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Review Article

A Survey on Deep Learning Techniques in Wireless Signal Recognition

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Wireless signal recognition plays an important role in cognitive radio, which promises a broad prospect in spectrum monitoring and management with the coming applications for the 5G and Internet of Things networks. Therefore, a great deal of research and exploration on signal recognition has been done and a series of effective schemes has been developed. In this paper, a brief overview of signal recognition approaches is presented. More specifically, classical methods, emerging machine learning, and deep leaning schemes are extended from modulation recognition to wireless technology recognition with the continuous evolution of wireless communication system. In addition, the opening problems and new challenges in practice are discussed. Finally, a conclusion of existing methods and future trends on signal recognition is given.

1. Introduction

With the increasing innovation in wireless communication system, numerous wireless terminals and equipment are constantly emerging, which has brought profound changes to our daily life. Unfortunately, the limited spectrum resource can hardly meet the ever-changing demand of the coming 5G [1] and Internet of Things (IoT) networks [2], which poses a significant challenge to the spectrum utilization and management. The Federal Communications Commission (FCC) and European Union (EU) authorities have attached high priority to spectrum policy and committed to further improve the performance of spectrum sensing as well as signal recognition algorithms to satisfy the demand of spectrum management. Some concepts including dynamic spectrum access (DSA) and cognitive spectrum-sharing techniques have aroused widespread discussions in academia. However, much work is limited to specific scenarios and poor in adaptability to the different channel conditions and device types. Therefore, new spectrum sensing schemes and novel signal recognition mechanisms have attracted more and more attention, which pave the way to cognitive radio (CR) [3].

Wireless signal recognition (WSR) has great promise on military and civilian applications [4], which may include signal reconnaissance and interception, antijamming, and devices identification. Generally, WSR mainly includes modulation recognition (MR) and wireless technology recognition (WTR). MR also known as automatic modulation classification (AMC) is first widely used in military field and later extended to civilian field. MR classifies radio signals by identifying modulation modes, which facilitates to evaluate wireless transmission schemes and device types. What is more, MR is capable of extracting digital baseband information even under the condition of limited prior information. Recently, WTR attracts much attention with the various wireless communication technologies emerging and developing. Wireless technology usually contains various technical standards, not just a single modulation mode. Moreover, different technical standards may adopt the same modulation mode. WTR is able to leverage more comprehensive features to identify technical standards, which has important practical significance in current increasingly tense electromagnetic environment. In addition, the estimation of some parameters, such as frequency, bandwidth, and symbol rate, may also contribute to WSR. Due to the variety and complexity of signal transmission mechanisms, it is difficult to recognize complex signals by only estimating single or few parameters. Therefore, the MR and WTR technologies are focused in this paper.

Traditional algorithms of MR could mainly be separated into two groups: likelihood-based (LB) and feature-based (FB) approaches [5]. LB approaches are based on hypothesis testing theory; the performance based on decision-theoretic is optimal but suffers high computation complexity. Therefore, feature-based approaches as suboptimal classifiers were developed for application in practice. In particular, the feature-based approaches usually extracted features for the preprocessing and then employed classifiers to realized modulation classification. Conventional FB approaches heavily rely on the expert's knowledge, which may perform well on specialized solutions but poor in generality and suffer high complexity and time-consuming. To tackle these problems, machine learning (ML) classifiers have been adopted and shown great advantages, for example, support vector machine (SVM) in [6]. Although ML methods have the advantage of classification efficiency and performance, the feature engineering to some extent still depends on expert experience, resulting in degradation of accuracy rate. Therefore, the self-learning ability is very important when confronted with unknown environment. A new dawn seems to have arrived, since the DL performs very well in computer vision (CV) [7], machine translation (MT) [8], and natural language processing (NLP) [9]. DL architecture has also been introduced to MR, for instance; the convolutional neural networks (CNN) model is employed in modulation classification without expert feature extraction [10], which demonstrates excellent performance both on efficiency and accuracy.

On the other hand, current communication systems tend to be complex and diverse, various new wireless technologies are constantly updated, and the coexistence of homogeneous and heterogeneous signals is entering a new norm. As a result, the detection and recognition of complex signals will be confronted with new dilemma, and the methods for signal recognition are needed to keep up with the pace. Fortunately, some literature on WTR has emerged, in which ML and DL model with explicit features have also been done to realize the recognition of specific wireless technologies. Meanwhile, some emerging applications are been explored, such as base station detection, interfere signals recognition, and localization in mobile communication network [11].

