IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 27, 2021, accepted September 12, 2021, date of publication September 20, 2021, date of current version October 4, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3114191

Differential Complex-Valued Convolutional Neural Network-Based Individual Recognition of Communication Radiation Sources

LONG YING[1], JINGCHAO LI[2], AND BIN ZHANG[3], (Member, IEEE)
[1]School of Computer and Software, Nanjing University of Information Science and Technology, Nanjing 210044, China
[2]School of Electronic and Information, Shanghai Dianji University, Shanghai 201306, China
[3]Department of Mechanical Engineering, Kanagawa University, Yokohama 221-8686, Japan

Corresponding author: Jingchao Li (lijc@sdju.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 61902193 and Grant 62076160.

ABSTRACT Data assaults from unauthorized access to the Internet of Things will induce severe intrusion and hazard to the whole network. Employing only traditional application layer password authentication approaches cannot guarantee the security of the communication system. Therefore, it is critical to develop a capable and efficient radio frequency fingerprints based physical layer authentication system. To incorporate the domain knowledge in more capable feature extracting and reduce information loss caused by converting RF baseband I/Q signals, we propose a novel differential complex-valued convolutional neural network based individual recognition approach of communication radiation sources in the paper. The proposed method can fully capture the nonlinearity of the RF baseband I/Q signals while decreasing the unfavorable impact of phase rotation induced by carrier frequency offset, which also significantly reduces the required data length of the collected steady-state data transmission section. The recognition performance evaluation on 20 wireless network card devices with duplicate batch, type, and manufacturer shows that the proposed approach has the best recognition performance compared with two conventional approaches whose recognition accuracies are lower than 95%, achieving the total recognition accuracy of 99.7%. Moreover, compared with constellation based approaches, which require at least 5,000 to 10,000 data points as input parameters, the proposed method can reduce the required data length of the collected steady-state data transmission section effectively, which is easier to implement in practical applications.

INDEX TERMS Radio frequency fingerprint, constellation figure, physical layer authentication, differential processing, complex-valued convolutional neural network.

I. INTRODUCTION

Information security is crucial for constructing reliable and resilient Internet of Things (IoT). Data assaults from unauthorized devices of wireless communication induce severe intrusion and hazard to the entire network. The major challenge to be solved by the utilization of IoT is how to reliably identify and authenticate IoT devices, frustrating user impersonation, and device cloning. The conventional authentication approaches are implemented on the application layer in the communication system, employing cryptographic algorithms to provide encoding outputs, hard for third parties to forge. However, these approaches are vulnerable to hazards such as protocol security flaws and key leaking. The terminal device, which belongs to the perception layer of the Internet of Things, exhibits variety, intelligence, complexity, and a wide variety of features. Moreover, the conventional authentication approaches are not befitting for large-scale networks and incidental large-scale data, hard to fulfill the information security demands in the Internet of Things, although they can provide some extent of information security. As a result, individual recognition approaches with low error rates, high efficiencies, and low costs are critical to maintaining the steady performance of the Internet of Things. Constructing a radio frequency fingerprints based effective physical layer authentication system is momentous [1].

The existing frequency fingerprints based identity verification techniques can be classified into two categories depending on the exploited physical layer resources: the channel-based [2] and transmission signal based [3], [4]

The associate editor coordinating the review of this manuscript and approving it for publication was S. M. Rezaul Hasan.

fingerprint recognition technologies. The latter can be father further partitioned as transient signal based [3], [4] identification approaches and steady signal based identification approaches. Initially, transient signals are utilized to extract radio frequency fingerprints since the fingerprints present in the steady-state signal are hard to calculate. In contrast, the steady-state signal has a long duration and is easier to obtain when the transmitter is working in stable state.

To extract the radio frequency fingerprint features, two kinds of methods have been proposed: waveform domain based and modulation domain based feature extraction methods. The waveform domain based fingerprint feature extraction methods include Hilbert-Huang transform [5], wavelet transform, Synchrosqueezing transform [6], improved fractal box dimension [7], Fourier transform, et cetera. Ali *et al.* [8] extract thirteen features in three feature groups from the transient signals of Bluetooth devices obtained by an improved energy envelope technique along with their time-frequency-energy distributions (TFED), which are produced by the Hilbert-Huang transform (HHT). Three different classifiers, including the complex decision tree, Linear Support Vector Machine (L-SVM), and Linear Discriminant Analysis (LDA), are implemented to get final identification results on different levels of signal to noise ratio (SNR) levels. Aghnaiya *et al.* [9] propose a method using variational mode decomposition (VMD) in extracting features from Bluetooth transient signals. The transient signals are decomposed into a series of band-limited modes, and higher order statistical (HOS) features are extracted both from band-limited modes and reconstructed transient signals individually. The L-SVM classifier is employing for recognition, with which the performance bounds of VMD are scrutinized.

The modulation domain based fingerprint feature extraction methods contain I/Q offset, carrier frequency offset, modulation offset, constellation trace figure [10], differential constellation trace figure [11], constellation based contour stellar [12], et cetera, and their combinations [13]. A CB-DNA based radio frequency fingerprint recognition approach [14], [15] is proposed by Carbino. The fingerprint was generated from the Ethernet card's unintended cable radiation in order to improve the conventional MAC-based ID verification and decrease illegal network penetration. Following the extraction of radio frequency fingerprints using feature engineering approaches, classifier construction is an important step in the recognition process.

