Electronics, Communications and Networks
A.J. Tallón-Ballesteros et al. (Eds.)

doi:10.3233/FAIA231237

Lightweight Radio Frequency Fingerprint Identification for LoRa

Zhongliang LI [a], Chunlong HE [b,1], Riqing LIAO [a] and Chiya ZHANG [a,c]
[a] *School of Electronic and Information Engineering, Harbin Institute of Technology, Shenzhen, 518055, China*
[b] *College of Information Engineering, Shenzhen University, Shenzhen, 518060, China*
[c] *Peng Cheng Laboratory, Shenzhen 518066, China*

Abstract. Radio frequency fingerprinting is a key technology that plays an important role in enhancing the security of Internet-of-Things applications. In this paper, we present a new radio frequency fingerprinting system based on a novel feature extraction technique. We first convert the collected steady-state signals to grayscale images by byte without the need for any prior knowledge. Next, the collected data is fed into a lightweight neural network called MobileNet for training and classification. To evaluate the performance of the proposed system, we then conduct experiments with 10 Long Range (LoRa) devices and a general software radio receiver. Experimental results show that the proposed model outperforms some mainstream models. Moreover, we input mobile phone device data into our system. Experimental results demonstrate that our proposed model can achieve a significant classification accuracy of 99.23%.

Keywords. Radio frequency fingerprint, lightweight network, LoRa

1. Introduction

By 2030, there will be five billion consumer devices connected to the Internet-of-Things (IoT) [1]. In this context, ensuring the accurate identification of IoT devices becomes crucial for maintaining the security of IoT applications and preventing malicious user attacks. Among the various types of traditional wireless attacks, the most significant threat stems from the use of altered software addresses that carry out impersonation attacks.

The concept of Radio Frequency (RF) fingerprint identification technology was first proposed in 2003 [2]. Due to the unique characteristics exhibited by individual hardware devices during their operation, such as the internal circuitry, this technology is also referred to as fingerprint identification [3].

Long Range (LoRa) is a low-power wireless communication technology known for its long-range capabilities in sub-GHz frequency bands. In addition to its primary use,

[1]Corresponding Author: hclong@szu.edu.cn. This work was supported in part by the National Natural Science Foundation of China under Grant 62101161, in part by the Shenzhen Basic Research Program under Grant JCYJ20220531103008018, and 20200812112423002.

LoRa has gained attention for indoor localization applications [4]. By leveraging the RF fingerprinting method, LoRa can accurately determine the location of devices within indoor environments. This approach offers advantages such as cost-effectiveness, low power consumption, and scalability. Research in this field has explored the use of LoRa for indoor localization, enabling precise positioning without the need for additional infrastructure or complex hardware [5].

RF fingerprint identification is achieved through transient RF fingerprinting, as the steady-state part of the signal is not visible in all transmitters. However, due to the short duration of the transient signal, a higher sampling rate is necessary for extraction. This presents a significant challenge in the field, as the reliability of phase and amplitude information is crucial [6]. Existing solutions to this issue mainly include modulation error [7,8], In-phase/Quadrature (I/Q) imbalance [9], permutation entropy [10], IQ offset and phase error [11], Carrier Frequency Offset (CFO), Hilbert spectrum and constellation analysis.

Steady-state-based methods extracted unique features from the modulated part of the signal. Carroll et al. [8] treated the nonlinear system as a black box with only signal output, and the results showed that the system can better identify the transmitter when the output signal is embedded in a phase space. Methods based on I/Q imbalance have also been used to classify radio frequency identification (RFID) devices. Yan et al. [9] identified MIMO devices based on the modulation domain features of the device, and this method has better stability against feature drift. Huang et al. [10] extracted the normalized permutation entropy of the wireless signal to characterize the individual radiation source, and the recognition rate for different radio stations achieved 95%.

In this paper, we aim to convert the extracted steady-state signal into grayscale image processing. First, we utilize LoRa devices with the same model from the same manufacturer and obtain a new small dataset by collecting signals from these devices. Then we use a lightweight network to classify the processed signals, and the classification accuracy can achieve 99.33%. Moreover, we implement the classification of different types of mobile phone Bluetooth datasets on the RF fingerprint recognition system, and the classification accuracy achieves 99.22%. In addition, we employ some mainstream models including long-short term memory (LSTM) and vision transformer (ViT) to conduct comparative experiments. Experiment results show that these mainstream frameworks are not effective for small datasets, while our proposed RF fingerprint recognition framework can efficiently complete the classification task on small datasets.

