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Research on the Internet of Things Device Recognition Based on RF-Fingerprinting

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ABSTRACT Internet of Things (IoT) technology provides a large-scale network for information exchange and communication with big data. Because of the openness of IoT devices in the process of signal transmission, the recognition and access of different IoT devices are directly related to the wide application of its system. The radio frequency fingerprinting (RFF) is a unique characteristic closely related to the hardware of IoT devices themselves, which is difficultly tampered. In this paper, four kinds of RF fingerprint feature extraction algorithms based on statistical features are studied. Robust principle component analysis (RPCA) is used for the dimensionality reduction and the support vector machines (SVM) is used for classification. Through theoretical modeling and experimental verification, the reliability and distinguishability of RFFs are extracted and evaluated, and the classification results are displayed in the real IoT equipment environment.

INDEX TERMS Internet of Things, radio frequency identification, robust principle component analysis, support vector machines.

I. INTRODUCTION

Internet of Thing (IoT), which is one of the most important and powerful communication paradigms of the 21st century has been a considerable attention from last few years [1]–[3]. It has been widely used in many fields, such as industrial control [4], network physical system [5], public security equipment [6], military investigation [7]. With the development of the intelligent and cognitive techniques, we enter the IoT era in which the communication network is becoming increasingly dynamic, the IoT technology is being confronted with a series of new challenges [8]–[12], more secure and reliable IoT device recognition technology need to be researched to adapt to the increasingly complex application environment.

RF fingerprinting is a physical layer identification method that identifies a specific wireless device based on features present in the analog signal waveform. The identification and authentication of IoT devices based on radio frequency fingerprinting (RFF) is a hot issue in recent years, which have been widely used in intrusion detection [13], access control [14], wormhole detection [15], cloning detection [16]. On this basis, Radio Frequency-Distinct Native Attribute (RF-DNA) refers to the further extraction of statistical features from the extracted features to comprehensively characterize signal details. RF fingerprinting based on RF-DNA has been extensively studied and proven to be effective. Extracted features include modulation error [17], frequency offset [18], phase shift [19], multi-scale wavelet coefficients [20] and so on. In addition, the short-time Fourier transform is used to obtain the envelope feature of the signal [21], and image features of the modulated signal are used in the modulation domain, such as the differential artifact of the radio frame [16], the constellation map feature [22], [23]. The entropy-based method is also widely used, similar examples are based on approximate entropy, permutation entropy, dispersion entropy, multi-dimensional permutation entropy, normalized Shannon entropy [24], [25]. What's more, with the wide application of artificial intelligence technology in interdisciplinary disciplines, deep learning-based algorithm was also proved to be very accurate and efficient [26], [27] for device recognition.

The rest of this paper is organized as follows. Section II provides the signal processing algorithms. Then section III describes the identification system design, include signal collection, feature extraction, dimensional reduction and fingerprint matching. The simulation result for IoT devices are presented in Section IV. Finally, a summary concluding remarks follow in Section V.

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II. BACKGROUND

A. TIME DOMAIN RF-DNA FINGERPRINTING

For Time Domain (TD) signal characteristics, RF-DNA can be generated by the instantaneous amplitude, frequency and phase response of radio signal's subsequence [24].

Generally, a complex time domain (TD) sampled signal has the following main features: instantaneous amplitude, phase and frequency. The Hilbert transform yields the following signal analytical expression:

$$s_{TD}(n) = I_{TD}(n) + jQ_{TD}(n) \tag{1}$$

where $I_{TD}(n)$ and $jQ_{TD}(n)$ are the in-phase and orthogonal components of $s_{TD}(n)$.

$$a(n) = \sqrt{I_{TD}^2(n) + Q_{TD}^2(n)} \tag{2}$$

$$\phi(n) = \tan^{-1}\left[\frac{Q_{TD}(n)}{I_{TD}(n)}\right] \tag{3}$$

$$f(n) = \frac{1}{2\pi}\,\frac{\phi(n) - \phi(n-1)}{\Delta n} \tag{4}$$

B. WAVELET DOMAIN (WD) RF-DNA FINGERPRINTING

For signal analysis, the Discrete Wavelet Transform (DWT) is an effective tool. However, this method does not satisfy the time-shift invariance problem, which has a great impact on the signal analysis. The Dual Tree Complex Wavelet Transform (DT-CWT) is an improved method of DWT, which used to overcome the disadvantage of DWT. The DT-CWT is implemented by real-valued filter banks as follow figure.

