Wireless Channel Scene Recognition Method Based on an Autocorrelation Function and Deep Learning

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Abstract Wireless channel scene recognition plays a key role in cognitive radio (CR) mobile communication systems. This paper proposes a wireless channel scene identification framework based on the autocorrelation function and deep learning. First, a feature extraction (FE) method is developed to perform a channel scene date analysis based on the autocorrelation function (AF). The AF is used to realize the FE method because it can be combined with Fourier transform (FT) to accurately extract the characteristics accurately from a time-varying channels scene. Second, a deep belief network (DBN) with a robust learning approach is introduced to perform wireless channel scene recognition. A novel learning architecture is employed, which combines the feature parameter and classification techniques to achieve a high classification correct recognition rate. Third, the k-step contrastive divergence (CD-k) algorithm is introduced as the preliminary training method to optimize the traditional DBN network. This method can effectively calculate the logarithmic gradient of the Boltzmann machine. Moreover, the up-down optimization algorithm is applied to optimize the network parameters. Finally, the theoretical implementation is described in detail, and the method is verified by constructing an experiment platform for an engineering application. The experimental results indicate that the proposed classifier is an excellent approach to realize channel scene recognition through advanced methods. The classification accuracy of the proposed approach is higher than that of several existing techniques.

Index Terms Wireless channel, scene recognition, autocorrelation function, deep belief network (DBN).

I. INTRODUCTION

Cognitive radio has developed rapidly in recent years. The main goal is to achieve reliable communication by enhancing the spectrum utilization. To this end, the key step is to identify and analyse the scene of the wireless channels. In wireless communication, we call the different types of wireless channels models in different environments as wireless channel scenarios. After identifying the wireless channel scene, the physical layer technology suitable for the channel can be adapted to further enhance the performance of the communication system. However, the electromagnetic environment is complex, with diverse signals that change rapidly in the wireless communication domain [1], [2]. Moreover, the wireless channel environment involves large-scale fading [3], [4], small-scale fading [5], [6], and Doppler effects [7], [8]. Consequently, realizing scene recognition in wireless channels is challenging. In this scenario, it is necessary to adopt an advanced intelligent method to comprehensively identify the complex communication environments comprehensively. Therefore, the study of wireless channel scene recognition is of significance.

To solve the problem of the challenging identification in an additive noise channel environment, an unbiased blind
adaptive channel identification and equalization algorithm was proposed in [9]. The considered structural property can be observed in many array processing applications. Paper [10] recommended measures for non-line-of-sight (NLOS) identification, which is based on the space-time-frequency channel. This method can achieve a high recognition performance for line of sight (LOS) and NLOS channels. To reduce the influence of noise in blind channel identification, a subspace tracking algorithm was proposed in [11], based on the robust statistics subspace tracking method. However, RLS-based algorithms are widely known to be sensitive to the impulse noise in an actual scene. Paper [12] proposed a channel recognition scheme to overcome this dilemma, which based on the robust statistics subspace tracking method. However, this method is applicable for only three different types of time-varying channel scenarios. A blind channel identification method based on a weighted statistical mixture model was introduced in [13] for indoor scenario clustering. It is a weighted statistical mixture model [13]. However, this method is suitable for only for indoor wireless channel scenarios. In [14], a method to realize wireless channel classification was introduced to combine convolutional neural networks, and this technique was successfully applied to realize modulation recognition. In [15], the authors proposed a channel status classification approach by using the Received Signal Strength Indicator (RSSI) in indoor scenarios. The threshold was changed according to the statistical features in the special channel environment. This algorithm yielded a classification accuracy of approximately 85%.

However, in general, transmitters are located far away from the base station, and there are many reflectors are present. Consequently, no direct path exists between the transmitter and receiver, and the channel obeys a Rayleigh distribution [16]. Clarke first proposed the classical Clarke model for the Rayleigh time variation channel in [17]. Jakes optimized the Clarke model; however, the model could not maintain the stability of the broadband [18]. Thus, an improved model was proposed by Pop and Beaulieu [19]. In addition, certain channels have been proposed for different channel scenarios and research fields. In general, Research on the wireless channels can be examined through computer simulations and platform construction. The simulation models can be divided into deterministic and statistical models [20]. Deterministic models are also known as sum-of-sinusoids methods, in which the key aspect is to simulate the characteristics of the fading channel by superposing a large number of sinusoidal signals with different information. In the statistical models is also known as the formed filter methods [21], the power spectral density is modified through white Gaussian noise to simulate different wireless channel scenarios.

