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An Effective Radio Frequency Signal Classification Method Based on Multi-Task Learning Mechanism

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***Abstract*—With the increasing popularity of Internet of things (IoT), the emergence of many IoT devices has led to security vulnerabilities. The classification of wireless signals is very important for secure communications. Most of existing signal classification tasks only focus on single signal classification task, while ignoring the relationship between radio frequency fingerprinting identification (RFFI) and automatic modulation classification (AMC). To solve the multi-task classification problem, this paper designs a multi-task learning convolutional neural networks (MTL-CNN). Real-radio datasets are generated by Signal Hound VSG60A and collected by Signal Hound BB60C to solve the lack of RFF samples with numerous modulation types. Experimental results confirm that the MTL-CNN method can work well by using the generated dataset. The MTL network designed in this paper improves the accuracy of RFFI by 1% relative to the single-task learning (STL) network. The keras code is released at https://github.com/LiuK1288/lhw-000.**

***Index Terms*—Radio frequency fingerprint, automatic modulation classification, deep learning, multi-task learning.**

I. Introduction

In recent years, with the rapid development of wireless communication technology, a large number of internet of things (IoT) devices have appeared, such as smart healthcare, smart transportation, smart education, smart home and smart education, among others [1]–[3]. A large number of IoT devices will cause security vulnerabilities [4]–[6]. For example, when IoT devices such as cameras and floor sweepers are attacked, their endpoint data can easily be leaked. If outlaws use the leaked data, it will reveal the user's privacy and even threaten the user's life.

Wireless signal classification is an emerging technique to identify and mitigate security weaknesses. Wireless signal classification mainly contains automatic modulation classification (AMC) [7]–[11] and radio frequency fingerprinting identification (RFFI) [12]–[14]. The signal receiver has to demodulate the signal according to the modulation type of the signal. However, the receiver does not know the modulation type of the transmitted signal in non-cooperative communication scenarios. If the signal receiver can automatically identify the modulation type of the signal, this will reduce communication overhead as well as recognize the unknown signal [15]. AMC is a new technology, which can be used by the signal receiver to automatically identify the modulation scheme of the signal. Radio frequency fingerprinting (RFF) is a unique physical layer feature of wireless devices that originates from random hardware defects in the manufacturing process, RFF usually manifests as harmonic distortion, direct-current (DC) biasing, phase noise, filter error, local oscillator leakage, I/Q gain imbalance, orthogonal offset, nonlinearity [16], [17] and carrier frequency offset.

With the rapid development of deep learning, deep learning has made remarkable achievements in computer vision [18], natural language processing [19] and intelligent communication technologies. However, deep learning needs a large-scale and high-quality dataset. At present, most of the emitter identification datasets contain only one modulation scheme [20]–[24]. Most current RFFI studies are based on specific signals with one modulation scheme in the past research. These methods do not consider the effect of modulation scheme on RFF. Theoretically, the same device should be able to extract its fingerprint features even if it sends signals with different modulation schemes. However, the extracted device fingerprint features are closely related to the modulation mode of the signal, modulation parameters, etc. For example, many radio devices can operate in different modes transmitter signals with varying schemes of modulation and parameters. If the convolutional neural network only considers RFFI for one modulation type, when the radio device transmits another modulation type, the convolutional neural network may incorrectly identify this device. This paper considers RFFI of various modulation types. The main contributions of this paper are as follows:

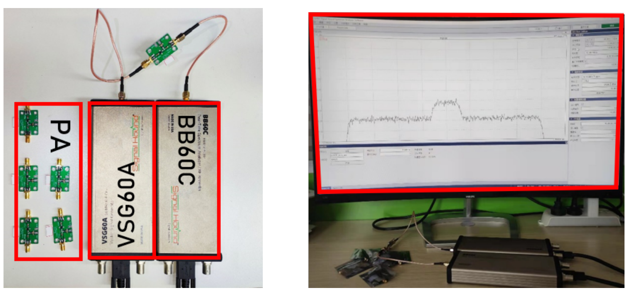
- This paper designs a multi-task learning network (MTL-CNN). MTL solves two signal classification (i.e., RFFI, AMC) tasks with small increase parameters and computational effort. The MTL network designed in this paper has better identification results in RFFI compared to STL.
- BB60C is used to collect a dataset containing six power amplifiers of eight modulation schemes to solve the lack of MTL datasets. This dataset will be publicly released in the future.

