Radio Frequency Fingerprint Recognition Based on Kalman Filtering and Random Matrix Theory

Yousong Zhang*, Jian Xiong*, Bo Liu† and Tianyi Huang*
*Department of Electronic Engineering, Shanghai Jiao Tong University, Shanghai, China
†School of Computer Science, University of Technology Sydney, Ultimo, NSW, Australia
Email:{$zhangyousong, xjarrow$}@sjtu.edu.cn

***Abstract*—Radio frequency fingerprint (RFF) technology is instrumental in achieving secure and dependable device identification by exploiting the unique imperfections inherent in hardware. Nonetheless, factors such as interference from noise, the complexities of multipath propagation, and fluctuations in environmental conditions can severely compromise the accuracy of RFF recognition. In this study, we introduce an innovative RFF recognition approach that melds Kalman filtering with random matrix theory (RMT) to enhance recognition accuracy. The Kalman filter is utilized to refine the raw I/Q data, mitigating noise and elevating signal integrity. Concurrently, RMT harnesses the eigenvalue distributions to discern the global characteristics of the signals. These refined features are subsequently input into a deep learning classifier to facilitate device identification. Our experimental findings, based on a substantial dataset, ascertain that the proposed method significantly surpasses conventional techniques in terms of recognition accuracy and robustness.**

***Index Terms*—Radio Frequency Fingerprint, Kalman Filtering, Random Matrix Theory, Convolutional Neural Network, Raw I/Q**

I. Introduction

With the rapid development of communication technology, radio frequency fingerprint (RFF) technology has attracted more and more attention due to its potential in device identification and network security. RFF is based on the inevitable minor defects in the hardware characteristics of the transmitting device, and accurately identifies the device by extracting the unique signal characteristics of the device. Since the hardware characteristics are difficult to replicate, RFF provides highly reliable security and uniqueness, becoming a promising physical layer authentication method [1].

Although RF fingerprints have natural uniqueness and anti-attack capabilities, their extraction and classification still face many challenges in complex wireless communication environments. Signals may be affected by multipath effects, noise, interference, and environmental changes, resulting in weakening and confusion of RF characteristics [2].

This paper proposes a RF fingerprint recognition method that combines Kalman filter and random matrix theory. First, the Kalman filter is used to preprocess the raw I/Q data to optimize signal quality and suppress noise interference. With its excellent performance in dynamic estimation and noise suppression, the Kalman filter can effectively eliminate multipath interference, phase noise and frequency offset in the signal, thereby enhancing the stability of the RF feature. Subsequently, the global features in the preprocessed signal are extracted using random matrix theory to generate a unique RF fingerprint of the device. Finally, these features are input into a deep learning classifier to complete device identification.

The main contributions of this paper include: (1) a signal preprocessing method based on Kalman filter is proposed to effectively enhance the robustness of RF fingerprint features; (2) combined with random matrix theory, an efficient RF fingerprint feature extraction method is constructed; (3) the superior performance of this method in low signal-to-noise ratio and complex environments is verified. Experimental results show that the framework proposed in this paper significantly improves the accuracy and robustness of RF fingerprint recognition, providing a new research idea for device identification in communication systems.

The remainder of the article is organized as follows. Some related works will be presented in Section II. The system model and our methodology will be introduced in Section III. The network and experiment design as well as simulation results are presented in Section IV, and the the paper is summarized in Section V.

II. Related Works

There are two main methods for RF fingerprinting: traditional methods and deep learning methods. Traditional methods usually involve the extraction of modulation features or statistical features based on the signal, followed by classification through machine learning algorithms. Common feature extraction methods include modulation features (such as frequency error, phase error, amplitude error [3]) and statistical features [4] (such as mean, standard deviation, power spectral density, etc.). For example, Jagannath et al. [5] proposed an RF fingerprinting method based on frequency offset and constellation diagram analysis; Abbas et al. [6] used time domain statistical features for classification, and Medaiyese et al. [7] used support vector machines (SVM) to classify the extracted signal features. Although these methods perform well in some specific scenarios, their performance is susceptible to noise

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Jian Xiong is with the Institute of Image Communication and Network Engineering, Shanghai Jiao Tong University and Zhengzhou Industrial Technology Research Institute of Shanghai Jiao Tong University(ZZITRISJTU), Shanghai 200240 China (e-mail: xjarrow@sjtu.edu.cn).

and signal distortion due to their reliance on artificial feature design [8].

