IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 12 July 2024, accepted 4 August 2024, date of publication 8 August 2024, date of current version 22 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3440350

SURVEY

Deep Learning-Based Modulation Recognition for MIMO Systems: Fundamental, Methods, Challenges

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This work was supported in part by the National Natural Science Foundation of China under Grant 61801319; in part by Sichuan Science and Technology Program under Grant 2020JDJQ0061 and Grant 2021YFG0099; in part by the Innovation Fund of Chinese Universities under Grant 2020HYA04001; in part by the Engineering Research Center of Integration and Application of Digital Learning Technology, Ministry of Education under Grant 1321002; and in part by the 2022 Graduate Innovation Fund of Sichuan University of Science and Engineering under Grant Y2023288.

ABSTRACT In non-cooperative communication systems such as radio spectrum resource regulation and modern electronic warfare, automatic modulation recognition is a key technology. Traditional modulation recognition methods mainly rely on manual feature extraction, decision theory, and recognition selection. The Deep Leaning (DL) algorithm automatically obtains signal features directly from massive data, and realizes feature extraction and recognition at the same time. However, most of the research on DL-AMR methods focuses on single input single output (SISO) systems, while there are few studies on DL-AMR methods in multiple-input, multiple-output (MIMO) systems, so the integration of deep learning models into modulation recognition of MIMO systems has attracted the attention of many researchers. The purpose of this paper is to provide a comprehensive review of modulation recognition methods for MIMOsystems based on DL. Firstly, the basic theory of MIMO and its derivative systems and modulation recognition is introduced in detail, then the traditional modulation recognition algorithms and deep learning-based modulation recognition algorithms of MIMO systems are introduced, and finally, on the basis of discussion and summary, the problems to be solved, the challenges and potential research directions are proposed.

INDEX TERMS Deep learning, MIMO systems, modulation recognition, neural networks, signal classification.

I. INTRODUCTION

With the evolution of the era, the new generation of communication technologies, led by 5G and 6G, has garnered significant attention from both the academic and commercial sectors. Among these, 5G technology supports three major application scenarios: enhanced mobile communication, ultra-reliable low-latency communication, and massive machine-type communication. Furthermore, it has facilitated the practical applications of artificial intelligence products [1]. The integration and development of 5G technology span various fields, as the demand for communication quality and efficiency continues to rise. Wireless communication technology is rapidly advancing towards digitization, intelligence, and integration. In increasingly complex communication environments, to enhance the effectiveness and reliability of information transmission, the sender needs to perform relevant processing such as modulation and channel coding on the raw data.In cooperative communication scenarios, where communication parties have pre-agreed on communication

The associate editor coordinating the review of this manuscript and approving it for publication was Qichun Zhang.

signal coding methods, modulation schemes, and parameters through communication protocols, the signal receiver can use the known information to demodulate the signal and thereby obtain the content of the communication. On the other hand, in non-cooperative communication scenarios such as communication reconnaissance and electronic warfare, due to the lack of communication means and many prior pieces of information, the party intercepting the signal has limited knowledge about the intercepted signal. To extract useful information from the communication content, the intercepting party needs to utilize automatic modulation recognition technology to identify the communication signal, thereby obtaining valuable information from the signal.

Automatic Modulation Recognition (AMR) serves as an intermediary step between signal detection and signal demodulation. This technology has the capability to identify the modulation type of a signal in the absence of known system parameters, thereby extracting information embedded within the signal. It is evident that AMR is a prerequisite for demodulating signals at the receiving end, playing a pivotal role in both civilian and military domains [2]. In civilian applications, AMR is primarily employed for spectrum monitoring and interference detection. Given the limited availability of spectrum resources in wireless communication, the extensive occupation of spectrum by various communication services poses a challenge, potentially leading to spectrum scarcity. AMR technology emerges as a solution to identify the modulation schemes of interfering signals compared to legitimate user signals, enabling the analysis of signal attributes and facilitating spectrum management [3]. In the military domain, AMR proves invaluable for identifying adversarial interference signals and extracting critical military intelligence. It aids military forces in formulating targeted reconnaissance and counter-reconnaissance strategies. The role of AMR extends beyond mere signal recognition; it contributes significantly to maintaining order in the dynamic and congested wireless spectrum environment. Its applications span from civilian spectrum governance to supporting military operations, showcasing its indispensable role in contemporary wireless communication scenarios [4].