The rest of this paper is organized as follows: in section II, this paper introduces signal collection and preprocessing. A MTL-CNN based multi-task identification method is proposed in Section III. The experiments are conducted and simulation results of MTL and single-task learning (STL) are shown in Section IV. Section V concludes our work in this paper.

II. Data Collection and preprocessing

A. Data Collection

As shown in Fig. 1, the collection device consists of a signal generator (VSG60A), a signal receiver (BB60C), a personal computer (PC) and six target power amplifiers (PAs). The stable hardware features of the transmitter, such as the signal's amplitude, phase and frequency distortion, can be reflected in the power amplifier's nonlinear distortion. As a result, the nonlinear distortion of the power amplifier is typically regarded as the main cause of RFF [25]. VSG60A can set many built-in parameters, such as symbol rate, modulation type and transmission power. BB60C has 27 MHz of real-time bandwidth, tunes from 9 kHz to 6 GHz, collects 80 million samples per second, and streams data to computer at 140 MB/sec.



(a) VSG60A, PAs, and BB60C (b) software interface

Fig. 1. Signal collection system.

The VSG60A is connected to the computer via USB 3.0. The power amplifier is connected to BB60C and VSG60A respectively via SMA RF coaxial connection cable. The BB60C transfers the acquired signals to the PC via USB 3.0. Many parameters of BB60C can be changed by spike spectrum analysis software. The obtained signal's center frequency is 2.4 GHz, and the sampling rate is 10 Msample/s. The raw I/Q data is 17.8 GB in size and comprises a total of eight modulation schemes, i.e., BPSK, QPSK, 8PSK, 16PSK, 16QAM, 64QAM, 256QAM, and 1024QAM from 6 PAs. Table I displays specific equipment.

TABLE I
Number of each devices.

Experiment parameters	Default setting
Number of device	6
Number of modulation	8
Center frequency	2.4 GHz
Symbol rate	1 MHz
Sampling frequency	10 MHz
Signal generator	VSG60A
Spectrum analyzer	BB60C

B. Data Preprocessing

The received signal can be expressed as:

$$y(n) = x(n) + w(n), \tag{1}$$

where $y(n)$ and $x(n)$ represent the transmitted and received signals, $w(n)$ is noise. The analog signal generated by the VSG60A is passed through a power amplifier and collected by the BB60C. The BB60C converts it into a digital signal for transmission to the computer. The sample rate of the BB60C is 10 MHz, the symbol transmission rate of the VSG60A is 1 MHz. The gathered signal's signal-to-noise ratio (SNR) is 20 dB. MATLAB is used to analyze the collected signals, MATLAB's AWGN function is used to add noise to the processed data. The SNR range for it is $\{0, 5, 10, 15, 20\}$ dB. The data is normalized and sliced, the dimension of the sliced data is 6000×2. The normalization function used to process the data is:

$$\widetilde{y_i} = \frac{y_i}{|y_i|_{\max}}, i\epsilon[1, N], \tag{2}$$

where $\widetilde{y_i}$ represents normalized data, y_i indicates the original time-domain signal data, $|y_i|_{\max}$ is the maximum absolute value of y_i. This paper also performs power normalization for RF signals with different modulation types. The normalized sample of the PA signal is shown in Fig. 2.

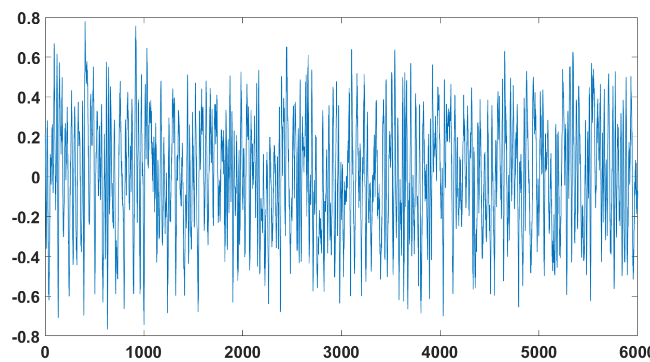


Fig. 2. PA time-domain sample after normalization.