In recent years, deep learning methods have been widely used in RF fingerprinting, especially classification methods based directly on raw I/Q data [9]. Deep learning methods can automatically extract time-frequency features from raw data, thereby reducing reliance on domain knowledge and artificially designed features. Yang et al. [10] proposed a method for classification based on convolutional neural networks (CNNs) to process raw I/Q data. This method can automatically learn the time-frequency characteristics of the signal and directly classify it. In addition, another type of deep learning method is to perform deep learning classification after feature extraction. Basak et al. [11] created a novel and realistic dataset using nine commercial drones and a WIFI signal, and proposed a new deep residual neural network to classify single and multi-drone scenarios using frequency RF fingerprints. Al-Sa'd et al. [12] exploited frequency domain features to detect and classify multiple drones, using a three-layer fully connected (FC) deep neural network (DNN) to detect and identify drones. Q. Wang et al. [13] introduced a robust RF-based UAV sensing approach using MVDR spectrum and a hybrid UAV-CTNet deep-learning network for detection and identification. Although deep learning methods are more robust than traditional methods and can adapt to complex environments, they still face certain challenges in dealing with noise and signal distortion [14].

III. System Model And Methodology

A. System Model

In the RF fingerprint problem, the goal is to uniquely identify the transmitting device through the characteristics of the physical layer of the wireless signal. This identification process relies on the extraction of unique features from device hardware defects and the achievement of classification through subsequent processing. However, since the signal is affected by multipath effects, noise interference, and environmental changes during transmission, directly using raw I/Q data may lead to degraded classification performance. Therefore, a systematic approach is needed to model, process and analyze the signal to improve the robustness and precision of the identification.

Given a set of signal samples $x_i, y_{i}{}_{i=1}^{N}$ of a device, where x_i represents the original I/Q signal data of device i and $y_i \in 1, 2, \ldots, C$ represents the category label of the device. The task is to construct a mapping function $f : x \to y$ so that for any input signal x, the predicted device category $\hat{y}$ meets the high-precision classification requirements.

This paper adopts a phased modeling framework to divide RF fingerprint recognition into the following steps:

Signal preprocessing: De-noise the received raw I/Q data to eliminate multipath effects and noise interference as much as possible, and retain key features related to hardware defects.

Feature extraction: Use feature extraction algorithms to map the preprocessed signals to a low-dimensional space so that the classification model can capture the differences between devices while enhancing robustness to noise and environmental changes.

Classification inference: Build an efficient classification model, predict the device category for the extracted features, and complete the final RF fingerprint recognition task.

The system model is shown in Fig. 1.

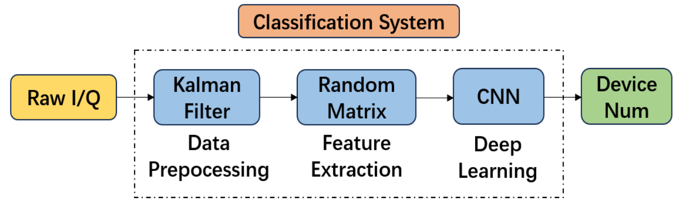

Fig. 1. System Model

B. Kalman Filter

Kalman filter is a recursive optimization algorithm widely used in the field of dynamic system state estimation and noise suppression [15] [16]. This paper uses it in the signal preprocessing stage in RF fingerprint recognition, aiming to improve the quality of raw I/Q data, suppress noise and interference, and provide more stable input for subsequent feature extraction and classification.

The Kalman filter dynamically estimates the signal in a noisy environment by constructing a state space model of the system, combining the current observations and the predicted state of the system [17]. Its recursive calculation process includes the following two steps. Symbols appear in the following formula are explained in Table I.

TABLE I
SYMBOL EXPLANATION

Symbol	Explanatoin
B_k	Control input matrix at time k
$\mathbf{EigTable}$	Feature table
F_k	State transition matrix at time k
H_k	Observation matrix at time k
I	Identity matrix
K_k	Kalman gain at time k
$P_{k\|k-1}$	Predicted error covariance matrix at time k
$\hat{P}_{k\|k}$	Posterior error covariance matrix at time k
Q_k	Process noise covariance matrix at time k
R_k	Observation noise covariance matrix at time k
u_k	Control input at time k
X	Data matrix
X^H	Hermitian transpose of the matrix X
$\hat{X}_{k\|k-1}$	Predicted state at time k
$\hat{X}_{k\|k}$	State estimate at time k
z_k	Observation at time k
λ_i	Eigenvalue of the covariance matrix Σ
λ_i'	Normalized eigenvalue
Σ	Covariance matrix

Prediction stage: predict the next state and error covariance of the system based on the state transfer equation.