The rest of the paper is organized as follows. Section 2 introduces the proposed feature processing method, the lightweight network, and the need to compare with the mainstream frameworks. Section 3 shows the detailed setting for the dataset and the network parameters, and the experimental results. The conclusion of this paper is in Section 4.

This paper makes the following contributions:

- A new method for extracting RF fingerprints based on constructing grayscale images using the amplitude of the signals is proposed.
- An RF fingerprint recognition system is proposed, which achieves higher accuracy compared to state-of-the-art (SoA) models.
- The utilization of lightweight networks enables easier training of the model and reduces the performance requirements of the RF fingerprint recognition system on devices.

Figure 1. Huawei Mate10 mobile phone signal feature map.

2. Methodology

2.1. Signal Feature Extraction Processing Method

In this paper, we propose a novel approach for extracting features from RF fingerprints, which uses signal assignments as pixel gray values to create an image that denotes a feature map. Specifically, it first intercepts the steady-state portion of the signal, which has 160,000 assignment points. Each assignment point is linearly assigned a value between 0-255, representing the grayscale of the pixels in the image. This creates an image with dimensions of 400×400, which is then resized to 224×224 to create a feature map for the device. Fig. 1 shows a sample feature map for the Huawei Mate10. It can be seen that the signal assignments are represented as grayscale values of the picture's pixel points.

We shall note that this method does not need any modulation information of the signal, such as operating frequency, bandwidth, delay, and spectrum. Instead, it is treated as a form of text, with the pixel's gray value serving as a feature. The requirements for the number of samples are minimal, and an accuracy rate of 99.23 % can be achieved with just 300 samples per classification. A lightweight neural network is then employed to accomplish fast and efficient classification tasks.

2.2. Small Data Size Processing by Lightweight Networks

Convolutional neural networks (CNNs) have made a lot of advancements in computer vision tasks, such as image recognition and object detection. However, the deployment of CNN on mobile devices remains a challenge because of the large size and slow speed of existing models. To solve this problem, some researchers have proposed many model compression techniques such as pruning, quantization, and knowledge distillation. Others have concentrated on designing efficient network structures like MobileNet [12] and ShuffleNet [13]. The Mobile module stands out because it can generate more feature maps with fewer parameters. Compared to a standard CNN, the Mobile module reduces the total number of parameters and computational complexity without changing the size of the output feature map. Therefore, we present an RF fingerprinting system based on the feature processing method and the MobileNet network. The system design is given in Fig. 2, and the structure of the RF fingerprint recognition system is illustrated in Fig. 3.

As shown in Fig. 2, the model of the RF collection device uses USRP L101-P, where the RF signal emitted by the RF device can be expressed as

$$X(t) = ((a_I x_I(t) + b_I) + j\,(a_Q x_Q(t) + b_Q))\,e^{-j2\pi f_{ct} t}, \tag{1}$$

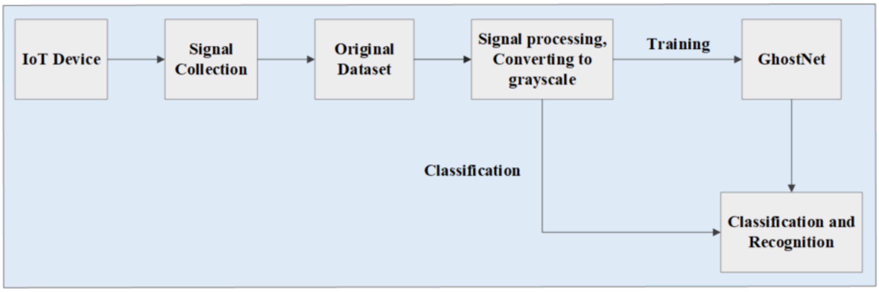

Figure 2. RF fingerprint identification system.