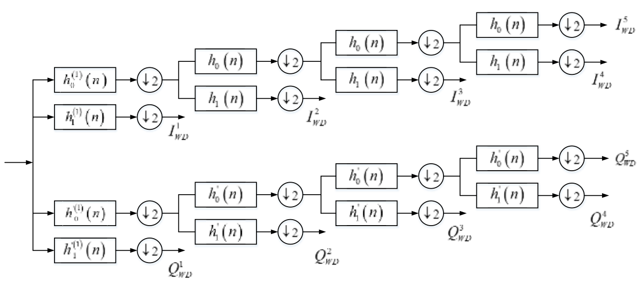

FIGURE 1. Four stage (five level) dual-tree complex wavelet transform.

In figure 1, the two filter banks represent two branches of Tree1 and Tree2 respectively. Where the filter coefficients $h_1(t)$, $h_0(t)$, $h_1^{'}(t)$ and $h_0^{'}(t)$ are implemented directly as the Analysis Filters (AF) given in [28].

For real-valued input radio signals, the WD coefficients I_{WD}^L and Q_{WD}^L of Tree1 and Tree2 represent the real and imaginary components of complex coefficients [29].

$$S_{WD}^l(n) = I_{WD}^l(n) + jQ_{WD}^l(n) \tag{5}$$

C. SHORT-TIME FOURIER TRANSFORM

Short-Time Fourier Transform (STFT) is a single resolution signal analysis method. Its main idea is to select a local window function, obtain different signal segments by moving the window function, and then perform Fourier transform on each segment of the signal. The time domain signal is $f(t)$ and the STFT is defined as:

$$STFT_z(f,\tau) = \int_{-\infty}^{\infty} \left[f(t)g^*(\tau - t)\right] e^{-j2\pi ft}\, dt \tag{6}$$

The inverse transformation formula is:

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} STFT(f,\tau)g(\tau - t)e^{j2\pi ft}\, df d\tau \tag{7}$$

where $g(t)$ is the sliding window function. When $g(t)$ is taken as a Gaussian window, the transform is called Gabor Transform (GT), which is defined as:

$$GT_x(t,f) = \int_{-\infty}^{\infty} x(\tau)g^*(t-\tau)e^{-j2\pi f t}\, d\tau \tag{8}$$

$$g^*(t-\tau) = (\pi\sigma^2)^{-\frac{1}{4}} \exp\left[-\frac{(t-\tau)^2}{2\sigma^2}\right] \tag{9}$$

where $g(t)$ is a Gaussian function with a variance of σ. The reason for choosing the Gaussian window is: 1) The Fourier transform of the Gaussian function is still a Gaussian function, which makes the inverse Fourier transform also localized by the window function, and at the same time reflects the localization of the frequency domain; 2) According to the Heisenberg uncertainty principle, the window area of the Gauss function has reached the lower bound of the uncertainty principle, which is the function that the time domain window area is the smallest, that is, the GT is the optimal STFT.

D. WIGNER-VILLE DISTRIBUTION

Wigner-Ville Distribution (WVD) is a quadratic time-frequency representation, which has the highest theoretical resolution in time-frequency analysis.

The instantaneous autocorrelation function of signal $x(t)$ is:

$$k_x(t,\tau) = x\left(t + \frac{\tau}{2}\right)x^*\left(t - \frac{\tau}{2}\right) \tag{10}$$

The definition of WVD can be obtained by Fourier transform of instantaneous correlation function $k_x(t,\tau)$:

$$W_x(t,f) = \int_{-\infty}^{\infty} x\left(t + \frac{\tau}{2}\right)x^*\left(t - \frac{\tau}{2}\right)\mathrm{e}^{-\mathrm{j}2\pi\tau f}\mathrm{d}\tau \tag{11}$$

where $x^*(t)$ is the analytical representation of the real signal $x(t)$, and the WVD can also be represented by the spectrum of the analytical signal as follows:

$$W_X(t,f) = \int_{-\infty}^{\infty} X^*\left(f + \frac{\nu}{2}\right)X\left(f - \frac{\nu}{2}\right)\mathrm{e}^{-\mathrm{j}2\pi t\nu}\mathrm{d}\nu \tag{12}$$

WVD has many good time-frequency characteristics. Considering that window functions are not included in equations (11) and (12), it avoids the contradiction between the time resolution and frequency resolution of STFT. Its time-bandwidth product can reach the lower bound given by the Heisenberg uncertainty principle.

III. METHODOLOGY

A. SIGNAL COLLECTION

This experiment mainly carries on the actual measurement data acquisition and the algorithm simulation verification to the IoT devices. 10 walkie-talkies of the same manufacturer and model Motorola A12 are selected for verifying the effectiveness of the algorithm. In order to ensure the quality of received signal, this experiment uses a certain type of spectrum analyzer equipment for signal acquisition. Specific equipment and acquisition parameters are shown in the following table:

TABLE 1. Introduction of experimental simulation parameters.