In this paper, the need of deep learning in signal recognition is reviewed in Section 2. Section 3 introduces the modulation recognition with various approaches. In Section 4, wireless technology recognition is presented. Opening problems are discussed in Section 5. Section 6 concludes the paper.

2. Need of Deep Learning in Wireless Signal Recognition

2.1. Wireless Signal Recognition. With the continuous expansion of military and civilian needs, communication systems

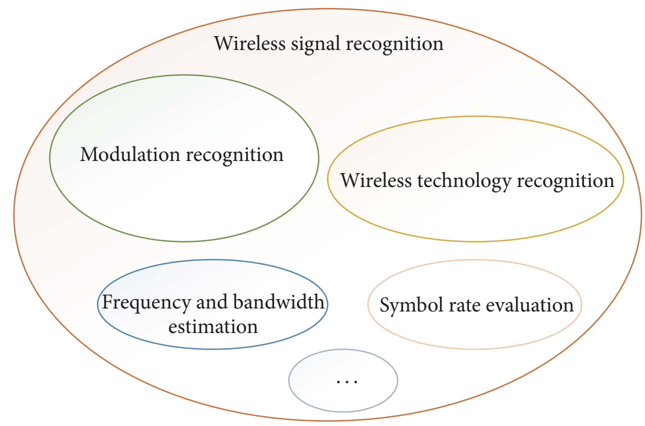

Figure 1: Wireless signal recognition.

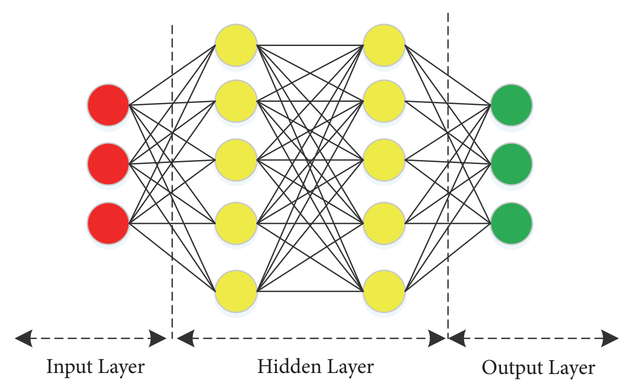

Figure 2: Neural network framework.

and electromagnetic environments have greatly changed over the past decades; the capability of detection and recognition of communication signals has also made significant progress and gradually become maturity. Generally, communication signal recognition takes advantage of some signal parameters to classify or identify the types of signals. These techniques may include frequency and bandwidth estimation, symbol rate evaluation, modulation type classification, and wireless technology identification, which could be collectively referred to as wireless signal recognition as shown in Figure 1. In this paper, we are concerned with the current two main technologies, namely, MR and WTR. MR commits to realize the modulation type recognition so as to evaluate wireless transmission schemes and device types, while WTR takes wireless technology identification as object for improving interference management and electromagnetic environmental assessment.

2.2. Definition of DL Problem. The concept of DL originates from the research on artificial neural network [12] and the goal is to understand data by mimicking the mechanism of the human brain [13]. The basic neural network framework consists of three parts: input, hidden, and output layer and is shown in Figure 2. Hidden layers maybe one layer or multilayer, and each layer consists of several nodes. The

Table 1: ML VS DL in wireless signal recognition.

Leaning model	Machine learning	Deep learning
Application scenarios	(i) small signal data (ii) signal under relatively ideal conditions	(i) high-dimensional signal data (ii) good feasibility in real field environment
Algorithms	(i) ANN [26, 37] (ii) KNN [38, 91] (iii) SVM [6, 27, 47, 48, 92] (iv) Naïve Bayes [39] (v) HMM [46] (vi) Fuzzy classifier [93] (vii) Polynomial classifier [40, 94]	(i) DNN [24, 30, 31, 61] (ii) DBN [49, 63] (iii) CNN [17, 19–21, 54, 64, 65, 70, 73–76, 79, 81, 82, 95, 96] (iv) LSTM [29, 69] (v) CRBM [53] (vi) Autoencoder network [50, 62] (vii) Generative adversarial networks [66, 67] (viii) HDMF [71, 72] (ix) NFSC [78]
Pros	(i) works better on small data (ii) low implementation cost	(i) simple pre-processing (ii) high accuracy and efficiency (iii) adaptive to different applications
Cons	(i) time demanding (ii) complex feature engineering (iii) depends heavily on the representation of the data (iv) prone to curse of dimensionality	(i) demanding large amounts of data (ii) high hardware cost