Update stage: use the current observations to update the predicted state and calculate the optimal estimate and error covariance.

The state of the Kalman filter is represented by the following variables:

$\hat{X}_{k|k} = E\left(X_k \mid Y_1, Y_2, \ldots, Y_k\right)$ represents the estimate of the state at time k.

$\hat{X}_{k|k-1} = E\left(X_{k-1} \mid Y_1, Y_2, \ldots, Y_{k-1}\right)$ represents the prediction of the state at time k given the known state at the past $k-1$ time points.

$\hat{P}_{k|k}$ represents the posterior estimation error covariance matrix, which measures the accuracy of the estimated value.

The prediction and update process is as follows:

$$\hat{X}_{k-1|k-1} \xrightarrow{\text{Prediction}} \hat{X}_{k|k-1} \xrightarrow{\text{Correction}} \hat{X}_{k|k} \tag{1}$$

1. Prediction $\hat{X}_{k-1|k-1} \Rightarrow \hat{X}_{k|k-1}$

In the prediction step, the current state is predicted based on the state and control amount at the previous moment. This prediction value is an estimate because it does not take into account the observed value at the current moment. The error covariance matrix of the predicted value is calculated by the error covariance matrix of the previous moment and the system noise covariance matrix.

$$\left\{ \begin{array}{l} \hat{x}_{k|k-1} = F_k \hat{x}_{k-1} + B_k u_k \\ P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \end{array} \right. \tag{2}$$

2. Updating $\hat{X}_{n|n-1} \Rightarrow \hat{X}_{n|n}$

In the update step, the current state estimate is calculated based on the current observation and prediction. This estimate is a more accurate estimate because it takes into account the current observation. The error covariance matrix of the state estimate is calculated by the error covariance matrix calculated in the prediction step, the observation noise covariance matrix, and the Kalman gain.

$$\left\{ \begin{array}{l} K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k\right)^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(z_k - H_k \hat{x}_{k|k-1}\right) \\ P_{k|k} = \left(I - K_k H_k\right) P_{k|k-1} \end{array} \right. \tag{3}$$

The application of Kalman filter brings many advantages to I/Q data preprocessing. First of all, it can effectively suppress the interference of random noise, phase noise and multipath effects, thereby significantly improving the noise immunity of the signal. Secondly, the filtered signal has higher time synchronization and frequency stability, which is crucial for subsequent processing. In addition, the Kalman filter can well retain the key features of radio frequency fingerprints while reducing noise, providing reliable input data for random matrix feature extraction and classification.

C. Random Matrix Theory

The random matrix theory is a mathematical tool capable of capturing the global characteristics of high-dimensional data [18], [19]. In RF fingerprinting, this method effectively extracts hardware-specific features from received I/Q data. The process is outlined below.

The received I/Q data $\{x_I[n], x_Q[n]\}_{n=1}^N$ is divided into a single matrix of size $K \times L$ by sequentially selecting $K \times L$ samples. The resulting matrix X is constructed as:

$$X = \begin{bmatrix} x[1] & x[K+1] & \cdots & x[(L-1)K+1] \\ x[2] & x[K+2] & \cdots & x[(L-1)K+2] \\ \vdots & \vdots & \ddots & \vdots \\ x[K] & x[2K] & \cdots & x[LK] \end{bmatrix} \tag{4}$$

where $x[n] = x_I[n] + jx_Q[n]$ is the complex I/Q sample at index n. This compact matrix representation retains the signal's temporal structure.

From X, the covariance matrix Σ is computed as:

$$\Sigma = XX^H, \tag{5}$$

where X^H denotes the Hermitian transpose of X. The eigenvalues $\{\lambda_1, \lambda_2, \ldots, \lambda_K\}$ of Σ are extracted to characterize the structural properties of the signal.

All eigenvalues are sorted and normalized, and the normalized eigenvalues are defined as λ_i'.