Recently, scholars have employed deep learning approaches to tackle the issues of feature extraction, feature selection, and recognition in radio frequency fingerprint identification [16], [17]. Ding *et al.* [18] propose a deep learning technique based on the steady-state section of the signals, which employs a convolutional neural network and compressed bispectrum to distinguish specific transmitters. Zhao *et al.* [19] propose a transfer learning approach using rejection sampling to update weights which are then coupled with rejection sampling to build a training set, making the trained model less influenced by time-varying and channel characteristics. A framework to use the complex baseband error signals in the time domain for training convolutional neural networks is proposed by Merchant [20], which successfully identified 7 ZigBee devices. This approach does not exploit the preamble sequence or the signal segment, which reemerges at a fixed position. And the obtained radio frequency fingerprint feature is not related to the content conveyed by the signal to be distinguished. Chatterjee *et al.* [21] develop a deep neural network framework based on the concept of RF-PUF, which only employs the waveform of the data portion and does not need a preamble sequence. According to simulation experiments, the identification rate of 10,000 transmitters can reach 99% under different channel conditions. The multi-sampling convolutional neural network [22], which is adopted by Yu *et al.*, performs robustly under LOS and NLOS in experiments. Yu *et al.* [23] also developed a denoising autoencoder based radio frequency fingerprint recognition model in the same year. Compared with traditional convolutional neural network (CNN), when the signal-to-noise ratio (SNR) is 10 dB to 5 dB under the additive white Gaussian noise channel, the recognition accuracy can be promoted by 14% to 23.5%, which can reach 97.5% even if the SNR is 10 dB.

Roy *et al.* [24] propose the Radio Frequency Adversarial Learning (RFAL) framework for building a robust system to identify rogue RF transmitters by designing and implementing a generative adversarial net (GAN). After detection and elimination of the adversarial transmitters, the learned feature embedding is used as fingerprints for categorizing the trusted transmitters. The eight trusted transmitters are correctly distinguished with 97% accuracy. In the approach proposed by Peng *et al.* [11], differential constellation trace figure (DCTF), a two-dimensional representation of the differential relation of signal time series, is utilized to extract radio frequency fingerprint features without requiring any synchronization. A convolutional neural network is then designed to identify different devices using DCTF features, which achieves 99.1% and 93.8% accuracy under SNR levels of 30 dB and 15 dB respectively when classifying 54 target ZigBee devices. Fadul *et al.* [25] propose RF Distinct Native Attributes fingerprint-based Specific Emitter Identification method, which utilizes a CNN initialized by Convolutional autoencoder under Rayleigh fading and degrading SNR conditions. Ma *et al.* [26] propose a novel identification approach based on long short-term memory (LSTM) and LabVIEW software, which use the particular gate structure inside to extract the distinguishing features, such as channel state information and RF device fingerprinting. The identification accuracy of the unauthorized broadcasting signals is 99.83% accuracy at the licensed frequency of 107.8 MHz in realistic electromagnetic environments. In the paper [27], Davaslioglu *et al.* use a deep learning based autoencoder to extract spectrum-representative features and train a deep neural network to classify waveforms reliably as idle, WiFi, or jammer. The Minimum Covariance Determinant outlier detection method is employed to authorize the signals, achieving the average accuracy of 89.8%. Moreover, an approach exploiting the deep sparse capsule network for signal recognition [28] has also been proposed.

The constellation figure based approaches will lose some original information when transforming baseband signals to the constellation figure and cannot be trained end to end. Most current deep learning based radio frequency fingerprint recognition approaches directly take baseband data as training data to learn fingerprint feature extraction models and have achieved some successes. However, to tackle the disadvantage caused by "black box" natures and large parameters optimization space, domain knowledge based constraints or modules should be incorporated to promote the generalization and interpretability ability of deep neural network models. In this paper, a novel differential complex convolutional neural network based individual recognition method used for communication radiation sources is proposed, and the main contributions of the paper are as below:

1) We propose a differential complex-valued convolutional neural network based radio frequency fingerprint extraction and identification framework, which can fully capture the nonlinearity of the RF baseband I/Q signals while reducing the unfavorable impact of phase rotation induced by carrier frequency offset and Doppler effect based on collected steady-state data transmission section.
2) The proposed method can reduce the required data length of the collected steady-state data transmission section effectively, without the need of converting the I/Q signals into a constellation figure, compared with the typical constellation based method.
3) Experiments on the measured signals from 20 wireless network card devices which have the duplicate batch, type, and manufacturer prove the validity and reliability of the proposed method.

We arrange the rest of this paper as follows: Section II describes the representative constellation based approaches and the proposed approach. The experimental analysis and performance evaluations are manifested in Section III. Section IV obtains the conclusions.

II. METHODOLOGY

Diverse modulation waveforms habitually produce diverse transition patterns in the I/Q complex plane. As a result, the constellation figures can characterize a unique feature of the radio frequency baseband I/Q signals.

Recently, quadrature modulation has been widely employed in communication, which makes the radio frequency fingerprint characteristics in the modulation domain greatly concerned. Researchers have proposed many methods containing constellation trace figure [10], differential constellation trace figure [11], and constellation based contour stellar [12] to represent and distinguish radio frequency fingerprints.