Acquisition parameters	Values
modulation mode	FM
working frequency	410MHz
Sampling rate	40MHz
Transient duration	4ms

B. FEATURE EXTRACTION

For the previous four basic signal features, if they are directly used for the classification of different devices, the high complexity may limit the performance of signals in data processing. If statistical characteristics are selected as classification features, the dimension of feature space for device classification and the computational burden can be significantly reduced. Statistical characteristics commonly used in feature extraction include variance (σ^2), skewness (γ) and kurtosis (κ), which are defined as:

$$\sigma_x^2 = \frac{1}{N_x}\sum_{k=1}^{N_x}[x(k)-\bar{x}]^2 \tag{13}$$

$$\gamma_x = \frac{1}{\sigma_x^3 N_x}\sum_{k=1}^{N_x}[x(k)-\bar{x}]^3 \tag{14}$$

$$\kappa_x = \frac{1}{\sigma_x^4 N_x}\sum_{k=1}^{N_x}[x(k)-\bar{x}]^4 \tag{15}$$

where $\bar{x}$ is the average of $\{x(k)\}$.

Through the signal transformation in Section II, we can get four different signal feature sequences. In order to obtain more specific feature information of signal, it is necessary to partition the signals before extracting statistical features. Then the unique features are obtained by the variance (σ^2), skewness (γ) and kurtosis (κ) from $N_R + 1$ subsequence of the original signal transformation. Where N_R represents the number of the subsequence. The statistics can be arranged as follows [24]:

$$F_{R_i} = [\sigma_{R_i}^2, \gamma_{R_i}, \kappa_{R_i}]_{1\times 3} \tag{16}$$

where R_i represents the i^{th} signal segment, and then we can get the statistical feature set of the whole region by formula (16), which is used for the final fingerprint identification process:

$$F_{R_i} = [F_{R_1}\ \ F_{R_2}\ \ F_{R_3} \cdots\ \ F_{R_{N_R+1}}]_{1\times 3(N_R+1)} \tag{17}$$

C. DIMENSIONAL REDUCTION

PCA is the most widely used statistical tool for data analysis and dimension reduction. However, PCA cannot show superior performance in the samples with serious noise interference. The Robust Principle Component Analysis (RPCA) is an improved method for PCA by matrix decomposition.

Assuming the sample matrix is $\boldsymbol{X} = \mathbb{R}^{l\times n}$, RPCA decomposes such a matrix into a low rank matrix $\boldsymbol{L}$ and a sparse matrix $\boldsymbol{S}$ with the same size as the original matrix. In general, this problem is tricky. Convex optimization method can effectively solve this problem under a wide range of conditions. Sparse matrices can be computed by solving the following convex optimization [30].

$$\min_{\mathbf{L},\mathbf{S}}\ \ \|\mathbf{L}\| + \lambda\,\|\mathbf{S}\| \quad s.t.\ \mathbf{X} = \mathbf{L} + \mathbf{S} \tag{18}$$

where $\|\cdot\|_*$ represents the kernel norm and $\|\cdot\|_1$ represents the l_1 norm of the matrix. $\lambda > 0$ is a parameter that balances the low rank matrix and the sparse matrix. The value of λ can be estimated according to the previous research institute's formula $\lambda = 1/\sqrt{\max(l,n)}$, and then fine-tuned according to the specific problem to achieve better results. It has also been proposed to use different values of k adjustments $\lambda_k = 1/\sqrt{\max(l,n)}$ to test the trade-off between $\boldsymbol{L}$ and $\boldsymbol{S}$.

D. FINGERPRINT MATCHING

Support Vector Machines (SVM) is a binary classification model. Its basic model is a linear classifier defined in feature space to maximize the interval. For linear separable data sets, there are infinite separable hyperplanes, but the separable hyperplanes with the greatest geometric interval are unique, and the maximization of interval here is also called the maximization of hard interval.

Assuming linearly separable data sets $T = \{(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)\}$, where $x_i \in \mathbf{R}^n, y_i \in \{-1, +1\}, i = 1, 2, \cdots, \mathrm{m}$, the learning problem of linear separable SVM can be reduced to the constrained optimization problem:

$$\max_{w,b}\ \gamma$$
$$\text{s.t. } \mathrm{y_i}\left(\frac{w}{\|w\|}\cdot x_i + \frac{b}{\|w\|}\right) \geq \gamma, \quad \mathrm{i} = 1, 2, \cdots \mathrm{m} \tag{19}$$

where w and b define the separation hyperplanes $w^*\cdot x + b^* = 0$ and γ as the geometric spacing of the signals. In fact, classification problems are often non-linear, meaning that there is no hyperplane that perfectly separates the data sets. In this case, the original space can be mapped to a high-dimensional space. If the data set in the high-dimensional space is linearly separable, it can be solved according to the linear separable SVM.