In recent years, artificial intelligence has been widely developed, and pattern recognition method based on neural network has been widely used. Wireless channel recognition based on neural network mainly includes feature extraction and classification recognition. A wireless channel often exhibits randomness and time variability, which increases the difficulty of extracting the wireless channel feature extractions. Certain researchers [22] used the wavelet transform technology to extract the fingerprint features of a wireless network. Moreover, an array-based feature extraction method was proposed to determine the radio frequency fingerprint [23]. The characteristic parameters were estimated considering the rotation invariance. The feature extraction functions usually involve a Fourier transform [24], Hilbert transform [25], linear discriminant analysis [26], principal component analysis [27], or other dimensionality reduction techniques [28]. However, it is difficult to extract the characteristic parameters of channel scenes. In this paper, a feature parameter extraction method based on the autocorrelation function is proposed. The power spectral density with more robust characteristics can be obtained by combining the autocorrelation function with Fourier transform, and PSD has more vital characteristic attributes. To realize channel scene recognition, after extracting the characteristic parameters the classification algorithm should be employed. The existing classification and recognition methods can be divided into two categories: decision-theory-based methods and pattern recognition methods [29], [30]. The identification problem is considered to be a compound hypothesis test problem based on the decision theory, and an appropriate threshold value is selected as the decision basis. For example, the power weighted statistical model applied is a decision-theory-based method to realize indoor wireless channel scene clustering [31]. However, this method cannot be widely applied owing to its complicated derivation and high operation cost. Methods based on pattern recognition can be roughly divided into neural network methods [32], radial basis neural network methods (RBF) [33], support vector machine methods (SVM) [34], and multiple kernel relevance vector machine (MKRVM) techniques [35]. These methods have been widely used in classification and recognition tasks. However, in the wireless channel scenarios with fast time-variations, large broadband, and multiple-dimensions, these traditional methods cannot achieve high recognition accuracy. To enhance the identification effect, this article proposes a wireless channel scene classification method based on a deep learning network. Compared with the traditional neural network method, the pattern recognition method based on deep learning has more vigorous learning and classification ability.

A new scene recognition method mainly includes two processes: feature extraction and classification based on the AF and DBN, respectively. The key contributions of this paper can be summarized as follows.

1. A feature extraction method based on the AF is proposed for a wireless channel based on AF. The AF is derived through the complex baseband impulse response in the wireless channel. The characteristic parameters are obtained by using the AF combined with a Fourier transform. In particular, a Fourier transform, windowing, and normalization are realized to achieve high quality characteristic parameters.
(2) A method is proposed to realize wireless channel scene recognition based on a DBN. This method constructs a hybrid classifier model by using the Boltzmann machine. The model includes both undirected and directed parts.

(3) The training of deep learning networks is realized using two processes, specifically, non-supervised pre-training and supervised parameter tuning. The CD-k learning algorithm is used to optimize the DBN network to promptly calculate the log-likelihood gradient of the constrained Boltzmann machine. The upper and lower algorithms are adopted to avoid large deviation during classification.

4) Two approaches are employed to verify the correctness and accuracy of the proposed method. One method is to obtain the Rayleigh fading channel of different scenarios through the forming filter method, and then the channel recognition is realized using the proposed approach. The other method is to build a wireless channel scene simulation platform by combining hardware and software. Subsequently, the proposed method in this paper is used to test and verify the wireless channel scene data collected by the platform.

The remaining paper is arranged as follows. In Section II, describes the Rayleigh time-varying channel and the process of feature parameter extraction, along with the DBN network. The DBN design and model structure of the recognition algorithm are described in Section III. The experiment and results analysis are presented in Section IV. Specifically, the section involves two parts. Part one corresponds to the channel simulation and method verification, and part two corresponds to the experiment platform and results in analysis of the results. Section V presents the concluding remarks.

II. RAYLEIGH TIME VARIATION CHANNEL AND FEATURE PARAMETER EXTRACTION

First, we describe the Rayleigh time variation channel, followed by the solution of the autocorrelation algorithm in the wireless domain. Subsequently, we describe the process of the feature parameters extraction by using the autocorrelation algorithm.

A. RAYLEIGH TIME VARIATION CHANNEL

In this section, we describe the modelling of the time-dependent channel variation with the movement of the mobile terminal. The actual environment is shown in Fig.1. A plane wave arrives at an angle. Suppose that a station moves at a certain velocity, and the wave arrives $x \rightarrow y$ horizontally in the plane.

When $x(t)$ is the baseband transmitting signal, the corresponding baseband transmitting signal is:

$$\tilde{x}(t) = \text{Re} \left[ x(t) e^{j2\pi f_c t} \right]$$

(1)

where, $\text{Re} \left[ \cdot \right]$ represents the real part.

Given a velocity $v$ and wavelength $\lambda$, the Doppler frequency shift can be defined as

$$f_i = f_D \cos \theta_i = \frac{v}{\lambda} \cos \theta_i$$

(2)

where, $f_D$ is the maximum Doppler shift, and $\theta_i$ is the angle of arrival (AOA) corresponding to the $i$th plane wave.

After the baseband transmitting signal passes the scattering channel through a strip propagation path, the received signal in the passband can be expressed as

$$\tilde{y}(t) = \text{Re} \left[ y(t) e^{j2\pi f_c t} \right] = \text{Re} \left[ \sum_{i=1}^{I} C_i e^{-j\phi_i(t)} x(t - \tau_i) e^{j2\pi f_c t} \right]$$

(3)

where, $y(t)$ is the baseband signal; $C_i$ and $\tau_i$ respectively represent the channel gain and delay of the $f_i$ propagation path; $f_i$ represents the Doppler frequency shift, with $\phi_i(t) = 2\pi \left( f_c + f_i \right) \tau_i - f_i \tau_i$. Therefore, the baseband signal can be modelled as a linear time-varying filter, as in formula (3), and the complex baseband impulse response can be defined as follows:

$$h(t, \tau) = \sum_{i=1}^{I} C_i e^{-j\phi_i(t)} \delta(t, \tau - \bar{\tau})$$

(4)

where, $\delta_i(\cdot)$ is the Dirac delta function. When the sampling period $T_s$ is considerably larger than the path delay difference, the path delay $\tau_i$ can be approximated as $\bar{\tau}$.