Store the processed feature values $\{\lambda_1', \lambda_2', \ldots, \lambda_N'\}$ into the feature set **EigTable** as the input features of the subsequent classifier:

$$\mathbf{EigTable} = \{\lambda_1', \lambda_2', \ldots, \lambda_N'\}. \tag{6}$$

IV. Simulation And Discussion

A. Dataset

The dataset used in this experiment is a large-scale, multi-channel RF signal dataset collected by the USRP X410 device, which is designed to support in-depth analysis of signal characteristics and device features in RF fingerprint recognition research. The dataset is stored in the SIGMF-DATA format, covers transient and steady-state signals, and has rich hardware characteristic information and signal performance in complex environments.

The acquisition device uses the USRP X410 platform, which supports high bandwidth and high-resolution sampling. Four channels work simultaneously to achieve synchronous acquisition of multi-channel data, ensuring consistency in time and frequency. Each channel file contains 500 samples, and each sample records complete signal information. The total data set reaches 826GB, including two independent acquisition tasks, 429GB and 397GB respectively. The data file is stored as a single file of fixed size, with a single file size of 218MB, for post-processing and analysis. The data collected by each channel consists of the following two parts:

Transient signal: records the sudden change of the signal from nothing to something, such as the dynamic characteristics of device startup or signal sudden events. These data reflect the performance of the hardware under non-steady-state working conditions.

Steady-state signal: records the characteristics of the stable transmission stage of the signal, which can describe the long-term stable output signal under the hardware characteristics. The separation design of transient and steady-state signals facilitates the study of the characteristic differences of the two signals and their role in RF fingerprint recognition.

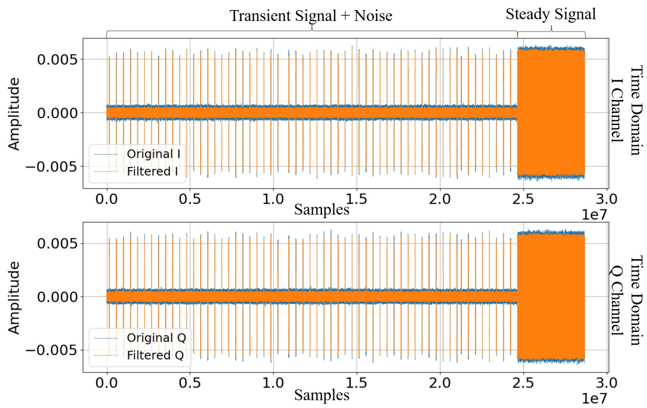

Fig. 2. Signal time domain comparison before and after Kalman filtering

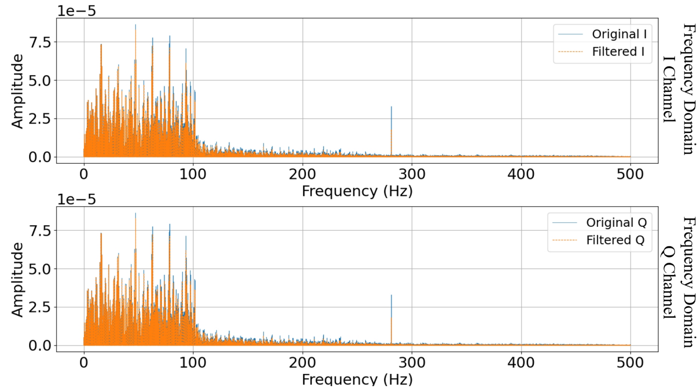

Fig. 3. Signal frequency domain comparison before and after Kalman filtering

The data is stored as a time domain I/Q dual signal, where each I/Q sample contains an in-phase component (I) and a quadrature component (Q) in complex form. The data set signal introduction and the time-frequency domain comparison after Kalman filtering are shown in Fig. 2 and 3.

B. Deep Learning Model

This paper designs a classification model that combines convolutional neural network (CNN) and fully connected network (FC) for feature extraction and device classification of RF fingerprint signals.

The convolutional neural network module is mainly used to extract local features from one-dimensional signals. It gradually compresses the feature dimensions through hierarchical convolution and pooling operations while retaining the significant patterns of the signal. It also uses Leaky ReLU as the activation function to introduce nonlinear enhancement. Feature extraction capability, the final convolutional layer output is flattened into the input of the fully connected module.

The fully connected module (FC) consists of multiple layers of linear mapping and activation functions, and is responsible for mapping the flattened features to the classification space(device category). Each layer uses the Leaky ReLU activation function to enhance the model's ability to fit complex nonlinear patterns. Our deep learning model frame is shown in Fig. 4.