Fig.1 illustrates the constellation figure corresponding to radio frequency baseband I/Q signals of a wireless network card device. Depending on the point density in the

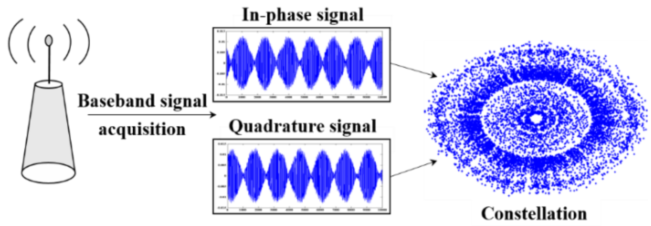

FIGURE 1. The constellation figure corresponding to radio frequency baseband I/Q signals of a wireless network card device.

2-dimensional constellation figure, different regions are allocated with different colors varying in a defined range, which converts the 1-dimensional signal into a 2-dimensional color image (similar to a high-definition X-ray photograph), more comprehensively describing the delicate properties of the signal.

This color constellation figure is called constellation based contour stellar and can be further processed by the filters of the convolutional neural network. Then, physical layer authentication for IoT terminal devices can be conducted, shown in Fig.2.

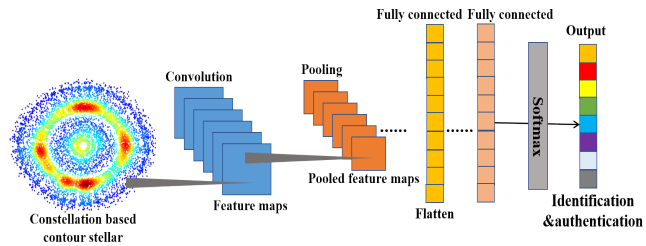

FIGURE 2. The physical layer authentication for IoT terminal equipment based on contour stellar.

Although constellation based methods have been extensively researched and developed, they need to convert original baseband I/Q signals to constellation figure, which may lose information and be computationally intensive. We design a novel RF fingerprint extraction and recognition framework to directly capture the characteristics of the RF baseband I/Q signals based on the collected steady-state data transmission section.

A. DIFFERENTIAL PROCESSING OF I/Q SIGNALS

We detailed analyze the phase rotation and deviation of the demodulated baseband signal as following, which may cause additional disturbances and errors for RF fingerprint identification.

Noting that f_c^t is the transmitter carrier frequency, and $X(t)$ stands for transmitter baseband signal, the RF signal transmitted by the transmitter can be depicted as below:

$$S(t) = X(t)\, e^{-j2\pi f_c^t t} \tag{1}$$

If we suppose that the RF circuit of the transmitter and the communication channel are both ideal, the received RF signal on the receiver is equal to that transmitted.

After the RF signal is received, the baseband signal can be generated by down-converting the received signal, described as:

$$Y(t) = R(t)\, e^{j(2\pi f_c^r t+\varphi)} \tag{2}$$

where φ is received signal phase offset, f_c^r stands for the receiver carrier frequency.

When $f_c^t \neq f_c^r$, the baseband signal can be characterized as below:

$$Y(t) = X(t)\, e^{j(2\pi\theta t+\varphi)} \tag{3}$$

where $\theta = f_c^r - f_c^t$.

It can be seen that each baseband signal sampling point has a phase rotation factor $e^{j2\pi\theta t}$, for there is residual frequency deviation θ in the demodulated signal. The phase rotation $e^{j2\pi\theta t}$ changes with the sampling point, commonly resulting in inadequate resilience and stability for the obtained constellation features, as illustrated in Fig.3.

The frequency deviation $\tilde{\theta}$ and phase deviation $\tilde{\varphi}$ can be estimated in most coherent demodulation systems to compensate for the received signal, generating a stable constellation.

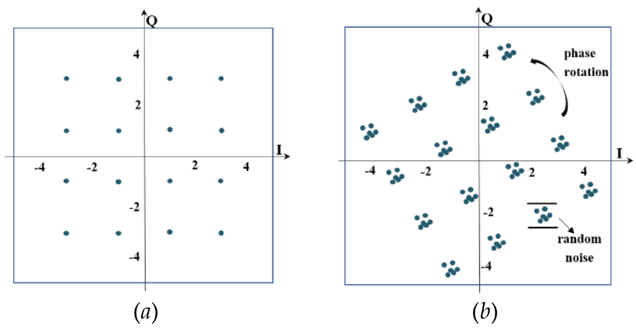

FIGURE 3. The transition patterns proportional to 16-QAM in the I/Q complex plane: (a) the ideal constellation; (b) the actually received constellation disturbed by offset of carrier frequency, random noise, and Doppler effect.

However, in RF fingerprint extraction, the receiver does not aim to demodulate every signal symbol correctly. The received baseband signals can be processed by performing difference in I/Q complex plane in accordance with special temporal interval n to produce a stable constellation diagram, depicted as:

$$\begin{aligned} D(t) &= Y(t)\cdot Y(t+n) \\ &= X(t)\, e^{j(2\pi\theta t+\varphi)}\cdot X(t+n)\, e^{-j(2\pi\theta(t+n)+\varphi)} \\ &= X(t)\cdot X(t+n)\, e^{-j2\pi\theta n} \end{aligned} \tag{4}$$

where Y^* stands for the conjugate value.