Therefore, equation (4) can be expressed as

$$h(t, \tau) = h(t) \delta(t - \bar{\tau})$$

(5)

In this case, $h(t) = \sum_{i=1}^{I} C_i e^{-j\phi_i(t)}$. When the baseband transmitting signal $x(t) = 1$, the passband receiving signal is

$$\tilde{y}(t) = \text{Re} \left[ y(t) e^{j2\pi f_c t} \right] = \text{Re} \left[ h_l(t) + jh_Q(t) e^{j2\pi f_c t} \right] = h_l(t) \cos(2\pi f_c t) + h_Q(t) \sin(2\pi f_c t)$$

(6)

where $h_l(t) = \sum_{i=1}^{I} C_i(t) \cos \phi_i(t)$ is the coaxial component, $h_Q(t) = \sum_{i=1}^{I} C_i(t) \sin \phi_i(t)$ is the orthogonal component, $\phi_0$ is the phase offset, and $\phi_i(t) = 2\pi f_c \tau_i(t) - \phi_0 - \phi_i$ is the delay.

If $I$ is sufficiently large, the central limit theorem can be used to approximate $h_l(t)$ and $h_Q(t)$ jointly as Gaussian

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig1.png}
\caption{Non-line-of-sight communication environment.}
\end{figure}
random processes. The Gaussian property holds for $I$ when the $\phi_i(t)$ is evenly distributed on $[-\pi, \pi]$, and $C_i(t)$ obeys the Rayleigh distribution.

### B. AUTOCORRELATION FUNCTION FOR WIRELESS CHANNELS

In this paper, the autocorrelation algorithm is used to extract the characteristic parameters in different channel scenarios. We use $h_I(t)$ and $h_Q(t)$ to represent the in-phase and quadrature received signal components, respectively. Our derivations are based on certain key assumptions which are applied to different Rayleigh channel models. The multipath is defined as $r_i(t)$, is defined as $C_i$, and Doppler frequency is defined as $f_D(t)$. We assume that these parameters change gradually and can be considered as constants for a brief period. Thus, $C_i(t) \approx C_i$, $f_D(t) \approx f_D$, and $r_i(t) \approx r_i$. Therefore, $\phi_D(t) = \int_0^t 2\pi f_D dt = 2\pi f_D t$. In this case, the phase is $\phi_i(t) = 2\pi f_c t_i - 2\pi f_D t - \phi_0$. Thus,

$$
E[h_I(t)] = E \left[ \sum_i C_i \cos \phi_i(t) \right] = \sum_i E[C_i] E[\cos \phi_i(t)] = 0
$$

where the equality indicates that the $C_i$ and $\cos \phi_i(t)$ are independent, and follows from the uniform distribution pertaining to $\phi_i$. Similarly, as we can prove that $E[h_Q(t)] = 0$.

Therefore, considering the autocorrelation of the $h_I$ and $h_Q$, we can obtain the following expression:

$$
E[h_I(t) h_Q(t)] = \sum_i \sum_j E[C_i C_j] E[\cos \phi_i(t) \sin \phi_j(t)] = \sum_i E[C_i^2] E[\cos \phi_i(t) \sin \phi_i(t)] = 0
$$

Thus, $h_I(t)$ and $h_Q(t)$ are uncorrelated, since these two variables are Gaussian processes.

We can obtain the autocorrelation $A_{h_I}(t, \tau)$ if following a similar derivation from formula (8).

$$
A_{h_I}(t, \tau) = E[h_I(t) h_I(t + \tau)] = \sum_i E[C_i^2] E[\cos \phi_i(t) \cos \phi_i(t + \tau)]
$$

By substituting $\phi_i(t) = 2\pi f_c t_i - 2\pi f_D t - \phi_0$ and $\phi_i(t + \tau) = 2\pi f_c t_i - 2\pi f_D t + \tau - \phi_0$ in formula (7), we can obtain

$$
E[\cos \phi_i(t) \cos \phi_i(t + \tau)] = 5E[\cos (2\pi f_D t)] + 5E[\cos (4\pi f_c t_i - 4\pi f_D t - 2\pi f_D t - \phi_0)]
$$

Therefore,

$$
A_{h_I}(t, \tau) = 5 \sum_i E[C_i^2] E[\cos (2\pi f_D t)] = 5 \sum_i E[C_i^2] \cos (2\pi \nu t \cos \theta_i/\lambda)
$$

Assume that $f_D = \nu \cos \theta_i/\lambda$ is fixed. Since $A_{h_I}(t, \tau) = A_{h_Q}(t)$, and $A_{h_I}(t, \tau)$ depends only on $\tau$, thus $h_I(t)$ is a wide-sense stationary random process.