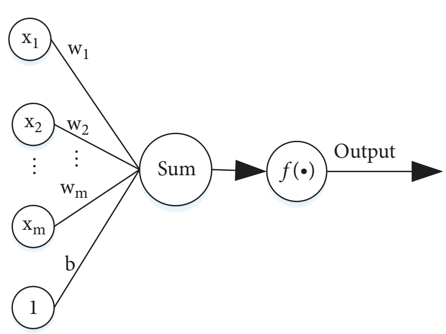

Figure 3: Hidden layer node.

node presented in Figure 3 is the basic operational unit, in which the input vector is multiplied by a series of weights and the sum value is fed into the activation function f. These operational units contribute to a powerful network, which could realize complex functions such as regression and classification. In fact, the study of DL makes substantial progress by Hinton in 2006 [14], which causes a great sensation. DL architecture is comprised of many stacked layers of neural networks, emphasizing the learning from successive layers to obtain more meaningful information or high-level representations. The fundamental idea is to utilize feedback information to iteratively optimize weight value in multilayer neural networks. Moreover, the layers with a relatively large scale will bring about amazing effects. Due to the superior performance, DL has been employed on a wide variety of tasks including CV, MT and NLP.

2.3. From ML to DL. Although ML is not a new field, with the explosive growth of the amount of data and the development of hardware technology ML has been one of research hotspots in both academe and industry [15, 16]. Recently, ML has also made great strides in signal recognition. ML works well on automatic signal classification for small signal dataset under relatively ideal conditions [17]. Most algorithms are easy to interpret and have the advantage of low implementation cost. While for a high-dimensional dataset, machine learning is prone to curse of dimensionality and the complex feature engineering is time demanding. In terms of algorithm theory, ML has a risk of falling into local optimum, which may lead to great performance degradation. Furthermore, ML models are trained for specific solutions and lack of generality in different real field environments. To overcome these issues, DL is developed and achieves high accuracy and efficiency [18]. Owing to multilayered artificial neural networks, DL needs few data preprocessing and shows adaptive to different application scenarios. A comparison between ML and DL is summarized in Table 1.

2.4. Advantage of DL Applied in Wireless Signal Recognition. The perfect combination of DL and signal recognition possesses notable superiority. On the one hand, large-scale data is essential for the training process in DL model, which is accessible to get for various communication pieces of equipment in daily life. On the other hand, feature engineering can be left out in DL architecture, which is an indispensable part for conventional recognition schemes. Feature selection from the received signal is usually difficult in practical applications. For example, the prior information is essential in the estimation of many parameters, which may be impractical or inaccurate [19]. Although some FB approaches perform well in certain solutions, the feature selection may suffer high complexity and time-consuming, so the feature self-learning model is of great significance for realistic scenarios to free from expert experience [20]. In addition, with the further improvement of DL algorithms and

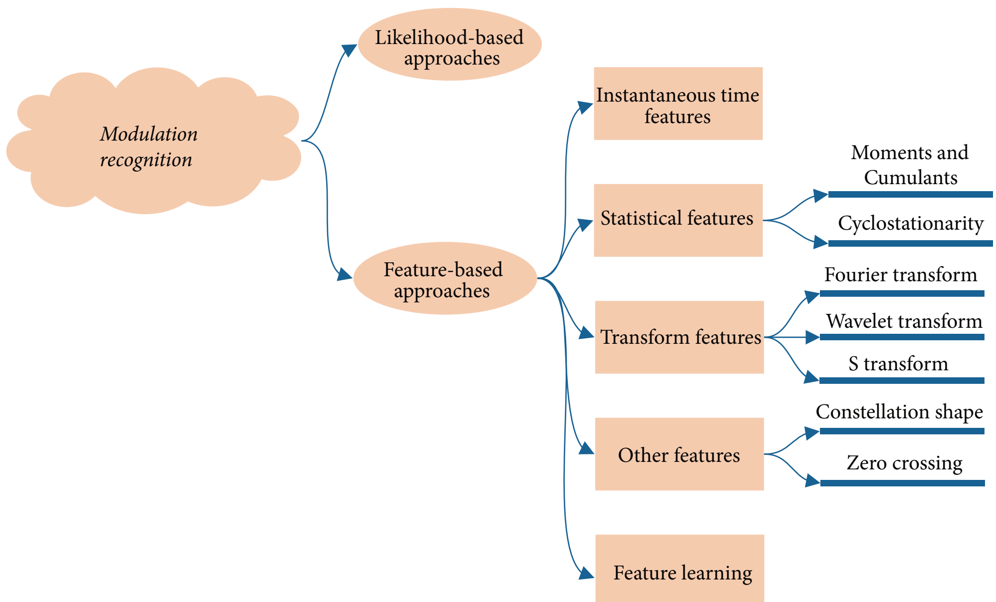

Figure 4: Modulation recognition.

theory research, more application prospects will be excavated for signal recognition in future communications systems [21].