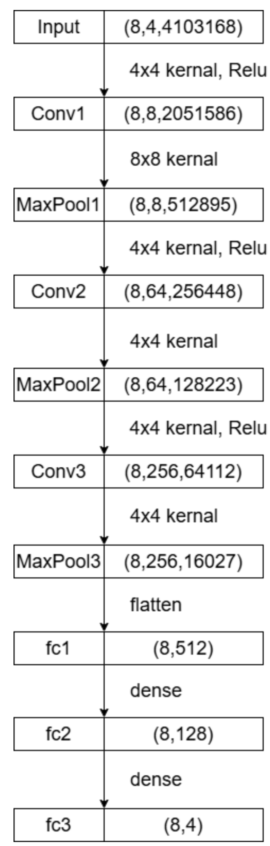

Fig. 4. Deep Learning Model Frame

C. Experiments and Results

In order to verify the effectiveness of the model and the robustness of RF fingerprint recognition, this paper designed two sets of comparative experiments:

1) *Classification accuracy with or without the Kalman filter*

This experiment aims to evaluate the effect of Kalman filter as a signal preprocessing step on the improvement of classification performance. By comparing the classification results of the original signal and the signal processed by Kalman filter, the effect of the filter on noise suppression and feature retention is verified.

Specifically, the same data set is used to take the original unfiltered I/Q data and the data processed by Kalman filter, and the classification model is fixed to the CNN + FC structure proposed in this paper, keeping other parameters consistent. Compare the classification results in the two cases. The identification confusion matrices are shown in Fig. 5 and Fig. 6.

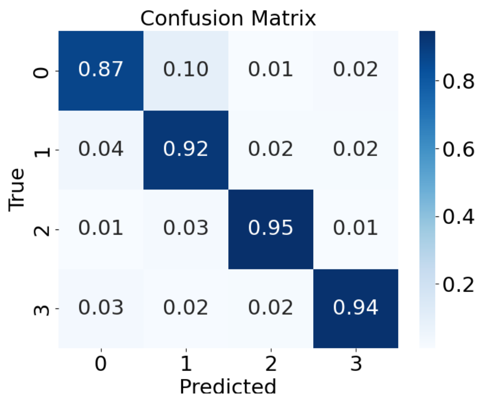

Fig. 5. Confusion Matrix without KF

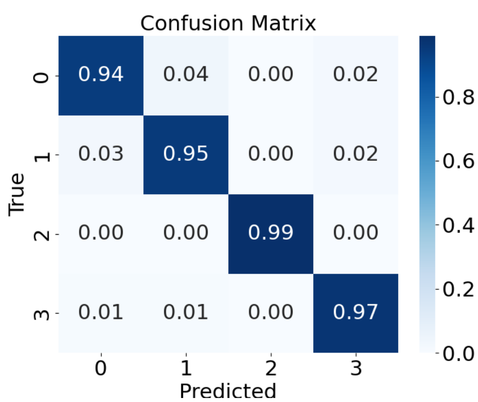

Fig. 6. Confusion Matrix with KF

From the confusion matrices shown in Fig. 5 and Fig. 6, we observe that the classification accuracy improves significantly when the Kalman filter is applied to the raw I/Q data. The classification accuracy without the Kalman filter is **91.79%** on the training set and **92.37%** on the testing set, while with the Kalman filter, the accuracy increases to **96.33%** on the training set and **96.53%** on the testing set. This increase in accuracy clearly demonstrates the positive impact of Kalman filtering as a signal preprocessing step.

In the confusion matrix without the Kalman filter (Fig. 5), we notice that some of the classes have relatively higher off-diagonal values, indicating misclassifications. These misclassifications are likely caused by the noise present in the raw signal, which could have altered the feature representation of the signal in a way that confuses the classifier. On the other hand, the confusion matrix with the Kalman filter (Fig. 6) shows a clearer distinction between classes, with fewer misclassifications, highlighting the filter's effectiveness in improving the quality of the signal and enhancing the separability of features.

An important aspect of deep learning models is their ability to generalize well to unseen data. The increase in testing accuracy from 92.37% (without Kalman filtering) to 96.53% (with Kalman filtering) indicates that the Kalman filter not only improves the training accuracy but also contributes to better generalization. The smoother signal processed by the Kalman filter enables the CNN + FC model to generalize better on unseen test data, reducing the likelihood of overfitting to noise or irrelevant features.