This paper collects eight schemes of modulation signals (Dataset A) and selects them. The selected dataset (Dataset B) accounts for 1/8 of the total dataset. The dataset contains eight modulation schemes of six PAs. The extraction model is shown in Fig. 3. The black-box is a window. Select one of the

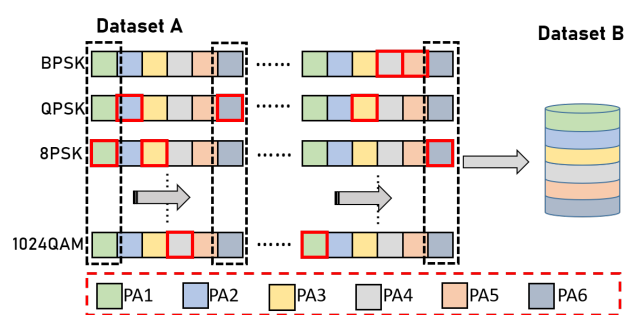


Fig. 3. Signal extraction model.

8 modulation schemes, which is marked by red box. Dataset A is a complete dataset. In order to facilitate the experiment,

this paper extracted one eighth of Dataset A as Dataset B for multi-task learning.

III. The Proposed MTL-CNN-based Multi-task Classification Method

Complex tasks can be decomposed into multiple single tasks and solved separately. Then combine the conclusions to obtain the results of complex problems. Many problems in the actual world cannot be divided into a single, independent subproblem, and even when they can, the various subproblems are interconnected. Some shared characteristics or shared representations bind them together. Treating real world problems as a single independent task ignores the related information between different problems. For example, numerous modulation schemes are possible for wireless RF signals, and there is a connection between these schemes and RFF. The majority of present deep learning-based signal identification tasks are single-task. MTL network puts multiple related tasks together to learn. Multi-tasks share some factors between them, and they can share the information they have learned during the learning process.

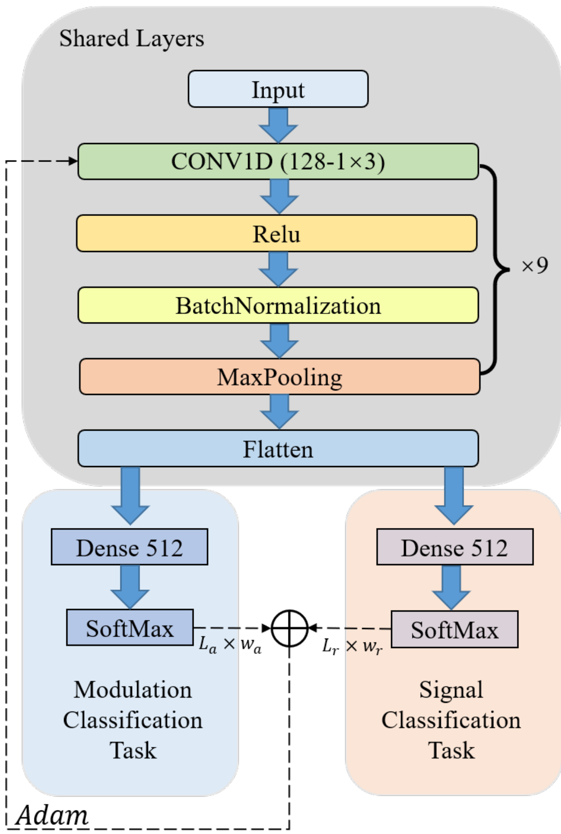


Fig. 4. The framework of the proposed MTC-CNN method for multi-task classification.

MTL is now widely used in computer vision and natural language processing. There are still few applications in signal identification. This paper uses RFFI and AMC as two subtasks of MTL. Given an input signal, the MTL network identifies both different devices and their modulation schemes. L_r denotes the loss function of RFFI, L_a denotes the loss function of AMC, and L_{MTL} denotes the loss function of MTL. The overall MTL loss function is represented as a weighted sum of losses over the two tasks as:

$$L_{MTL} = w_r L_r + w_a L_a, \tag{3}$$

where w_r and w_a denote the weights of RFFI and AMC, respectively. W_{sh} denotes the parameters of the shared layer and its gradient descent is expressed as:

$$W_{sh} = W_{sh} - \gamma(w_r \frac{\partial L_r}{\partial W_{sh}} + w_a \frac{\partial L_a}{\partial W_{sh}}), \tag{4}$$

where W_{sh} is affected by all the losses. The influence of different losses on W_{sh} can be achieved by adjusting the weights w. The network structure is shown in Figure 4. The MTL network in this paper used hard parameter sharing [26], which shares the hidden layers between all tasks while preserving the task-specific layers. The MTL-CNN network has nine convolution layers. The shared layers have nine convolutional layers and one Flatten layer, and the unique layers have two fully connected layers. Each convolutional layer has 128 convolution cores, the size of each core is 1 $\times$ 3. The MaxPooling size is 1 $\times$ 2. We only set a dropout behind the fully connected layer, and the dropout rate is 0.5.