A similar derivation yields similar results for the $h_Q(t)$ autocorrelation as $h_I(t) = h_Q(t)$. The cross-correlation between the $h_I(t)$ and $h_Q(t)$ can be expressed as

$$
A_{h_I, h_Q}(t, \tau) = A_{h_I, h_Q}(t)
$$

Thus $\tilde{y}(t) = h_I(t) \cos (2\pi f_c t) + h_Q(t) \sin (2\pi f_c t)$ is also wide-sense stationery (WSS), and

$$
A_{h_I, h_Q}(t) = E[h_I(t) h_I(t + \tau)] = A_{h_I}(t) \cos (2\pi f_c t) + A_{h_I, h_Q}(t) \sin (2\pi f_c t)
$$

We consider certain assumptions to simplify (11) and (12) in the context of the wireless communication environment, with the emphasis on ensuring a uniform scattering environment. We assume the angle of arrival of the multipath scattering components, $\theta = i\Delta \theta$, where $\Delta \theta = 2\pi / N$, and hypothesize that each multipath component has the identical received power, therefore $E[C_i^2] = 2P_h / N$. $P_h$ is the received power. In this case, (13) can be expressed as

$$
A_{h}(\tau) = E[h(t) h(t + \tau)] = A_{h_I}(\tau) \cos (2\pi f_c t) + A_{h_I, h_Q}(\tau) \sin (2\pi f_c t)
$$

We substitute $N = 2\pi / \Delta \theta$ into formula (14), and consider the limit of the number $N \to \infty$, and $\Delta \theta \to 0$. In this case then the summation in (14) can be expressed as an integral in (15).

$$
A_{h_I}(\tau) = P_h \int_0^{2\pi} \cos (2\pi \nu \cos (\theta/\lambda)) d\theta = P_h J_0(2\pi f_D \tau)
$$

where $J_0(\tau) = \int_0^{2\pi} e^{-j\nu \cos \theta} d\theta$ is a Bessel function.

Similarly, we obtain the autocorrelation $A_{h_I, h_Q}(\tau)$ of a uniform scattering environment.

$$
A_{h_I, h_Q}(\tau) = P_h \int_0^{2\pi} \sin (2\pi \nu \cos (\theta/\lambda)) d\theta = 0
$$

### C. FEATURE PARAMETERS EXTRACTION THROUGH AUTOCORRELATION

The power spectral density (PSD) of $h_I(t)$ and $h_Q(t)$ can be expressed as by $S_I(f)$ and $S_Q(f)$, respectively, acquired by the Fourier transform of the corresponding autocorrelation functions. Since the autocorrelation functions are equal, they
have the same PSD. Thus, the PSD of the in-phase received signal components can be expressed as

$$S_{h_1}(f) = \mathcal{F}[A_{h_1}(\tau)] = \begin{cases} \frac{1}{2\pi f_D} \sqrt{1 - \left(\frac{f}{f_D}\right)^2}, & |f| \leq f_D \\ 0, & |f| > f_D \end{cases} \quad (17)$$

The PSD of the received signal $\tilde{y}(\tau)$ is obtained using formula (13), with $A_{h_1, h_0}(\tau) = 0$, and the properties of the Fourier transform are used to determine the DSP formula of the classical model.

$$S_{h}(f) = \mathcal{F}[A_{h}(\tau)] = 25 \left[ S_{h_1}(f - f_c) + S_{h_2}(f + f_c) \right]$$

$$= \begin{cases} \frac{1}{4\pi f_D} \sqrt{1 - \left(\frac{f-f_c}{f_D}\right)^2}, & |f-f_c| \leq f_D \\ 0, & \text{else} \end{cases} \quad (18)$$

where $f_D$ is the maximum Doppler frequency shift. $f_D = f_c \cdot \nu/c$, where $f_c$ is the carrier frequency, $\nu$ is the vehicle speed, and $c$ is the velocity of light.

Following a similar derivation, the DSP can be theoretically obtained for other kinds for Rayleigh time-varying channels.

The DSP formula of a flat fading channel is expressed by

$$S_{h}(f) = \frac{P_h}{2f_D}, \quad -f_D \leq f \leq f_D \quad (19)$$

The DSP expression of the Rayleigh Gaussian channel can be expressed as

$$S_{h}(f) = \frac{P_h}{\sqrt{2\pi \sigma_g^2}} e^{-\frac{f^2}{2\sigma_g^2}}, \quad -f_D \leq f \leq f_D \quad (20)$$

where $\sigma_g$ is the statistical variance of $f_D$.

The DSP formula of the rounded fading channel can be expressed as

$$S_{h}(f) = P_h \left[ a_0 + a_2 \ast \left(\frac{f}{f_D}\right)^2 + a_4 \ast \left(\frac{f}{f_D}\right)^4 \right] \quad (21)$$

where the coefficients $a_0$, $a_2$, and $a_4$ correspond to the polynomial, Polynomial $= [a_0 \ a_2 \ a_4]$, which is a finite real vector, where $-f_D \leq f \leq f_D$.

The DSP expression of the Butterworth fading channel can be expressed as

$$S_{h}(f) = \frac{P_h}{\pi f_D \sqrt{1 - \left(\frac{f}{f_D}\right)^2}}, \quad -f_D \leq f \leq f_D \quad (22)$$

The PSD corresponds to the difference in the five different channels, determined by the Fourier transform of the corresponding AF respectively. Thus, the PSD can be used as a characteristic parameter to identify the different channel scenes.