Although the signal $D(t)$ processed by difference still contains a phase rotation factor $e^{-j2\pi\theta n}$, this factor is a constant which will not alter when the sampling point position t varies. Consequently, a stable constellation can be generated after differential processing.

B. DIFFERENTIAL COMPLEX-VALUED CONVOLUTIONAL NEURAL NETWORK

To reduce information loss by converting differential processed I/Q signals into constellation based contour stellar and incorporate the domain knowledge in more capable feature extracting, we propose a complex-valued convolutional neural network to fully capture the nonlinearity of the amplitude and phase information of the differential processed I/Q signals, shown in Fig.4.

The baseband signal is acquired by down-converting the received signal and can be naturally decomposed into In-phase and Quadrature signals. Delay and differential processing are then conducted to reduce the unfavorable impact of phase rotation. The processed In-phase signal and Quadrature signal can form complex-valued data matrix (sequence), whose characteristic can be effectively captured and extracted by the elaborate complex-valued convolutional neural network and aggregated by the subsequent pooling layer. The extracted informative and discriminative feature is used to identify communication radiation sources by a fully connected layer.

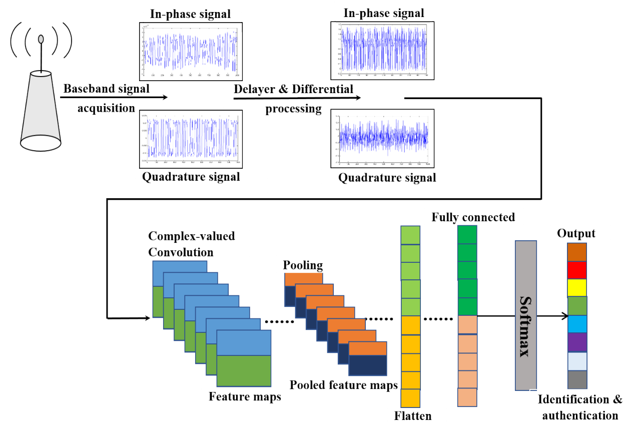

FIGURE 4. The framework of the proposed method which conducts physical layer authentication for IoT terminal equipment, including the baseband signal acquisition, I/Q signals differential processing, complex-valued convolution, and individual recognition.

Our method can also effectively reduce the required data length of the collected steady-state data transmission section,

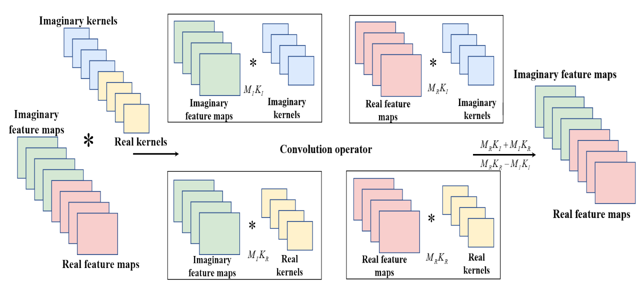

FIGURE 5. The calculation process of the complex convolution module.

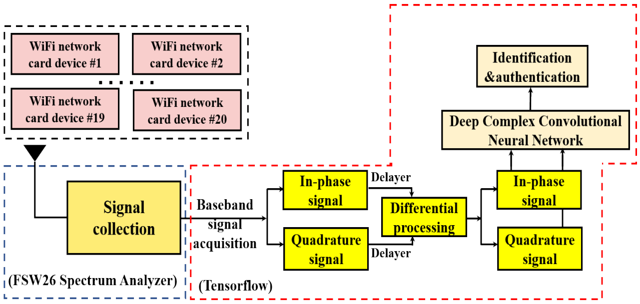

FIGURE 6. Experimental test scheme: the FSW26 spectrum analyzer is used to sample the signals of channel 6 in the 2.4GHz frequency band for 20 wireless network card devices. The proposed differential complex-valued convolutional neural network is employed to identify these devices by the baseband I/Q signals.

for the I/Q signals do not need to be converted into constellation diagram.

The calculation process of complex convolution is illustrated in Fig.5. A more detailed discussion of the complex convolution operator can be found in our previous work [29].

III. APPLICATION AND ANALYSES

In this paper, to validate the effectiveness of the proposed method, 20 wireless network card devices with duplicate batch, type, and manufacturer are utilized.

A. IMPLEMENT DETAILS

The experimental testing process is illustrated in Fig.6. The FSW26 spectrum analyzer is used as the receiver of radio frequency baseband to sample signals of channel 6 in the 2.4GHz frequency band for 20 wireless network card devices in the indoor laboratory scene. Fifty rounds of sampling are conducted in which signal sampling rate is 80MHz, and each sampling duration is 1.75ms, that is 140,000 points per round. The steady-state data transmission section of each sampling is used after excluding the channel noise section. In order to achieve data enhancement, the steady-state data transmission section is further equally divided into 80 segments. Therefore, the total number of sampling sequences is $80 * 50 * 20 = 80{,}000$. In Fig.7, a sampling sequence of baseband signal received by wireless network card device sampling sequence of a device is shown. While in Fig.8, an example of a processed I/Q signal which performs difference after delay is displayed.