IV. Experimental Setting and Results

In this section, firstly, the simulation environment and some simulation parameters of this paper are introduced. Secondly, it is verified that Dataset A can be used for RFFI, and the simulation results of Dataset A are shown. Thirdly, this paper shows the effect of different weights among multi-tasks on the identification accuracy. Finally, it is verified that Dataset B can be used as a dataset for RFFI and AMC. This paper uses MTL to improve the generalization performance and accuracy of RFFI.

A. Experimental Environment

Data preprocessing and noise addition are done using MATLAB 2021.b. The convolutional neural network used in this paper is based on Python. We implement our models in Keras with Tensorflow backend on Ubuntu 16.04.7 virtual machines running on four Geforce GTX 1080 Ti GPUs. The parameters of this simulation are shown in table II.

TABLE II
Parameters setting in experimental simulation.

Items	Setting
Data dimension	6000 $\times$ 2
Optimizer	Adam
Batch-size	32
Learning rate	0.001
Epoch	100
Patience	32
Total number of samples	36000
Ratio of training, validation, and test	7:2:1
SNRs	{0, 5, 10, 15, 20}dB

B. The Influence of RFFI Performance with Different Modulation Schemes

This part aims to verify whether each modulation schemes in Dataset A can be used as a dataset for RFFI and investigate the effect of different modulation schemes on RFFI. The network is devised as convolutional, long short-term memory, fully connected deep neural networks (CLDNN). The CLDNN network has three convolution layers, each convolutional layer has 128 convolution cores and the size of the convolution cores is 1×10. The Maxpooling size is 1×2. The dropout rates are set to 0.2 in both the convolutional and fully connected layers. The simulation results are shown in Fig. 5, the modulation scheme affects the accuracy of the RFFI. The accuracy of RFFI is proportional to the order of the modulation scheme. Under the SNR= 20 dB condition, the RFFI accuracy of all modulation schemes has reached more than 99% except for 1024QAM, whose accuracy is only 93.92%.

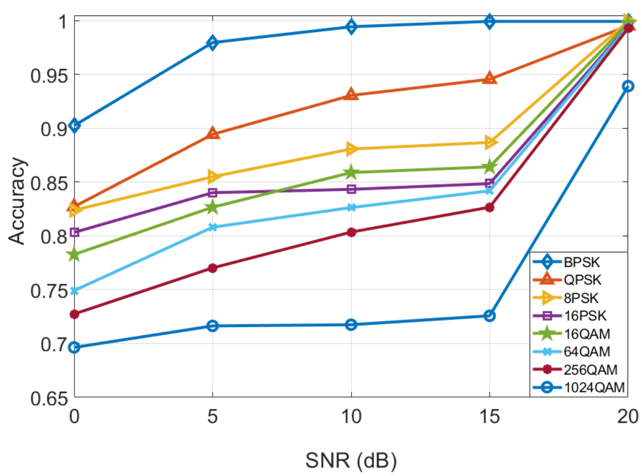


Fig. 5. Identification accuracy for different modulation methods.

C. Effect of Task Weight

The effect of different loss weights on MTL identification accuracy for MTL is studied here. This paper verifies the effect of different loss weights on the identification accuracy of RF signals at two SNRs, i.e., 0 dB and 20 dB. The network is devised as MTL-CNN. Fig. 6 shows the effect of different loss weights on the signal identification accuracy at 0 dB and 20 dB. The weight distribution of the two tasks varies from 0 to 1 in steps of 0.1. The boundary of the Fig. 6 is a task with a weight of 1. It can be seen that there is almost no difference between the identification accuracy of RFFI and AMC when the weights of RFFI range from 0.1 to 0.9. We decide the loss weights for both tasks at w_r = 0.8 and w_a = 0.2 for the proposed MTL-CNN.