### III. DBN DESIGN AND MODEL STRUCTURE OF THE WIRELESS CHANNEL RECOGNITION ALGORITHM

This section describes the design of the DBN networks classifier, and channel scene recognition algorithm.

#### A. DESIGN OF THE DEEP BELIEF NETWORKS CLASSIFIER

The DBN network established in this paper is a hybrid model network, as shown in Fig.2. The top two layers are undirected graphs that form an associative memory network, and while the other layers form a directed graph. From the bottom up, a visible vector and the hidden layer vector $h_k = (h_{k,1}, h_{k,2}, \cdots, h_{k,n})^t$ are present $G^1$, and the recognition weight is represented by $W^1$. $k = 1, 2, \cdots, r$. $r$ represents the number of layers.

![FIGURE 2. The architecture of the DBN.](image)

The generated weights between the $(k-1)$ hidden layer and the $f_D$ hidden layer are denoted as $G^k$, and the recognition weights are represented as $W^k$. However, the associative memory constitutes an undirected connection between the $(r-1)$ hidden layer and the $r$ hidden layer, the connection weights between these layers are known as associative weights $W^r$. The bias is represented by the visible layer, and the generation bias is represented as $b_k$. Identification offset is represented as $b_k^r$. $(1 \leq k \leq r-1)$, and $b_k^{r+1}$ is the identification offset of the label layer.

The joint probability distribution of the DBN can be expressed as

$$p(y, h_1, h_2, \cdots, h_r | \theta) = p(y | h_1) p(h_2 | h_1) \cdots p(h_{r-1} | h_{r-2}) p(h_r | h_{r-1}) p(h_{r-1} | h_r) \quad (23)$$

Parameter set $\theta = \{W^k, G^k, b^k, h_k, W^r, b^r, W^{r+1}, b^{r+1}, a\}$. Moreover, $p(y, h_{r-1}, h_r)$ is computed as a constrained Boltzmann machine, $(y, h_{r-1})$ is the visible vector, and $h_r$ is the implicit vector.
Using the probability sum technique to eliminate the label vector, the marginal distribution can be obtained as

\[ p(v, y, h_1, h_2, \ldots, h_r | \theta) = p(v | h_1) p(h_1 | h_2) \cdots p(h_{r-1}, h_r) \]  

(24)

The output classification probability can be calculated by using the maximum flexible output function:

\[ p(y = e_i | h_i) = \text{softmax}(W^{r+1} h_r + b^{r+1}) \]  

(25)

For the remaining layers, there are

\[ p(h_{k-1} | h_k) = \prod_i p(h_{k-1,i} | h_k) \quad \forall 1 \leq k \leq r - 1 \]  

(26)

### B. CHANNEL SCENE RECOGNITION ALGORITHM

Compared with general classifiers, the DBN network exhibits a stronger deep representation ability and can effectively solve classification problems well. Therefore, this paper employs a deep learning network.

**Algorithm 1 Learning Algorithm of DBN**

1. **Step 1**: numbers close to 0, where 1 ≤ i ≤ r + 1.
2. **Step 2**: Using the CD-k algorithm to train the first RBM, the visual layer of the RBM is v and the hidden layer is h₁.
3. **Step 3**: For 1 ≤ i ≤ r - 1, take h₁⁻¹ as the visual layer of the iᵗʰ RBM and hᵢ as the hidden layer of the iᵗʰ RBM, use the CD-k algorithm to train the RBM layer by layer.
4. **Step 4**: For i = r, taking the whole of hᵣ⁻¹ and y as the visual layer and hᵣ as the hidden layer, construct a classifier RBM, and use the label CD-k algorithm for training.
5. **Step 5**: The pre-trained DBN is expanded into a deep perceptron.
6. **Step 6**: The up-down optimization algorithm is used to optimize the network parameters.
7. **Step 7**: Stop training when the error meets the requirements.

In the unsupervised pre-training phase, the two adjacent layers (hᵢ⁻¹, hᵢ) are treated as an RBM of the deep belief network with no labels. Moreover, the top two layers are treated as classification constrained Boltzmann machines, trained using CD-k algorithm to initialize \( a, W^k, G^k, b^k \), and \( W^r, b^r, W^{r+1}, \) and \( b^{r+1} \). The training process is aimed at using the conditional probabilities \( Q(h_k | h_{k-1}) \) and \( Q(h_r, h_{r-1}, y) \) of these constrained BMs to estimate the conditional probabilities \( p(h_k | h_{k-1}) \approx Q(h_k, h_{k-1}) \) and \( p(h_r, h_{r-1}, y) = Q(h_r, h_{r-1}, y) \), respectively.

In the up-down optimization phase, the recognition weights \( G^k = (W^k)^{-1} \) are used to initialize the generated weights. All the networks are then tuned using the upper and lower algorithms. The up-down algorithm is a variation of the wakening algorithm, which consists of wakening and sleeping stages, as shown in Fig.2.

The learning discrimination process of the DBN is as algorithm 1. Step 1 - 4 is the unsupervised training stage. Step 5 - 7 is the supervised tuning phase.