3. Modulation Recognition

Modulation recognition has attracted much attention in last decades; quite a few scholars have presented a variety of excellent approaches, which can be approximately separated into two categories: LB [22, 23] and FB approaches, as shown in Figure 4. Theoretically, the LB approaches are capable of obtain optimal performance by considering all the unknown quantities for the probability density function (PDF) and are usually employed as the theoretical upper bound for the performance comparison of modulation recognition. However, such approaches are burdened with high computational complexity and are prone to mismatching when applying the theoretical system model to the actual scene. To consider the effects of frequency offset and time drift, a large number of computational operations bring about extremely high complexity in maximum likelihood-based detector [24].

To tackle the problem of high complexity in practice, a large number of suboptimal approaches come into being. The FB approaches usually extract certain features from the received signal; then reasonable classifiers are used to classify different modulation signals. Since the training samples are employed to train a good classifier, the robustness of FB approaches is significantly improved for various system models and channel conditions. In addition, effective features and enough training data are also significant for improving classification accuracy.

To reduce the difficulty in expert-feature extraction and enhance the flexibility for modulation classification applied in different system and channel fading environment, DL is applied for self-feature learning based on the I/Q raw data or sampling data.

In the following, we introduce the feature-based approaches and feature learning approaches in modulation recognition.

3.1. Feature-Based Approaches. These features can be summarized as follows: instantaneous time features, statistical features, transform features, other features including constellation shape, etc. The feature-based approaches are more robust and general for various signals. When combined with deep learning methods, the feature-based approaches will provide a significant improvement in the performance with high efficiency and robustness.

3.1.1. Instantaneous Time Features. Generally, instantaneous time features consist of a series of parameters, namely, carrier amplitude, phase, and frequency. These parameters and the variation of them are developed to modulation classification. Nine key features are summarized in the Table 2.

In [25], the authors use eight key features in the recognition procedure and compare with some manually selected suitable thresholds to classify both analogue and digital modulation signals.

Unlike the previous approaches with manual threshold, machine learning has been developed to improve the performance and reduce tedious threshold operations. To choose the threshold automatically and adaptively, artificial neural networks (ANN) is employed in some literature. In [26], a universal ANN was proposed for analogue as well as digital modulation types classification with nine key features employed. Although ANN has achieved success in modulation recognition, its overdependence on training sample data and easily getting into a local optimum restrict

Table 2: Instantaneous time features [26].

Feature	Definition description
γ_{max}	Maximum value of the power spectral density of the normalized-centered instantaneous amplitude
σ_{ap}	Standard deviation of the absolute value of the nonlinear component of the instantaneous phase
σ_{dp}	Standard deviation of the direct value of the nonlinear component of the instantaneous phase
σ_{aa}	Standard deviation of the absolute value of the normalized-centered instantaneous amplitude
σ_{af}	Standard deviation of the absolute value of the normalized instantaneous frequency
σ_{a}	Standard deviation of the normalized-centered instantaneous amplitude
P	Spectrum symmetry
μ_{42}^{a}	Kurtosis of the normalized instantaneous amplitude
μ_{42}^{f}	Kurtosis of the normalized instantaneous frequency

the performance and application, while the support vector machines (SVM) can effectively alleviate these problems. In [27], the straightforward ordered magnitude and phase were adopted by SVM classifier. The proposed method is close to the theoretical upper bound and has an advantage of easy implementation.

Recently, deep learning as an extension of ANN is showing its great potential in modulation recognition [28]. Complex features are learned by multiple hidden layers, so the processing of input data could be simpler in deep learning schemes. A new model Long Short Term Memory (LSTM) has been applied to modulation recognition, which is suitable for processing the time series data with relatively long intervals or delays [29]. The time domain amplitude and phase data were employed in the model without complex feature extraction. Simulations show that the method could achieve high classification accuracy at varying SNR conditions. The flexibility of the proposed model was also validated in scenarios with variable symbol rates. Unlike the existing methods which only focus on modulation types classification, in [30, 31], they propose a novel scheme for classifying modulation format and estimating SNR simultaneously. The asynchronous delay-tap plots are extracted as the training data and two multilayer perceptron (MLP) architectures are adopted for real-world signal recognition tasks.