D. Multi-Task Learning and Single-Task Learning

This part aims to verify whether Dataset B can be used for MTL and whether MTL network can improve the identification

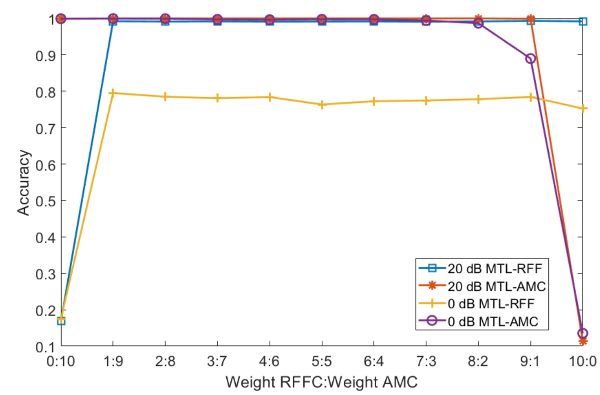
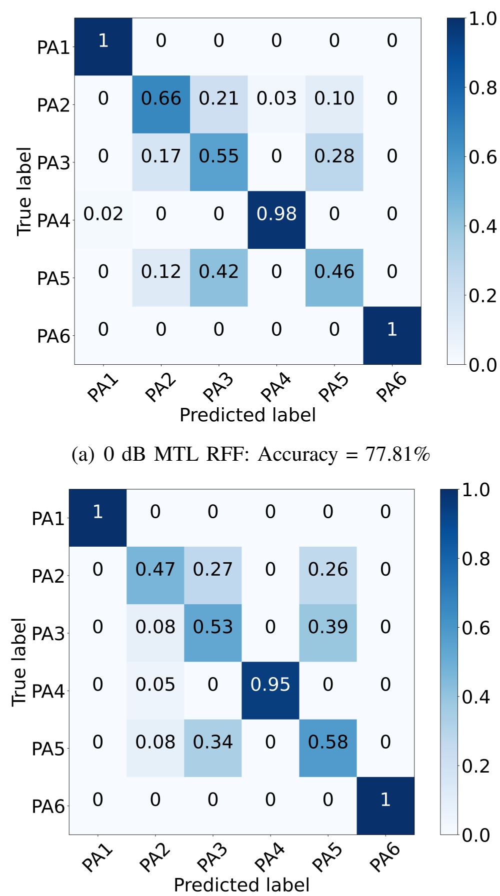


Fig. 6. Effect of task loss weight distribution on AMC and RFFI at 20 dB and 0 dB.



(a) 0 dB MTL RFF: Accuracy = 77.81%

(b) 0 dB STL RFF: Accuracy = 75.67%

Fig. 7. Confusion matrices comparison of the proposed MTL-CNN method.

accuracy of RFF. The simulation results are shown in Table III. From Table III, we can see that MTL improves the accuracy of RFFI while ensuring the accuracy of AMC is close to 100%. The multi-task executes the two signal identification tasks simultaneously with fewer parameters by combining the characteristics of RFFI and AMC to discover the relationship. This paper also plots the two confusion matrices Fig. 7 for

TABLE III
CLASSIFICATION ACCURACY OF THE PROPOSED MTL-CNN METHOD.

SNR (dB)	**0**	**5**	**10**	**15**	**20**
STL-RFF	75.67%	80.67%	85.47%	91.17%	99.17%
MTL-RFF	**77.81%** (2.14%↑)	**81.67%** (1.00%↑)	**86.03%** (0.56%↑)	**91.56%** (0.39%↑)	**99.19%** (0.02%↑)
STL-AMC	**99.92%**	**100%**	**99.94%**	**99.94%**	99.94%
MTL-AMC	98.69% (1.23%↓)	99.42% (0.58%↓)	99.81% (0.13%↓)	99.69% (0.25%↓)	**100%** (0.06%↑)

the RFFI of STL and MTL at 0dB, and we can see that MTL improves the identification accuracy of PA2, PA3, and PA4.

V. CONCLUSION AND FUTURE WORKS

In this paper, we propose a MTL-CNN method to solve two identification tasks, i.e., AMC and RFFI. The proposed MTL-CNN method can achieve better identification performance than existing methods especially at the low SNR scenario. We collect a RFF dataset which includes eight modulation schemes. The dataset is validated by the network designed in this paper. This paper finds that different modulation types have an effect on the accuracy of RFFI. We hope it can be used to attract more researchers in the field and can provide better deep learning methods to improve identification performance.

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