The signal sampling rate is set to 80 MHz according to previous works and additional experiments, which is adequate for sampling steady-state signals. Steady-state regions are determined by the variance trajectory detection method, which calculates variances of the signals and then sets the energy threshold to obtain the results.

3200 sampling sequences are randomly chosen for each device to gather the training set for the complex-valued convolutional neural network after differential processing for each sampling sequence, and the remaining 800 sampling sequences per device are used for testing. To validate the

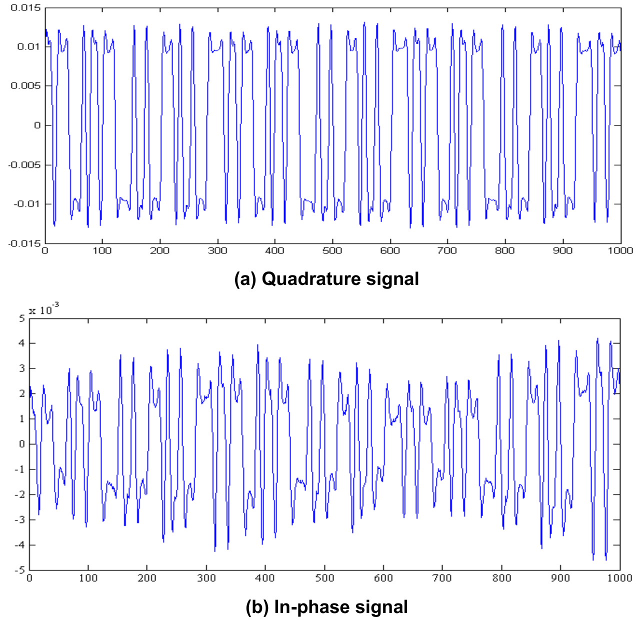

FIGURE 7. A sampling sequence of baseband signal received by wireless network card device.

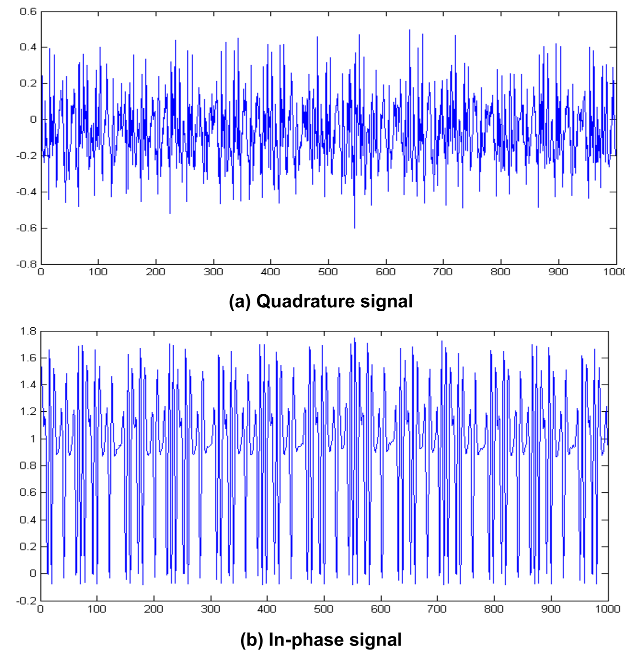

FIGURE 8. An example of processed I/Q signals which perform differential processing after delay.

effectiveness of the proposed approach, two representative methods are implemented for comparison. One is the constellation based contour stellar method [12], and another is the complex convolutional neural network based method without differential processing [30]. For the constellation based contour stellar method [12], the structure of convolutional neural network is presented in Table 1. And for both the complex-valued convolutional neural network based method without differential processing [30] and the proposed

TABLE 1. The structure of convolutional neural network for the constellation based contour stellar method.

Layer	Input	Conv	Max Pooling	Batch Normalization	Conv	Max Pooling	Batch Normalization	Conv
Output shape	227×227×3	55×55×96	27×27×96	27× 27×96	27× 27×256	13× 13×256	13× 13×256	13× 13×384
Layer	Conv	Conv	Max Pooling	Batch Normalization	Flatten	FC/Relu	FC/Relu	FC/Softmax
Output shape	13× 13×384	13×13×256	6× 6×256	6× 6×256	9216	4096	4096	20

TABLE 2. The structure of complex-valued convolutional neural network for both the complex-valued convolution based approach without differential processing [30] and the proposed approach.