2) *Classification accurary under different signal-to-noise ratios (SNRs)*

This experiment aims to evaluate the robustness of the RF fingerprint recognition model under varying signal-to-noise ratios (SNRs) and explore the impact of noise on classification performance.

In this experiment, different SNR levels are simulated by adding Gaussian white noise with varying intensities to the original I/Q data. The classification model used in this experiment is fixed to the CNN + FC architecture proposed in this paper. The classification accuracy at each SNR level is being recorded to assess the model's ability to maintain performance under different noise conditions.

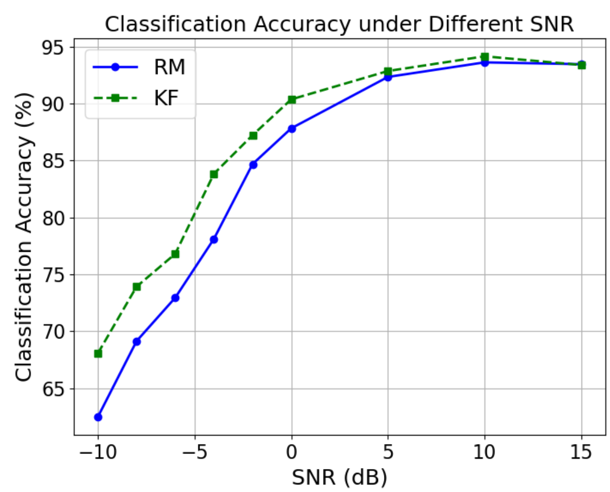

Fig. 7. Classification Accuracy under Different SNR

From the results, the classification accuracy of both methods increased significantly with the increase of SNR. This shows that as the signal strength increases, the interference of noise decreases, and the performance of the model is optimized.

RM method: As the SNR increases from -10 dB to 15 dB, the classification accuracy of the RM method continues to improve, especially under low SNR conditions, the RM method performs poorly, but as the SNR increases, the accuracy gradually increases, and finally approaches 93.46%.

KF method: The classification accuracy of the KF method shows stability over the entire SNR range. Even under low SNR conditions (such as -10 dB), the accuracy of the KF method is much higher than that of the RM method, which indicates that the KF method may have stronger robustness in noisy environments. The overall trend of KF is similar to that of the RM method, and its accuracy can reach 94.15% at high SNR.

It can be clearly seen from the graph that the gap between the two methods is large under low SNR, and as the SNR increases, the accuracy of the two methods gradually approaches. This shows that under high SNR conditions, the impact of noise is small, and the classification performance is mainly affected by the model itself, while under low SNR conditions, the KF method shows stronger noise suppression ability than the RM method.

This result suggests that in practical applications, the KF method may be suitable for environments with high noise, while the RM method can fully exert its performance under high-quality signal conditions. Future research can consider combining noise suppression technology or more robust learning strategies to further improve the classification accuracy under low SNR.

3) *Comparison with other advanced RFF recognition methods*

In this study, in addition to using CNN for radio frequency fingerprint (classification, we also introduced SVM as a baseline method and compared them with other advanced methods. As a classic machine learning method, SVM has strong generalization ability, especially in classification tasks with small samples and high-dimensional feature spaces [7].

Based on the same dataset, we obtained the following results:

The accuracy of SVM is 82.46%, which is significantly lower than the 96.53% accuracy of KF on the test set. This shows the superior performance of KF in RFF recognition, especially in the environment of dealing with complex signals and more noise, its performance is significantly better than traditional machine learning methods.

By comparing these two methods, we can deeply analyze their advantages and disadvantages in the RFF recognition task. The lower accuracy of SVM may be related to its decision boundary selection in high-dimensional feature space, while the KF method significantly improves the classification accuracy through more efficient feature extraction and noise suppression.

V. Conclusions

This paper proposes an RF fingerprinting method integrating Kalman filtering for noise suppression and Random Matrix Theory for feature extraction. Experimental evaluation on a multi-channel dataset demonstrates that the method significantly improves classification accuracy, particularly in low SNR environments. Compared to conventional methods, the Kalman+RMT+CNN approach enhances robustness and accuracy while maintaining model efficiency, making it suitable for real-world device identification scenarios.

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