In the sleep phase, to estimate the generation weights and generate offsets using the recognition weights and recognition bias are used repeatedly. The wake phase is aimed at realizing overall tuning according to the estimated recognition weight and identification bias.

In step 5, in the supervised tuning phase, the DBN is first expanded into a deep perceptron. The weight and bias are initialized using \( W^k, b^k \), respectively, trained layer by layer in the deep perceptron, and through the back-propagation algorithm to optimize the global network. Moreover, the back-propagation algorithm is used to optimize the overall adjustment.

The overall architecture of the DBN based classification is shown in Fig.3. The architecture involves four major parts, a wireless channel, feature extraction, deep learning network construction and training, and classification.

**FIGURE 3. The overall architecture of the DBN based classification.**

### IV. EXPERIMENT AND ANALYSIS RESULTS

This section describes the experiment and the results of the recognition method based analysis. This section consists of two parts. The first part corresponds to the channel simulation and method verification, and the second part describes the experiment platform and results in analysis results.

Considering the static or quasi-static nature of the indoor channel, outdoor channels can be typically characterized according to the time variation of the channel gain, which depends on the mobile platform. The outdoor channel is mostly characterized by a Doppler spectrum that governs the time variation in the channel gain. In this paper, channel scenarios are examined through two paths of the theoretical simulation and channel simulator. The method is applied to the simulated and the measured channels pertaining to the feature extraction and classification, respectively. This part is divided into two subparts. Section A describes the implementation of the proposed method of this paper through a simulation experiment. Section B describes the accuracy validation of the proposed channel scenario platform.

**A. WIRELESS CHANNEL SCENE AND VERIFICATION OF THE RECOGNITION METHOD**

The simulation methods of the Rayleigh fading channel include the sine wave superposition method and forming filter method. Although the formed filter method has a high design complexity, its statistical accuracy is higher than that of the sinusoidal superposition method, and it can better simulate
the fading channel model. In this paper, the Doppler filter method is used to generate Rayleigh fading channel, and the channel implementation model is shown in Fig.4.

The channel model is devised under the assumption that the scattering components around a mobile station are uniformly distributed with an equal power for each component. Fig.4 shows the block diagram for the channel model, involving two branches, one branch corresponds to the real part, and the other branch corresponds to the imaginary part. In each branch, a complex Gaussian noise is first generated in the frequency domain and filtered by a Doppler filter such that the frequency component is subject to the Doppler shift. Finally, the Doppler-shifted Gaussian noise is transformed into the time-domain signal through an IFFT block. Since the output of the IFFT block must be a real signal, its input must always be conjugate symmetric. By constructing a complex channel gain by adding a real part to the imaginary part of the output, a channel following the Rayleigh distribution can be generated.

1) RELATED PARAMETER SETTINGS IN THE RAYLEIGH WIRELESS CHANNEL SCENE SIMULATION
Sample rate = $10^4$; random number seed = ‘m19937ar with seed’; seed = 34; maximum Doppler shift $f_D = 500 \text{ Hz}$; channel length = 6000 (function calls the impulse response points of a channel); The Gaussian parameters $\sigma^2 = 0.7071$; The cycle number of channel produces = 20; The length of the window function is 100, and the overlap number for each segment is window$*3/4$; The waveforms of the five kinds of simulated channels are shown in Fig. 5.

2) CHANNEL ASSESSMENT
Mutual movement occurs between the transmitter and receiver. The time-varying characteristics correspond to the scattering multipath channel, and the amplitude sum is the time-varying aspect of the in-phase component and the orthogonal component, which belong to the received signal. It has been proved that the Rayleigh distribution can be applied when the multipath number $I$ is sufficiently large enough. This characteristic is used to evaluate the simulation channel model.

According to the definition of the Rayleigh distribution, the amplitude of PDF ($p(\tilde{y})$) should obey amplitude (27) belongs to the received signal $\tilde{y}(t)$:

$$p(\tilde{y}) = \frac{\tilde{y}}{\sigma^2} \exp \left( -\frac{\tilde{y}^2}{2\sigma^2} \right)$$

(27)

When $f_D = 500 \text{ Hz}$, $T_s = 50 \mu s$ is statistically the envelope of the received signal $\tilde{y}(t)$.

The probability statistics method is used to calculate the amplitude in the five channels. The channel validation results are shown in Fig.6. All five channels exhibit Rayleigh channel characteristics. Equations (16) indicate that $h_I(t)$ and $h_Q(t)$ are simultaneously independent of each other at the same time. When $f_D = 500 \text{ Hz}$, $T_s = 50 \mu s$, and statistical analysis was conducted considering the phase of the different channel scenarios. The statistical results are shown in Fig.6 (b). The results indicate that all five channels exhibit a Rayleigh distribution.