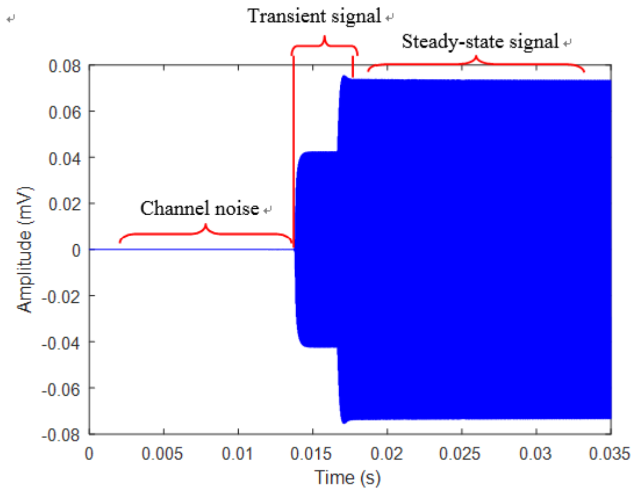

FIGURE 2. **The instantaneous amplitude of the original signal.**

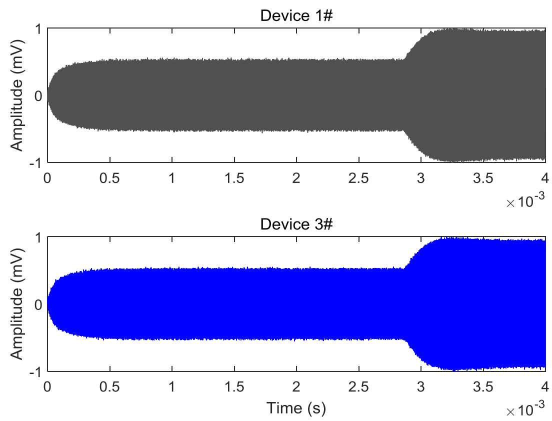

FIGURE 3. **Transient signals of two IoT devices.**

IV. SIMULATION RESULT

A. SIGNAL PRE-PROCESSING

Wireless communication signals often adopt different formats and protocol standards. In the device identification, a target segment need to be intercepted from the received signal to extract the unique features of the device, which is also called ''identifiable signal''. As shown in figure 2, the signals collected in this paper mainly contain three components: channel noise, transient signal, and steady-state signal.

In order to preserve the original signal information as much as possible and decrease the influence of noise signal on the identification accuracy, the method of variance trajectory detection is used to find and intercept the beginning point of target signal. Each device collected 50 samples and obtained a total of 500 turn-on transient datasets. For verifying the generalization performance of the algorithm, a cross-validation method is used to divide the training and test datasets. And the ratio of training samples to test samples is 2:3.

Figure 3 shows the turn-on transient data of the device that was intercepted. Since the devices are from the same model of the same manufacturer, the differences between the devices are small and difficult to identify. It can be seen that it is very necessary to study effective feature extraction methods for device fingerprint feature identification.

B. DIMENSIONALITY REDUCTION

The original feature set often contains abundant device information, but at the same time there are some redundancy and noise. If these features are directly used for classification, it will not only increase the amount of calculation, but also affect the final classification decision-making. In this paper, Principle Component Analysis (PCA) is used to decrease the dimension of the original feature data set. In order to test the performance of dimension reduction algorithm and facilitate the selection of subsequent dimension reduction algorithm, this paper compares PCA and RPCA methods. figure 4 displays the energy ratio of the original feature after dimensionality reduction using two methods under 20 dB noise environment.