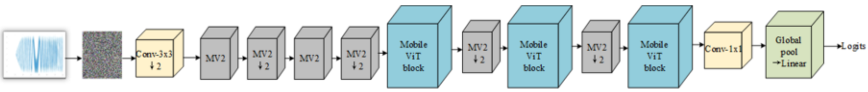

Figure 3. The structure of the RF fingerprint recognition system, where MV2 refers to MoblieNet2 block and $\downarrow 2$ means down-sampling.

where $x_I(t)$ and $x_Q(t)$ are the two branches of the I and Q channels, f_{ct} is the carrier frequency of the transmitting signal device, a is the direct current offset of both I and Q channels, and b denotes the gain. Assume that the channel and receiver are ideal, the received signal can be expressed as

$$Y(t) = y_I(t) + jy_Q(t) = X(t)e^{j2\pi f_{cr} t}, \tag{2}$$

where $y_I(t)$ and $y_Q(t)$ are the baseband signals received by the two branches of the I and Q channels, respectively. f_{cr} is the carrier frequency of the receiver. Although additional noise may influence the accuracy of the system judgment, our method does not use frequency domain information. Therefore, it can achieve a high classification rate.

2.3. LSTM and ViT

In this part, we employ two mainstream models: LSTM and ViT for comparative experiments on the LoRa dataset. In specific, the LSTM model is designed to address the issue of gradient dispersion in RNN models. Self-attention-based architectures, particularly transformers, have become the preferred models in natural language processing (NLP). Their major approach involves pre-training on large text corpora and then fine-tuning on small and task-specific datasets. In this paper, we utilize the ViT model to train an image classification model in a supervised manner. Based on this discussion, we can conduct comparative experiments using the aforementioned three networks.

3. Experiments Result

3.1. Mobile Phone Bluetooth Dataset and Collected LoRa Device Dataset

This dataset includes 10 common mobile phones: iPhone 5s, iPhone 6s, iPhone 7, Samsung Note 3, Samsung S3, Samsung S4, Sony C4, Huawei Mate 10, and Xiaomi 6. The dataset is stored in the form of signal assignment text. Each category contains RF signals from two mobile phones, with 300 samples collected from each phone.

Figure 4. LoRa devices.

Figure 5. The device of USRP N210.

The main devices used in the process of signal collection include a signal transmission device and an RF signal acquisition machine. The signal transmission device used is the 'Smart IoT' company's WH-L102-L-P low-power module, and the RF signal collection device is the USRP N210 device. In this collection process, the transmission power was set at 20dB, the center frequency was 433MHz, and the receiver sensitivity was set to 25dB.

The Fig. 4 shows two Lora terminal devices emitting signals, the Fig5 shows a USRP N210 device used for receiving Lora signals. The Lora terminal devices transmit RF signals, which are captured by the USRP device. The USRP device is connected to a high-performance computer through a gigabit Ethernet port for data interaction. Signal processing is conducted to obtain Lora RF fingerprints.

Without loss of generality, we use software radio technology to collect the RF signal datasets from 10 LoRa devices of the same model and manufacturer. The LoRa devices can communicate with each other. A software radio is used as the receiver to capture the signal from the LoRa device and store the received signal assignment as a binary signal. A small dataset is created by collecting 300 samples per device. This dataset stores the value points of the signal in text form with a sampling rate of 2M.

3.2. Performance of the Proposed Method

In the experiments all parameters of the neural network were set to the same values. The batch size was set to 32, with an epoch of 80. The dropout rate applied was 0.2, and the learning rate was set to 0.001. The data were divided as follows: 70% for the training set, 10% for the validation set, and 20% for the testing set.

Fig. 6 shows the confusion matrix for the mobile phone Bluetooth dataset using MobileNet. It can be seen from the matrix that the probability of correct classification can be accurately predicted for most classifications.

Fig. 7 shows the iterative curve of prediction accuracy and loss for the mobile phone Bluetooth dataset. We can see that the accuracy achieve 0.8 in less than 100 epochs and reaches 0.9923 after 400 epochs. The loss also decreases significantly, dropping to 0.3 in a short time and finally approaching 0.