3.2. Statistical Features. Moments, cumulants, and cyclostationarity will be introduced as following.

3.2.1. Moments and Cumulants. In mathematics, moments are employed to describe the probability distribution of a function. The p-th order and q-th conjugations moment [32] for a received signal $y(n)$ can be given as

$$M_{pq} = \mathbf{E}\left[y(n)^{p-q}\left(y^{*}(n)\right)^{q}\right] \quad (1)$$

where $\mathbf{E}[\bullet]$ is expectation operator and $(\bullet)^{*}$ is complex conjugate. Although moments have been widely used in the field of signal process for the advanced ability on noise suppression, most practical applications tend to cumulants for its superiority on non-Gaussian random processes.

Table 3: Cumulants formulas.

Cumulants	Formulas
C_{40}	$M_{40} - 3M_{20}^{2}$
C_{41}	$M_{41} - 3M_{21}M_{20}$
C_{42}	$M_{42} - \left\|M_{20}\right\|^{2} - 2M_{21}^{2}$
C_{60}	$M_{60} - 15M_{20}M_{40} + 30M_{20}^{3}$
C_{63}	$M_{63} - 6M_{20}M_{41} - 9M_{42}M_{41} + 18M_{20}^{2}M_{21} + 12M_{21}^{3}$
C_{80}	$M_{80} - 35M_{40}^{2} - 28M_{60}M_{20} + 420M_{40}M_{20}^{2} - 630M_{20}^{4}$

In statistical theory, cumulants are made up of moments and can be regarded as an alternative to the moments. Commonly used cumulants are expressed in Table 3.

Cumulants are often employed for modulation classification to against the carrier offsets and non-Gaussian noise. In [33], fourth-order cumulants were utilized in the task of signal classification. Higher-order cumulants (HOC) are conducive to further enhance the performance and extend the range of recognition signals. In [34], sixth-order cumulants show significantly performance improvement than the fourth-order cumulants. In [35], eighth-order cumulants are employed to distinguish between 8PSK and 16PSK signal. Additionally, higher-order cyclic cumulants are developed to further expand the signal types including 256-QAM in [36].

Some methods combined cumulants with machine learning for modulation classification have been proposed in recent works, such as ANN, K-Nearest Neighbor (KNN), SVM, Naïve Bayes (NB), and polynomial. To improve the performance, two updated ANN training algorithms are presented in [37]. KNN is attractive due to its easy implement. In [38], the authors propose a KNN classifier using cumulants-based features of the intercepted signal. Satisfactory performance was verified by numerous simulations. SVM has great potential on the recognition of small-scale and high dimensional dataset. Another interesting scheme combined HOC with SVM is presented for digital modulation classification in NB model originates from classical mathematical theory and the major advantages lie in simplicity and less sensitive to missing data. In [39], the authors proposed a new scheme combined HOC with NB classifier. Simulations indicated that the NB classifier was superior to both Maximum Likelihood and SVM model on computational complexity and close to SVM on performance. To further reduce the complexity, a novel AMC system based on polynomial classifier was presented in [40]. Second, fourth and sixth HOC were utilized to classify M-PSK and M-QAM signals with low computational complexity. In addition, a comprehensive comparison among KNN, SVM, NB, and the proposed polynomial classifier combined with extraction of higher order cumulants features is carried out in [41]. The proposed method achieves good tradeoff in terms of accuracy and structure simplicity.

3.2.2. Cyclostationarity. A cyclostationary process is a signal whose statistical characteristics change periodically with time [42]. Cyclostationarity is an inherent physical property of most signals, which is robust against noise and interference [43]. Spectral correlation function (SCF) is usually used to examine and analyze the cyclostationarity of the signal [44] and can be defined as

$$S_x^{\alpha}(f) = \lim_{\Delta f \longrightarrow \infty} \lim_{\Delta t \longrightarrow \infty} \frac{1}{\Delta t} \cdot \int_{-\Delta t/2}^{\Delta t/2} \Delta f X_{1/\Delta f}\left(t, f + \frac{\alpha}{2}\right) \cdot X_{1/\Delta f}^{*}\left(t, f - \frac{\alpha}{2}\right) dt \tag{2}$$

where

$$X_{1/\Delta f}(t, v) = \int_{t-1/2\Delta f}^{t+1/2\Delta f} x(u)\, e^{-i2\pi v u} du \tag{3}$$

is the complex envelope value of $x(t)$ corresponding to the frequency v and the bandwidth Δf and α represents cyclic frequency and Δt is the measurement interval.

As a continuation, the spectral correlation function of digitally modulated signals was provided in [45]. Hidden Markov Model (HMM) was employed to deal with the features extracted from the cycle frequency domain profile in [46]. Simulations show that the presented model was able to classify the signals at a range of low SNRs. Another classification scheme with spectral correlation feature and SVM classifier is developed in [47]. The results demonstrate that the algorithm is robust under the condition of low SNR and maintain high accuracy. In [48], four features based on spectral correlation were selected for SVM classifier. The proposed method performs more efficiently in low SNR and limited training data.