Layer	Input	Complex-valued Conv	Average Pooling	Complex-valued Conv	Average Pooling	Complex-valued Conv	Average Pooling	Complex-valued Conv
Output shape	1000×2	500×32	250×32	125×64	62×64	62×128	31×128	31×128
Layer	Average Pooling	Complex-valued Conv	Complex-valued Conv	Average Pooling	Flatten	FC/Relu	FC/Softmax	
Output shape	15×128	15×256	15×256	7×256	1792	2048	20	

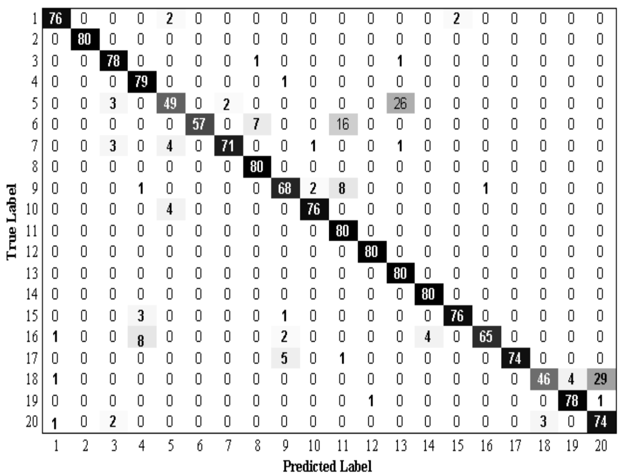

FIGURE 9. The recognition results on the basis of the contour stellar approach [12].

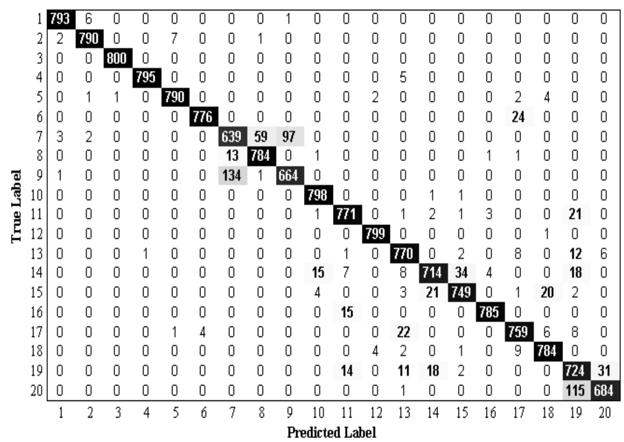

FIGURE 10. The recognition results on the basis of the complex-valued convolutional neural network based approach [30].

method, the structure of the complex-valued convolutional neural network is illustrated in Table 2.

B. EXPERIMENTAL RESULTS AND ANALYSES

At last, the recognition results are obtained over the above three methods, as shown in Fig.9, Fig.10, and Fig.11.

For the constellation based contour stellar method [12], the collected steady-state data transmission section of each sampling sequence, which contains 80,000 points, is used after excluding the channel noise section. The steady-state data transmission section of each sampling sequence is further equally divided into eight segments. Therefore, the total number of sampling sequences is $8 * 50 * 20 = 8000$. And each new sampling sequence is used to generate a contour stellar, and then 320 contour stellars of each device are chosen randomly for training, and the remaining 80 contour stellars of each device are used for testing.

The detailed individual recognition results across different approaches are illustrated in Table 3.

It can be seen from the results that the proposed approach achieves the best identification performance compared with other representative approaches. The total recognition rate by the proposed method can reach 99.7%, and eight wireless network card devices are completely identified correctly. The reason is that the employed differential processing can significantly decrease the unfavorable effect of phase rotation, while the proposed approach can fully capture the nonlinearity of the amplitude & phase information of the differential processed I/Q signals.

According to the experimental results, device 5, device 7, and device 9 are highly misclassified. It can be deduced

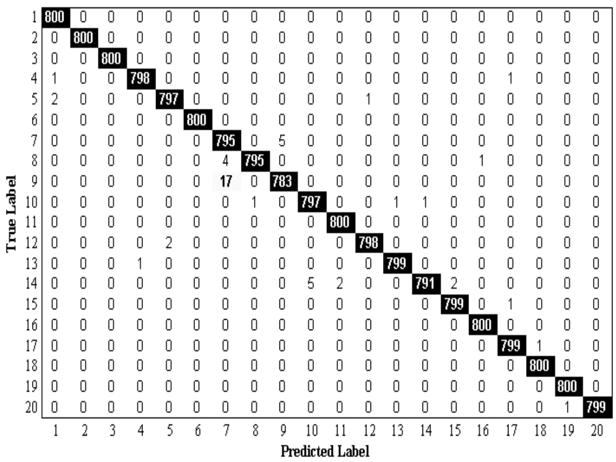

FIGURE 11. **The recognition results on the basis of the proposed approach.**

TABLE 3. **The recognition results of comparison among the experimental three methods.**

device ID	Recognition results		
	Approach 1	Approach 2	Approach 3
device #1	95%	99.1%	100%
device #2	100%	98.8%	100%
device #3	97.5%	100%	100%
device #4	98.8%	99.4%	99.8%
device #5	61.3%	98.8%	99.6%
device #6	71.3%	97%	100%
device #7	88.8%	79.9%	99.4%
device #8	100%	98%	99.4%
device #9	85%	83%	97.9%
device #10	95%	99.8%	99.6%
device #11	100%	96.4%	100%
device #12	100%	99.9%	99.8%
device #13	100%	96.3%	99.9%
device #14	100%	89.3%	98.9%
device #15	95%	93.6%	99.9%
device #16	81.3%	98.1%	100%
device #17	92.5%	94.9%	99.9%
device #18	57.5%	98%	100%
device #19	97.5%	90.5%	100%
device #20	92.5%	85.5%	99.9%
Total	90.4%	94.8%	99.7%

Note: approach 1 is the constellation based contour stellar method [12], approach 2 is the complex-valued convolutional neural network based method without differential processing [31], and approach 3 is the proposed method.

that the RF fingerprints produced by transmitter imperfection of these three electronic devices are difficult to identify, which are highly relevant to the characteristics of transmitter imperfection caused by random factors in the manufacturing process. The different approaches have different feature extraction modules and identification frameworks, which make the devices show different performances, reflecting the recognition ability of different approaches. The proposed approach achieves the best recognition performance, which is the main contribution of our work.