Five hundred Monte Carlo simulations were performed for each channel. The extraction method was used to extract the feature parameter for the five channels in this paper. The PSD functions were obtained for the in different channels. Fig.7 shows the 200 groups characteristic parameters obtained using the Monte Carlo method in four kind channels. The X-, Y-, and Z-axes show the Doppler frequency, experiment number and power of the PSD, respectively.
The results of the proposed method were compared with those of the BP neural network method, support vector machine (SVM) method, and Radial Basis Function (RBF) neural network method. The number of nodes in the input layers and output layer of these three recognition methods was the same as those of the proposed DBN. The training and testing data of all the methods were the same, and several classification methods were trained and tested. During the training process, we performed the manual tuning of several methods. To present the comparative results more objectively, the final relevant experimental parameters of the identification methods are presented.
The hidden layer structure of the BP neural network corresponded to 128-4. The learning rate of the BP was 0.1, and the training accuracy was $10^{-3}$. The BP was trained through the adaptive gradient descent method, and training da was used as the training function. The optimal parameter (penalty factor) of the SVM was obtained through cross-validation. The kernel function of the SVM was the radial basis function, and the training accuracy of the SVM was set as $10^{-3}$. The RBF neural network was built automatically using the Newrbe function in MATLAB. The spread of the radial basis functions was set as 0.5. The Gaussian function was selected as the transfer function of the RBF neural network. The two-dimensional feature distribution is shown in Fig. 8.

Fig. 8 (a) shows the two-dimensional feature distribution diagram results obtained using the back-propagation (BP) neural network. As shown in Fig. 8 (a), the curves for the Gaussian channel and rounded channel are partially overlapped, indicating that these curves cannot be well differentiated by the BP neural method. Moreover, the flat channel and Butterworth channel exhibit results that are overlapped to a certain extent, indicating that the neural network method had a mediocre performance in the recognition task.

Fig. 8 (b) shows the effect of the application of the SVM neural network method in the scene recognition task. The three channels overlapped to different degrees from the two-dimensional feature diagram. This result indicates that the method cannot well distinguish the Gaussian channel from the rounded and Butterworth channels.

Fig. 8 (c) shows the two-dimensional feature distribution diagram for the scene recognition based on the RBF neural network. Although this method can effectively classify the rounded, classical, and Gaussian channels, a considerable overlap occurs between the flat channel and Butterworth channel. This method cannot effectively identify the two-channel scenarios.

Fig. 8 (d) shows the two-dimensional feature distribution diagram corresponding to the proposed method. The two-dimensional features exhibit a notable degree of differentiation for the different channel scenes. No overlap occurs between the different channels, which indicates that this method exhibits a satisfactory scene recognition effect.

To clearly illustrate the recognition effect for different methods in the simulation channel environment. Table 1 presents the correct recognition rates for the four different scene recognition methods.

Table 1 indicates that the optimal channel scene recognition corresponds to the proposed method, which has a theoretical correct recognition rate of 100%. The BP neural network based method has the worst recognition effect, with a correct recognition rate of only 72.6%. The results of SVM and RBF results are comparable, with the correct recognition rates of 82.4% and 87.4%, respectively. The theoretical experimental results show that the proposed DBN method has a more powerful learning ability than the other methods. The proposed deep learning method exhibits a better representation and classification ability in terms of the channel characteristics.
TABLE 1. Comparison of correct recognition rates of four different methods under simulation environment.

| Recognition rate Classifier type | Channel                  | Classical fading channel | Flat fading channel | Rayleigh Gaussian channel | Rounded fading channel | Butterworth fading channel | Five kinds channel |
|---------------------------------|--------------------------|--------------------------|--------------------|--------------------------|------------------------|---------------------------|-------------------|
| BP neural network method        | 100%                     | 98%                      | 42%                | 56%                      | 67%                    | 72.6%                     |                   |
| SVM method                      | 100%                     | 94%                      | 96%                | 53%                      | 68%                    | 82.4%                     |                   |
| RBF neural network method       | 100%                     | 79%                      | 100%               | 100%                     | 58%                    | 87.4%                     |                   |
| This paper methods              | 100%                     | 100%                     | 100%               | 100%                     | 100%                   | 100%                      |                   |

TABLE 2. Confusion matrix of the channel scenario recognition on deep learning under physical platform.

| Actual channel type | Classical | Flat | Gaussian | Rounded | Butterworth |
|---------------------|-----------|------|----------|---------|-------------|
|         | Identify channel type |         |          |         |             |             |
|         | Classical | Flat | Gaussian | Rounded | Butterworth |
| Classical | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Flat     | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 |
| Gaussian | 0.00 | 0.00 | 0.97 | 0.03 | 0.00 |
| Rounded  | 0.00 | 0.00 | 0.02 | 0.98 | 0.00 |
| Butterworth | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |

TABLE 3. Comparison of correct recognition rates of four different methods under physical platform.

| Recognition rate Classifier type | Channel | Classical fading channel | Flat fading channel | Rayleigh Gaussian channel | Rounded fading channel | Butterworth fading channel | Five kinds channel |
|---------------------------------|---------|--------------------------|--------------------|--------------------------|------------------------|-----------------------------|-------------------|
| BP neural network method        | 100%    | 97%                      | 40%                | 52%                      | 57%                    | 69.2%                      |                   |
| SVM method                      | 100%    | 89%                      | 90%                | 51%                      | 63%                    | 78.9%                      |                   |
| RBF neural network method       | 100%    | 92%                      | 85%                | 86%                      | 77%                    | 80.0%                      |                   |
| This paper methods              | 100%    | 100%                     | 97%                | 98%                      | 100%                   | 99.2%                      |                   |