Deep learning methods employed spectral correlation function features have been applied to signal classification. In [24], the method using 21 features of baseband signal and a full-connected DNN model is proposed to recognize five modulation mechanisms. The simulations verify that the proposed algorithm outperforms the ANN classifier under various channel conditions. Deep Belief Network (DBN) is introduced to pattern recognition tasks in [49]. With spectral correlation function (SCF) signatures, the DBN classifier achieves great success in the field of modulation classification in various environments. In [50], cyclic spectrum statistics are also adopted in the signal preprocessing and a stacked sparse autoencoder and softmax regression with DL model are employed to recognize communication signals. The comparison of the proposed methods and several traditional machine learning schemes was analyzed by simulations. Another modulation classification method for very high frequency (VHF) signal is presented in [20]. The received signals are transformed into cyclic spectrum; then the denoised spectrum images are fed into CNN model to self-learn the inner features and train classifier to recognize modulation formats finally.

3.3. Transform Features

3.3.1. Fourier Transform. Fourier transform is a significant technique in signal processing and analysis. For most signals, frequency domain analysis is more convenient and intuitive than time domain, and the Fourier transform provides convenience in decomposing a function of time (a signal) into the frequencies. In [51], in order to analyze the signal modulation method, discrete Fourier transform (DFT) and the calculated amplitude and phase values were employed to classify MFSK, MPSK signals. In [52], a classifier adopted fast Fourier transform (FFT) has been proposed to classify the received MFSK signal.

Joint time-frequency transforms play an important role in characterizing time-varying frequency information, which could compensate for the insufficiency of the one-dimensional solution and process the time and frequency characteristics simultaneously. The short time-frequency transform (STFT) is known as a classical time-frequency representation and has been widely adopted in signal processing. In [53], a novel learning scheme with STFT features based on DL is proposed, which could automatically extract features and do decision-making in complex missions. The performance of the proposed method is verified in the spectrum application of classifying signal modulation type. In [54], the authors propose a DCNN method that transforms modulation mode to a new time-frequency map and successfully recognize the hybrid communication signals under low SNR condition.

3.3.2. Wavelet Transform. Compared with the Fourier transform, the wavelet transform (WT) can provide the frequency of the signals and the time associated to those frequencies, which offers refined local signals analysis and low computations. The paper [55] proposed a WT modulation classifier without requiring any a priori knowledge. The combination of WT and SVM is a popular scheme in modulation identification. The wavelet kernel function and SVM for modulation recognition is employed in [56]. The proposed method is capable of classifying BPSK, QPSK, and AM signals with good accuracy. The paper extended the SVM classifier with key features of WT to recognize 8 kinds of digital modulated signals.

In [57], the authors use higher-order statistical moments features based on continuous WT and multilayer feed-forward neural network for modulation recognition. Taking into account for various distracters including different SNR, fading channels, and frequency shift, the authors in [17] propose an improved CNN architecture based on [10], in which the pooling layer is employed to retain principal components and reduces the dimension of features. The recognition rate and performance are further enhanced by wavelet denoising technology and appropriate order of the wavelet transformation.

3.3.3. S Transform. S transform (ST) has unique advantages in possessing both the phase and frequency estimations of the FT and the super-resolution of the WT [58]. Early application of the ST was in electrical power networks with power quality analysis. In [59], ST based features extraction for digital modulation classification was presented. A comparison with the WT was given by employing different machine learning classifiers.

3.4. Other Features

3.4.1. Constellation Shape. In digital modulation, the constellation is usually used to map the signal into scattered points. The constellation diagram provides an intuitive way to represent signal basic structure and the relationship between different modulation modes. In [60], the constellation shape was employed as a reliable signature to realize digital modulation recognition.

DL has been effectively used in constellation-based approaches for automatic modulation classification. In [61, 62], the authors use the DL network combined with IQ components of constellation points as features. In [63], a simple graphic constellation projection (GCP) scheme for AMC is presented. Unlike FB approaches, the AMC task is turned to image recognition technology. Reference [64] proposed a DL-based intelligent constellation analyzer that could realize modulation type recognition as well as OSNR estimation. The authors utilized CNN as DL models and treat constellation map as original processing features. Due to the automatic feature extraction and learning, CNN is capable of processing original constellation distribution without the knowledge of any other parameters. In [21, 65], the signals were transformed to the images with topological structure and the CNN algorithm was used to deal with the classification. In [66], the authors explore a new framework for generating additional images in CNN training through using auxiliary classifier generative adversarial networks (ACGAN) for data augmentation to solve the modulation classification problem. Reference [67] extended a new semisupervised learning model combined with generative adversarial networks (GANs). The proposed scheme was verified to be a more data-efficient classifier.