IV. CONCLUSION

Individual recognition approaches with low error rates, high efficiencies, and low costs are critical to guarantee the security of the Internet of Things and maintain steady performance. A novel differential complex convolutional neural network based individual recognition method of communication radiation sources is proposed in the paper. After evaluating the recognition performance of 20 wireless network card devices with duplicate batch, type, and manufacturer, the main conclusions of the paper can be drawn as below:

1) Compared with the other two representative methods of which the recognition accuracies are lower than 95%, the proposed approach achieves the best recognition performance with the total recognition accuracy of 99.7%.
2) The employed differential processing can significantly decrease the unfavorable impact of phase rotation induced by carrier frequency offset and Doppler effect. The proposed approach can fully capture the nonlinearity of the amplitude & phase information of the differential processed I/Q signals.
3) Compared with constellation based methods, which require at least 5,000 to 10,000 data points as input parameters, the proposed method can reduce the required data length of the collected steady-state data transmission section effectively, which is easier to implement in practical applications.

REFERENCES

[1] T. Zheng, Z. Sun, and K. Ren, “FID: Function modeling-based data-independent and channel-robust physical-layer identification,” in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Apr. 2019, pp. 199–207.
[2] Y. Shu, Y. Huang, J. Zhang, P. Coue, P. Cheng, J. Chen, and K. G. Shin, “Gradient-based fingerprinting for indoor localization and tracking,” *IEEE Trans. Ind. Electron.*, vol. 63, no. 4, pp. 2424–2433, Apr. 2016.
[3] J. Li, D. Bi, Y. Ying, K. Wei, and B. Zhang, “An improved algorithm for extracting subtle features of radiation source individual signals,” *Electronics*, vol. 8, no. 2, p. 246, Feb. 2019.
[4] J. Li, Y. Ying, G. Duan, C. Ji, and C. Sun, “Study on radio-frequency signal gene characteristics from the perspective of fractal theory,” *IEEE Access*, vol. 7, pp. 124268–124282, 2019.
[5] Y. Yuan, Z. Huang, H. Wu, and X. Wang, “Specific emitter identification based on Hilbert–Huang transform-based time-frequency-energy distribution features,” *IET Commun.*, vol. 8, no. 13, pp. 2404–2412, 2014.
[6] G. Baldini, R. Giuliani, and G. Steri, “Physical layer authentication and identification of wireless devices using the synchrosqueezing transform,” *Appl. Sci.*, vol. 8, no. 11, p. 2167, Nov. 2018.
[7] X. Chen, J. Li, H. Han, and Y. Ying, “Improving the signal subtle feature extraction performance based on dual improved fractal box dimension eigenvectors,” *Roy. Soc. Open Sci.*, vol. 5, no. 5, May 2018, Art. no. 180087.
[8] A. M. Ali, E. Uzundurukan, and A. Kara, “Assessment of features and classifiers for Bluetooth RF fingerprinting,” *IEEE Access*, vol. 7, pp. 50524–50535, 2019.