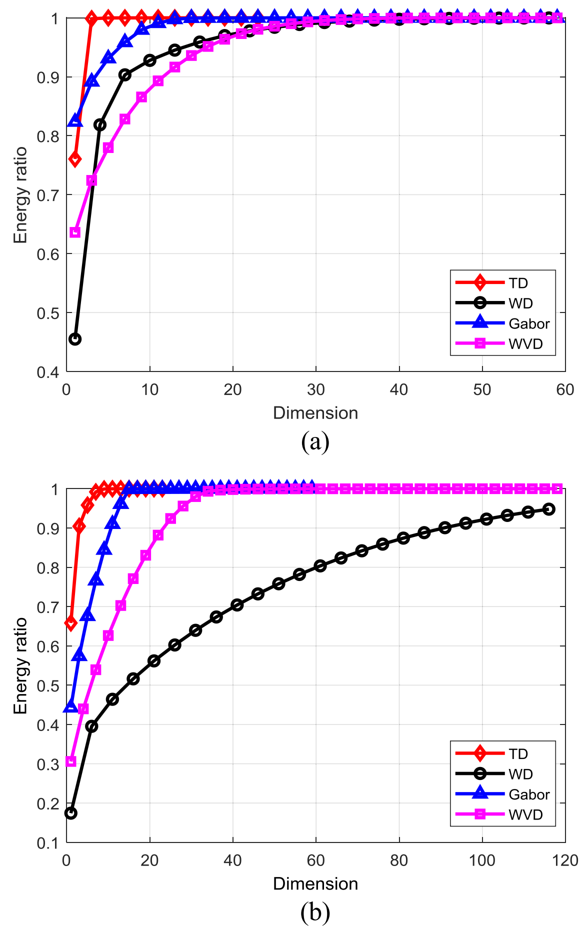

FIGURE 4. **The energy ratio of the original feature curves varying with dimensions.**

According to the energy ratio curve in figure 4, RPCA has a higher proportion of energy curves with the same dimension after dimensionality reduction, which shows that this method is more efficient and retains more original feature information of signals in the same dimension after dimensionality reduction. The following table shows the characteristic dimensions of the RPCA method when the energy proportion is 85%, 90% and 95%.

In this paper, the experiment is mainly to select the dimension reduction characteristics when the energy ratio is 95%. It can be seen from Table 2 that the dimensions of the above four feature extraction methods are 3, 14, 7 and 17.

TABLE 2. Energy proportion varies with dimensions.

Energy ratio		85%	90%	95%
Dimension	TD	-	-	3
	WAV	5	7	14
	Gabor	2	4	7
	WVD	9	12	17

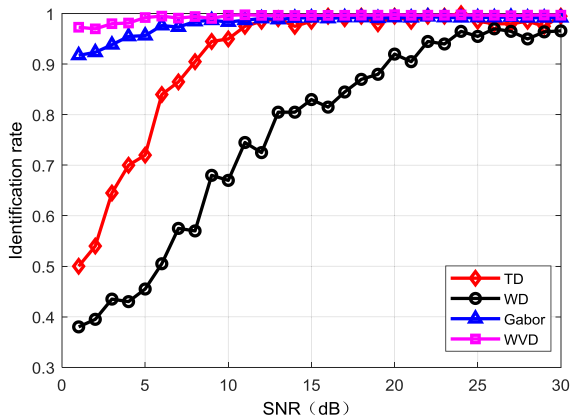

FIGURE 5. The identification rate of four fingerprint feature extraction algorithms with SNR curve.

C. IDENTIFICATION RESULT

In order to preserve the original feature information while reducing the feature dimension, RPCA was used to select the multi-dimensional principal component for classification experiments, and finally SVM was used for the identification of the features after dimensionality reduction. The curve of the specific identification rate as a function of SNR is shown in figure 5.

It can be seen that all the four feature extraction algorithms can effectively identify the measured data of wireless devices in high SNR. The feature extraction algorithm based on time-domain and time-frequency distribution can achieve more than 95% identification rate in 10 dB environment, and the identification rate of the three methods in 15 dB noise environment is close to 100%, basically realizing the effective recognition of all experimental equipment.

V. CONCLUSIONS

In this paper, RF Fingerprints extraction algorithms for IoT devices based on statistical features are studied. By extracting the instantaneous characteristics of signal in time domain, the characteristics of wavelet coefficients and time-frequency distribution characteristics, 10 IoT devices are effectively identified. The feature extraction algorithm based on time-domain and time-frequency distribution can achieve more than 95% identification rate in 10 dB environment, and the identification rate is close to 100% in 15 dB environment. Simulation result shows the validity of the feature extraction algorithm proposed in this paper. However, further research is required to study the influencing factors of time-frequency distribution characteristics. For example, noise interference, cross-coherent interference in non-linear time-frequency, etc.

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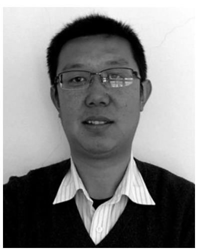

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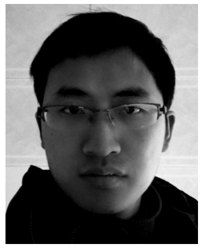

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