending patents, and proposed 21 technical proposals on IEEE 802.15 (WPAN) PHY/MAC. He is one of the members of the IEEE, IEICE, KICS, and KIEE. His research interests include multiple access communication systems, cognitive radio, UWB radio systems and WBAN, WPAN, and sensor networks.