[9] A. Aghnaiya, Y. Dalveren, and A. Kara, "On the performance of variational mode decomposition-based radio frequency fingerprinting of Bluetooth devices," *Sensors*, vol. 20, no. 6, p. 1704, Mar. 2020.
[10] Y. Jiang, L. Peng, A. Hu, S. Wang, Y. Huang, and L. Zhang, "Physical layer identification of Lora devices using constellation trace figure," *EURASIP J. Wireless Commun. Netw.*, vol. 2019, no. 1, pp. 1–11, Dec. 2019.
[11] L. Peng, J. Zhang, M. Liu, and A. Hu, "Deep learning based RF fingerprint identification using differential constellation trace figure," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 1091–1095, Jan. 2020.
[12] Y. Tu, Y. Lin, J. Wang, and J.-U. Kim, "Semi-supervised learning with generative adversarial networks on digital signal modulation classification," *Comput. Mater. Continua*, vol. 55, no. 2, pp. 243–254, 2018.
[13] D. A. Knox and T. Kunz, "Wireless fingerprints inside a wireless sensor network," *ACM Trans. Sensor Netw.*, vol. 11, no. 2, pp. 1–30, Mar. 2015.
[14] T. J. Carbino, M. A. Temple, and T. J. Bihl, "Ethernet card discrimination using unintentional cable emissions and constellation-based fingerprinting," in *Proc. Int. Conf. Comput., Netw. Commun. (ICNC)*, Feb. 2015, pp. 369–373.
[15] T. J. Carbino, M. A. Temple, and J. Lopez, "Conditional constellation based-distinct native attribute (CB-DNA) fingerprinting for network device authentication," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2016, pp. 1–6.
[16] K. Merchant, S. Revay, G. Stantchev, and B. Nousain, "Deep learning for RF device fingerprinting in cognitive communication networks," *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 160–167, Feb. 2018.
[17] C. Zhao, M. Shi, Z. Cai, and C. Chen, "Research on the open-categorical classification of the Internet-of-Things based on generative adversarial networks," *Appl. Sci.*, vol. 8, no. 12, p. 2351, Nov. 2018.
[18] L. Ding, S. Wang, F. Wang, and W. Zhang, "Specific emitter identification via convolutional neural networks," *IEEE Commun. Lett.*, vol. 22, no. 12, pp. 2591–2594, Dec. 2018.
[19] C. Zhao, Z. Cai, M. Huang, M. Shi, X. Du, and M. Guizani, "The identification of secular variation in IoT based on transfer learning," in *Proc. Int. Conf. Comput., Netw. Commun. (ICNC)*, Mar. 2018, pp. 878–882.
[20] K. Merchant, S. Revay, G. Stantchev, and B. Nousain, "Deep learning for RF device fingerprinting in cognitive communication networks," *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 160–167, Feb. 2018.
[21] B. Chatterjee, D. Das, S. Maity, and S. Sen, "RF-PUF: Enhancing IoT security through authentication of wireless nodes using *in-situ* machine learning," *IEEE Internet Things J.*, vol. 6, no. 1, pp. 388–398, Feb. 2019.
[22] J. Yu, A. Hu, G. Li, and L. Peng, "A robust RF fingerprinting approach using multisampling convolutional neural network," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 6786–6799, Aug. 2019.
[23] J. Yu, A. Hu, F. Zhou, Y. Xing, Y. Yu, G. Li, and L. Peng, "Radio frequency fingerprint identification based on denoising autoencoders," in *Proc. Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, Oct. 2019, pp. 1–6.
[24] D. Roy, T. Mukherjee, M. Chatterjee, E. Blasch, and E. Pasiliao, "RFAL: Adversarial learning for RF transmitter identification and classification," *IEEE Trans. Cognit. Commun. Netw.*, vol. 6, no. 2, pp. 783–801, Jun. 2020.
[25] M. K. M. Fadul, D. R. Reising, and M. Sartipi, "Identification of OFDM-based radios under Rayleigh fading using RF-DNA and deep learning," *IEEE Access*, vol. 9, pp. 17100–17113, 2021.
[26] J. Ma, H. Liu, C. Peng, and T. Qiu, "Unauthorized broadcasting identification: A deep LSTM recurrent learning approach," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 9, pp. 5981–5983, Sep. 2020.
[27] K. Davaslioglu, S. Soltani, T. Erpek, and Y. E. Sagduyu, "DeepWiFi: Cognitive WiFi with deep learning," *IEEE Trans. Mobile Comput.*, vol. 20, no. 2, pp. 429–444, Feb. 2021.
[28] M. Liu, G. Liao, Z. Yang, H. Song, and F. Gong, "Electromagnetic signal classification based on deep sparse capsule networks," *IEEE Access*, vol. 7, pp. 83974–83983, 2019.
[29] S. Wang, H. Jiang, X. Fang, Y. Ying, J. Li, and B. Zhang, "Radio frequency fingerprint identification based on deep complex residual network," *IEEE Access*, vol. 8, pp. 204417–204424, 2020.
[30] C. Trabelsi, O. Bilaniuk, Y. Zhang, D. Serdyuk, S. Subramanian, J. F. Santos, S. Mehri, N. Rostamzadeh, Y. Bengio, and C. J. Pal, "Deep complex networks," 2017, *arXiv:1705.09792*. [Online]. Available: http://arxiv.org/abs/1705.09792

LONG YING received the B.E. and M.S. degrees in biomedical engineering from Beijing Institute of Technology, Beijing, China, in 2009, and the Ph.D. degree in pattern recognition and intelligent systems from the Institute of Automation, Chinese Academy of Sciences, Beijing, in 2015.

He is currently an Assistant Professor with the School of Computer and Software, Nanjing University of Information Science and Technology, China. His current research interests include multimedia content analysis, machine learning, and graph neural networks.

JINGCHAO LI received the B.S. and M.S. degrees in electrical information engineering from Harbin Engineering University (HEU), in 2010 and 2011, respectively, and the Ph.D. degree from the Faculty of Communication and Information System, HEU, in June 2014. From 2012 to 2013, she was with The University of Electro-Communication (UEC), Japan, as an Exchanged Student. From April 2014 to June 2014, she stayed at Western New England University Springfield, MA, USA, as a Visiting Scholar. She is currently an Assistant Professor with Shanghai Dianji University. Her main research interest includes area of communication signals' recognition, which concludes feature extraction and classifier design. She has published over 40 articles on these topics.

BIN ZHANG (Member, IEEE) received the B.E. degree in automation from Harbin Engineering University (HEU), China, in 2011, and the M.E. and Ph.D. degrees in mechanical engineering and intelligent systems from The University of Electro-Communications (UEC), Japan, in 2013 and 2017, respectively. From April 2017 to March 2018, he worked as an Engineer at Nissan Motor Company Ltd., Japan. He is currently an Assistant Professor with the Department of Mechanical Engineering, Kanagawa University (KU). His research interests include intelligent robotics, human–robot interaction, signal processing, and artificial intelligence.