3.4.2. Zero Crossing. A zero-crossing sampler is used for recording the number of zero-crossing voltages of input signals, which could provide precise information about phase conversion in wide frequency range. Therefore, the zero-crossing of the signal can also be applied to modulation classification. The paper [68] develops a modulation recognition algorithm with zero-crossing techniques. Both the phase difference and the zero-crossing interval histograms are employed as features. The recognizer could identify CW, MPSK, and MFSK signals with a reasonable classification accuracy.

3.5. Feature Learning. Feature learning is based on the raw data or sampling data instead of crafting of expert features. A recently proposed AMC scheme based on DL model takes advantage of CNN classifier [10]. The time domain IQ samples are directly fed to CNN model and suitable matched filters can be learned automatically in different SNRs. In [69], the classification accuracy of CNN architectures with different sizes and depths was analyzed. The authors also provided a hybrid learning scheme, which combines CNN model and long short term memory (LSTM) network to achieve better classification performance. Reference [70] constructs a CNN model with 5 layers for the recognition of very high frequency signals. Simulation and actual signals are verified that the frequency offset and noise have a great impact on accuracy. Reference [19] proposed a novel model to obtain the estimation of the frequency offset as well as phase noise for improving accuracy rate. To further improve the performance of CNN-based recognition schemes in [10], the authors present a signal distortion correction module (CM) and results show that this CM+CNN scheme achieves better accuracy than the existing schemes. In [71, 72], a heterogeneous deep model fusion (HDMF) approach is proposed, and the two different combinations between CNN and LSTM network without prior information are discussed. The time-domain data are delivered to fusion model without additional operations. The results show that the HDMF approach is an excellent alternative for a much better performance in heterogeneous networks.

4. Wireless Technology Recognition

Various radio pieces of equipment make an increasing shortage of spectrum resources. As a result, the interference for transmissions is unavoidable in a coexistence environment, which leads to a decline in spectrum efficiency. What is more serious is that the diversity of communication technologies and heterogeneous networks cause a more complex electromagnetic environment. Therefore, the recognition of signal technology is of great significance in spectrum sharing and interference management.

Similar to MR, the feature-based approaches can also be developed for WTR. Due to the development of machine learning and deep learning, WTR favors explicit features, such as time, frequency, and time-frequency features. The literature related to DL in MR and WTR is summarized in Table 4.

4.1. Time Domain Features. Time features are the most explicit representation of a signal, such as amplitude, phase, and even IQ raw data, and can be obtained easily. In [73], the author uses time domain features such as IQ vectors and amplitude/phase vectors to train CNN classifiers. The results demonstrate that the proposed scheme is well suited for recognizing ZigBee, WiFi, and Bluetooth signals. In

Table 4: Summary of DL in wireless signal recognition.

	Modulation recognition	Wireless technology recognition
Algorithms	(i) DNN [24, 30, 31, 61] (ii) DBN [49, 63] (iii) CNN [17, 19–21, 54, 64, 65, 70, 95] (iv) LSTM [69] (v) CRBM [53] (vi) Autoencoder network [50, 62] (vii) Generative adversarial networks [66, 67] (viii) HDMF [71, 72]	(i) CNN [73–76, 79, 81, 82, 96] (ii) LSTM [29] (iii) NFSC [78]

[74], the amplitude and phase difference representation were employed for CNN training procedure. The results indicate that the recognition of radar signals has been realized successfully with the proposed scheme even under the condition of LTE and WLAN signals coexisting at the same time. Reference [75] extended the deep CNN model for radio signal classification by heavily tuning deep residual networks based on previous works. A discussion was carried on the robustness of the proposed model under different channel parameters and scales of training sets. Reference [76] proposed a radio fingerprinting method, which adopted CNN model and IQ dataset for network training. Their method is capable of learning inherent signatures from different wireless transmitters, which are useful for identifying hardware devices. The results demonstrated that the proposed method outperformed ML methods in the recognition of 5 same hardware devices.

4.2. Frequency Domain Features. In contrast to time features, frequency features contain more useful characteristics, such as bandwidth, center frequency, and power spectral density, which are essential for wireless technology recognition. What is more, effective frequency domain data can greatly alleviate the problems of data transmission and storage in actual deployment process.