Since this dataset is classified based on different types of devices, which naturally have differences between them. Therefore, it is not sufficient to demonstrate the strengths

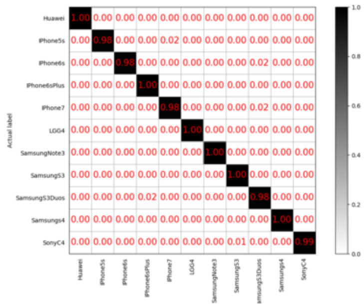

Figure 6. Mobile phone Bluetooth dataset confusion matrix.

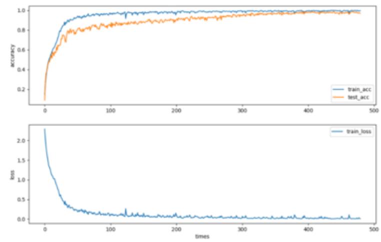

Figure 7. Accuracy and loss value of mobile phone Bluetooth dataset.

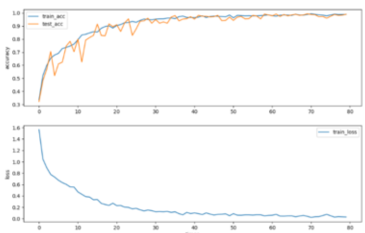

Figure 8. Accuracy and loss value of LoRa device using MobileNet model.

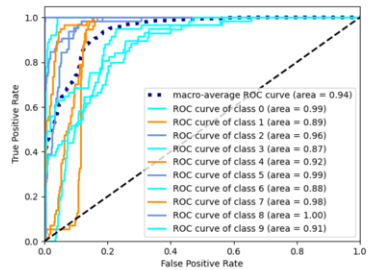

Figure 9. ROC of LSTM.

and weaknesses of the RF fingerprint identification system. To further evaluate the system performance, we conduct the following experiments where RF signals from LoRa devices of the same model and manufacturer are collected and the RF fingerprint identification system is used. A mainstream classification framework is also used as a baseline. It can be observed from the experimental result that our proposed scheme is much more effective than the mainstream framework.

Fig. 8 illustrates the classification results using the proposed RF fingerprinting system on the LoRa dataset, where the MobileNet model is employed for classification. Initially, each classification is vertical, meaning that the prediction accuracy is close to 1. This demonstrates that, even with a small dataset, the RF fingerprint identification system can rapidly achieve a high accuracy rate using a lightweight network. Furthermore, with a very small sample size and equipment from the same model and manufacturer, this method can still achieve an accuracy of 0.9933 in a very short time.

3.3. Comparative Experiments on the LoRa Device Dataset

From Figs. 9 and 10, we can see that the accuracy of the LSTM model only achieves 0.7 and does not work well on small datasets.

Fig. 11 shows the accuracy and loss value of the ViT model for the classification of the LoRa RF signal dataset. In the training set, after 400 epochs, it shows a gradual stabilization trend, and its highest accuracy can only achieve 93.14 %. In the test set, the

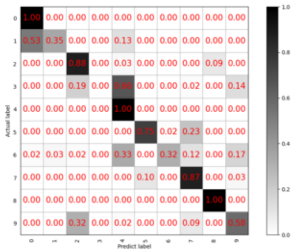

Figure 10. Confusion matrix of LSTM.

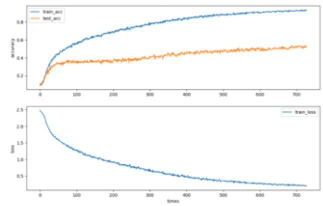

Figure 11. Accuracy and loss value of ViT.

Table 1. Contrastive block diagram of the conclusion

Number	Classification	Dataset	Technique	Accuracy
1	Multiclass(10)	Bluetooth	MobileNet	99.23%
2	Multiclass(10)	LoRa	MobileNet	99.33%
3	Multiclass(10)	LoRa	LSTM	70%
4	Multiclass(10)	LoRa	ViT	80%

highest accuracy is 53.79% after 700 epochs. It can be seen that the large mainstream network does not work well for small datasets. The reason is that the ViT model has certain requirements on dataset size.