B. EXPERIMENT PLATFORM AND RESULTS

To further verify the accuracy of the proposed method, the author builds a comprehensive platform for the wireless channel scenario simulation was developed and analyzed. The application value of the method was further verified. A photograph of the comprehensive analysis test physical platform is shown in Fig.9. An analog signal generator and a vector signal generator were used to generate low-frequency signals and radio frequency signals, respectively. The signal analyzer conducted Doppler translation monitoring for the generated RF signal. A sub-5 GHz radio channel emulator with a bandwidth of 150 MHz, including eight input ports and eight output ports was employed. A radiofrequency (RF) down converter was combined with a 1-to-8 RF splitter in one module. Moreover, an RF up-converter was combined with one 8-to-1 RF combiners in another module, as shown in Fig.9. The frequency response of the channel simulator was recorded using a vector network analyser. The tested wireless channel data were imported into the computer processor to verify the recognition effect of the proposed method.

The test platform was used to test the signals of different wireless channel scenarios, using the autocorrelation function method to extract the parameters.

Fig.10 shows the extracted characteristic parameters in different Rayleigh channels through a physical platform. According to the extracted feature parameters, the proposed feature extraction method in this paper is still effective even in the actual simulation channel platform. The method can extract the characteristic parameters of different wireless channel scenarios. The characteristic parameters are significantly different in different channel scenarios. Moreover, the extracted feature parameters can also be used as the training data of the DBN.

The DBN was trained and tested using the test data. The relevant parameter settings were the same as those described in Sections A-C). The results were compared with those of the BP method, SVM method, and RBF method. The two-dimensional feature distribution corresponding to the wireless channel scene recognition results is shown in Fig.11.

Fig.11 (a) shows the two-dimensional feature distribution diagram of the scene recognition results obtained by using the BP neural network. As shown in Fig.11 (a), the curves for the Gaussian and Rounded channel are overlapped, indicating these channels cannot be well differentiated using the BP neural method. Moreover, the flat channel and the Butterworth channel are overlapped to a certain extent, indicating that the
neural network method exhibits a mediocre performance in the recognition task. The platform test results are similar to the simulation results.

Fig. 11 (b) shows the application effect of applying the SVM method in the scene recognition task. The four channels exhibit varying degrees of overlap, with considerable overlap between the Gaussian and rounded channels. This finding indicates that the BP method cannot well distinguish the Gaussian channel from the round and Butterworth channels.

Fig. 11 (c) shows the two-dimensional feature distribution diagram of the scene recognition based on the RBF neural network. The RBF method can effectively identify the classical and Gaussian channels. However, a critical overlap occurs between the flat channel and the Butterworth channel. This method cannot effectively identify the two-channel scenarios.

Fig. 11 (d) shows the two-dimensional feature distribution diagram for the proposed method. The two-dimensional features for different channel scenes exhibit a notable differentiation. Only a small amount of overlap can be noted between the Gaussian and rounded channels.

Table 2 presents the confusion matrix of the recognition results for the proposed method. The proposed method can accurately identify the scenes for the five channels when using the physical platform, with an extremely high correct recognition rate.

Table 3 presents the correct recognition rates for four different scene recognition methods. The classical fading channel can be identified through the four methods, with an accuracy rate of 100%. This result indicates that the four
methods can well identify the Gaussian fading channel. For the flat and Butterworth fading channels, the recognition rate of the proposed method is 100%, even though the recognition rates for the other three conventional methods are low. The results indicate that for these two channels, the representation based on deep learning is the highest performing approach. For the Rayleigh Gaussian channel and Butterworth fading channel, the recognition rate of the proposed method is higher than that of the other three methods. The experimental results show that compared with other methods, the proposed deep learning method has a stronger learning ability for wireless channel scenarios. This method can more effectively realize the feature extraction and classification.

As shown in Table 3, the proposed method can realize the most effective channel scene recognition. The overall correct recognition rate of the proposed method is 99.2%. The BP method exhibits the worst recognition effect, with a correct recognition rate of only 69.2%. The results of the SVM and RBF are comparable, with a correct recognition rate of 82.4% and 87.4%, respectively. In the wireless channel scenarios with fast time-variations, large bandwidth, and multiple dimensions, the traditional methods cannot achieve a high recognition accuracy. Overall, the proposed identification method exhibits the strongest recognition ability.

V. CONCLUSION
This paper proposes a wireless channel scene recognition method based on feature parameter extraction and deep learning. The autocorrelation function is used to extract the characteristic parameters of a wireless channel scene. The windowing and overlap techniques are adopted to realize the process of time-frequency transformation. Normalized pre-processing is recognized in the frequency domain, and the satisfactory characteristic parameters are obtained from the wireless channel. A deep learning algorithm with a robust taxonomy ability is applied to realize the wireless channel scene recognition. A hybrid model is built by using the restricted Boltzmann machine of the DBN. The CD-k learning algorithm is used to initialize the network parameters, and the up-down-optimization algorithm is used to optimize the identification weights and offset parameters. The theoretical simulation results demonstrate the correctness and accuracy of the method. Finally, a wireless channel scene recognition platform is built by combining hardware and software. The experimental results show that the proposed algorithm exhibits high performance in the wireless channel scene recognition task. The proposed method can accurately identify the different channel scenes and thereby demonstrates high engineering application value.

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