As one of machine learning, fuzzy classifier has been concerned in wireless technology recognition. In [77], a new fuzzy logic (FL) method was presented to recognize WLAN, BT, and FSK signals. The power spectral density (PSD) information was used to get the bandwidth and center frequency for labelling the signals corresponding to standards. Results demonstrated that the proposed strategy is efficient for explicit signal features extraction. Likewise, neurofuzzy signal classifier (NFSC) to recognize nanoNET, WLAN, Atmel, and BT signals by utilizing measured PSD information is presented in [78]. Results show that the performance is improved by using wideband and narrowband data acquisition modes in real-time coexistence environments.

As a way forward, deep learning has also been developed in recent literatures. In [73], the time-domain data was also mapped into frequency-domain representation by FFT. Results show that the CNN model trained on FFT data has significant improvement in accuracy compared to time domain features. Similarly, a reduced CNN model with frequency-domain data is proposed in [79]. The approach is capable of identifying several common IEEE 802.x signals in coexistence. Simulations indicate that the performance of reduced CNN model is superior to most state-of-the-art algorithms. In [29], the authors explore the combination of averaged magnitude FFT processing and LSTM model with distributed sensor architecture. The result shows that the proposed scheme could classify DVB, GSM, LTE, Radar, Tetra, and WFM signals.

4.3. Time-Frequency Domain Features. Time-frequency distribution has unique advantages in the comprehensive analysis of signals. In [80], frequency-time representations such as spectral bandwidth, temporal width, and center frequency are extracted for neural networks. In [81], the authors applied CNNs to identify IEEE 802.x protocol family operating the ISM band. The time-frequency power values with matrix form were fed into the CNN classifier for data training. The result indicates that the CNN model outperforms traditional machine learning techniques. A semisupervised model based on CNN is developed in [82]; a series of time-slices spectrum data with pseudolabels scheme are trained in CNN. Experiments show that this model performs well in devices recognition, even at the condition of fewer labeled data in training process.

5. Opening Problems in Signal Identification

Although in last decades, large amounts of literatures have proposed various schemes for signal recognition, it cannot be denied that the technology makes little sense in real electromagnetic environment. Many papers are based on ideal assumptions, such as AWGN channel or enough prior knowledge, and the identified signals are limited to a set of several known types. DL is the tendency in future, but large-scale training data are required to get rid of overfitting and attaching precise labels to large-scale data is difficult to accomplish, especially in a short time. Semisupervised and unsupervised mechanisms can be explored to alleviate tedious label operations for DL model in the future. More innovative technologies and solutions are envisaged in future research.

5.1. Burst Signal Recognition. Burst signal has been widely used in military field and there will be broad prospects for dynamic spectrum access in the future. The burst signal has the characteristics of short duration and uncertainty of starting and ending time, which poses great challenges to signal recognition [83–85]. Generally, the processing flow of signal recognition includes data acquisition, preprocessing, classification, and decision. The high quality labels have a crucial role for a satisfactory recognition accuracy but are relatively time-consuming in burst communication systems. Therefore, there are still research prospects on the identifying burst signals.

5.2. Unknown Signal Recognition. In the present literatures, the type of signal to be recognized is assumed to be within a known set and few literatures are capable of coping with unknown signals. Even if the spectral characteristics and background noise are obtained in practical situations, it is unrealistic to know the set of signal types in advance and unexpected interference may occur at any instant [86, 87]. Many proposed approaches lack universality for the signals outside of the set. So a comprehensive set of signal types or a more reasonable model design may be needed for the unknown signal recognition.

5.3. Coexistence Signal Recognition. Signal monitoring and interference management under the condition of multisignal coexistence have attracted much attention recently [88, 89]. With the advent of 5G and the IoT commercialization, crowded spectrum resources are likely to lead to an overlap of multiple signals. Moreover, the increasing types of signals and diverse wireless networks will undoubtedly bring challenges on the signal recognition in the coexistence environment [90]. Predictably, the recognition of homogeneous and heterogeneous signal in an overlapped bandwidth may be a novel development trend of signal recognition and highly effective and accurate DL algorithms will create a new centre.

6. Conclusion

In this paper, an overview of modulation recognition and wireless technology recognition is presented. Signal recognition has made considerable progress on both theory and practice in traditional fields of device identification and interference detection. It is noticeable that the area of signal recognition has extended from modulation recognition to wireless technology recognition. With the development of machine learning and deep learning, simple feature extraction in the preprocessing and even raw data are becoming a trend to realize signal recognition. However, many works are based on ideal assumption or some known conditions and most results are obtained by simulations. There is still a long way for signal recognition in real electromagnetic environment and practical application.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors' Contributions

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