Table I presents the results of the entire experiment. We can observe that when the obtained steady-state signal is linearly transformed into the pixel point of a grayscale image as well as used as a feature map, the MobileNet network can process and achieve high classification accuracy on both the mobile phone Bluetooth dataset and the LoRa device dataset. Instead, when conducting comparative experiments on LoRa devices, the classification accuracy of LSTM and ViT is much lower because of the insufficient data samples. Additionally, it is verified that the proposed feature extraction method is also effective for small datasets, and the device identification using non-mainstream frameworks is accurate as well. Furthermore, the proposed RFID method can process signals in a short time, extract corresponding features, and achieve a high classification rate.

4. Conclusion

In this paper, we have proposed an efficient framework for RF fingerprint recognition, which mainly consists of processing steady-state signals by converting them into grayscale images. Experiments have shown that using the MobileNet network achieves better results than existing mainstream frameworks, including the LSTM and ViT models. This RF fingerprint identification system has a relatively new guiding significance in signal feature processing. Besides, from the comparison of experimental results and the speed of classification, it can be seen that the extraction of signal features does not depend on prior knowledge. Therefore, it significantly reducing the cost of RF fingerprinting. For future research, we plan to conduct additional experiments related to noise to further explore the proposed model.

References

[1] L. S. Vailshery, "Number of IoT connected devices worldwide 2019-2030. [Online], https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/ Published Jun. 2022.

[2] J. Hall, M. Barbeau, and E. Kranakis, "Detection of transient in radio frequency fingerprinting using signal phase," Wireless and Optical Communications, pp. 13–18, 2003.

[3] N. Soltanieh, Y. Norouzi, Y. Yang, and N. C. Karmakar, "A review of radio frequency fingerprinting techniques," IEEE Journal of Radio Frequency Identification, vol. 4, no. 3, pp. 222–233, 2020.

[4] Simka M, Polak L. "On the RSSI-based indoor localization employing LoRa in the 2.4 GHz ISM band[J]," Radioengineering, 2022, 31(1): 135-143.

[5] L. Polak, F. Paul, M. Simka, R. Zedka, J. Kufa and R. Sotner, "On the Interference between LoRa and Bluetooth in the 2.4 GHz Unlicensed Band," 2022 32nd International Conference Radioelektronika (RADIOELEKTRONIKA), Kosice, Slovakia, 2022, pp. 1-4.

[6] Y. Lin, X. Zhu, Z. Zheng, Z. Dou, and R. Zhou, "The individual identification method of wireless device based on dimensionality reduction and machine learning," The Journal of Supercomputing, vol. 75, no. 6, pp. 3010–3027, 2019.

[7] I. O. Kennedy, P. Scanlon, F. J. Mullany, M. M. Buddhikot, K. E. Nolan, and T. W. Rondeau, "Radio transmitter fingerprinting: A steady state frequency domain approach," in 2008 IEEE 68th Vehicular Technology Conference, Calgary, Alberta, Canada, 2008, pp. 1–5.

[8] T. Carroll, "Phase space method for identification of driven nonlinear systems," Chaos (Woodbury, N.Y.), vol. 19, no. 3, p. 033121, 2009.

[9] Y. Shi and M. A. Jensen, "Improved radiometric identification of wireless devices using mimo transmission," IEEE Transactions on Information Forensics and Security, vol. 6, no. 4, pp. 1346–1354, 2011.

[10] G. Huang, Y. Yuan, X. Wang, and Z. Huang, "Specific emitter identification based on nonlinear dynamical characteristics," Canadian Journal of Electrical and Computer Engineering, vol. 39, no. 1, pp. 34–41, 2016.

[11] V. Brik, S. Banerjee, M. Gruteser, and S. Oh, "Wireless device identification with radiometric signatures," in Proceedings of the Annual International Conference on Mobile Computing and Networking (MOBICOM), San Francisco, California, USA, 2008, pp. 116–127.
1095, 2019.

[12] Howard A G, Zhu M, Chen B, et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications". arXiv preprint arXiv:1704.04861, 2017.

[13] Zhang X, Zhou X, Lin M, et al. "Shufflenet: An extremely efficient convolutional neural network for mobile devices"//Proceedings of the IEEE conference on computer vision and pattern recognition. 2018: 6848-6856.