In traditional SISO systems, the problem of modulation recognition is relatively simplified [5]. Satisfactory results can usually be obtained through traditional methods based on likelihood or features. As the modulation recognition of SISO systems gradually matures, the continuous development of communication systems and the introduction of MIMO systems bring new challenges and opportunities to modulation recognition technology. The relatively simple signal transmission structure and lower complexity of SISO systems make the problem of modulation recognition relatively easy to solve. However, with the rise of MIMO systems, the introduction of multiple transmitting and receiving antennas leads to a significant increase in signal space dimensions, making the problem of modulation recognition more complex.

To further enhance the capacity and anti-interference capability of the system, Multiple Input Multiple Output technology was developed. By deploying multiple antennas at both transmitting and receiving ends, MIMO establishes independent parallel transmission channels in space, utilizing spatial freedom to improve information transmission rates and increase system capacity. With a minimum number of transmit and receive antennas, MIMO can linearly increase channel capacity without requiring additional power or bandwidth. Compared to single antenna systems, MIMO offers significant advantages in communication distance, reliability, and throughput; as such it is widely used in mobile phones, wireless local area networks (WLANs), and wireless metropolitan area networks (WMANs) [6].

Improving the accuracy of AMR in MIMO systems remains a challenge in current wireless communication systems [7]. Modulation recognition techniques in MIMO systems, developed over decades, can be broadly categorized into two types: likelihood-based methods and feature-based methods. Likelihood-based methods, while theoretically optimal, require extensive computation; feature-based methods rely on manual feature extraction, making the recognition results heavily dependent on the expertise of the extractor. Hence, both approaches are unsuitable for increasingly complex MIMO systems. In recent years, deep learning has been successfully applied in image processing [8] and speech recognition [9], entering the communication field and successfully constructing AM schemes [10], [11], modulation classifiers [12], [13], and channel estimators [14], [15]. Deep learning-based modulation classification automatically and efficiently categorizes received signals without prior knowledge. By feeding raw signal data or its transformations into neural networks and obtaining modulation categories directly at the network output, deep learning approaches signal classification [17], [18], [19], [20], [21], [22], [23] with higher accuracy and less computational overhead compared to traditional methods based on expert features, such as higher-order cumulants [12] and time-frequency analysis [16].

In this paper, modulation recognition of MIMO systems based on deep learning is reviewed. The recent summaries of deep learning-based modulation recognition methods in MIMO systems are enhanced by this review, and the contributions of this paper are as follows:

1) This paper conducted a comprehensive investigation into the traditional modulation recognition algorithms for MIMO systems, providing a detailed summary of the advantages and disadvantages of these conventional algorithms.
2) The application of deep learning in modulation recognition for MIMO systems is introduced in this paper, presenting a comprehensive summary of modulation recognition algorithms based on deep learning.
3) Authors must convince both peer reviewers and the editors of the scientific and technical merit of a paper;

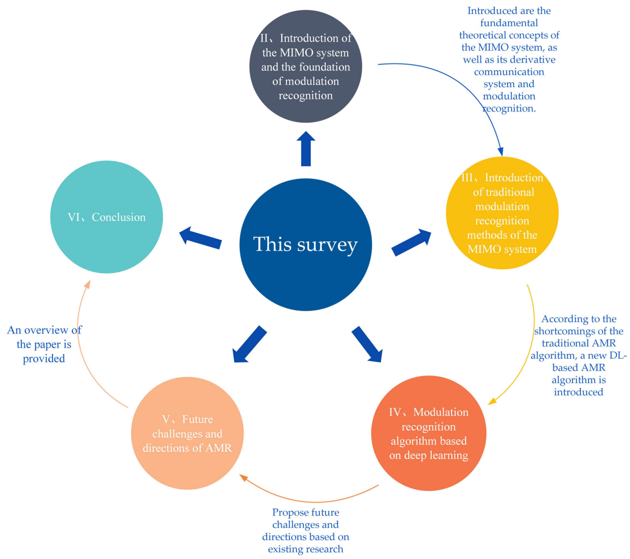

FIGURE 1. The structural layout of this paper.

the standards of proof are higher when extraordinary or unexpected results are reported.

4) The challenges faced by current deep learning approaches in recognizing modulated signals in MIMO systems are outlined in this paper, and potential future research directions are identified.

The organizational structure of this paper is as follows: Section II introduces the fundamental theoretical knowledge of MIMO systems, MIMO-OFDM, MIMO-STBC, massive MIMO systems, and modulation recognition. In Section III, traditional modulation recognition algorithms for MIMO systems are described, and a summary of the advantages and disadvantages of traditional modulation recognition algorithms is provided. Section IV presents deep learning-based modulation recognition algorithms for MIMO systems, along with a discussion of modulation recognition algorithms based on MIMO-OFDM systems, MIMO-STBC systems, and massive MIMO systems. Section V outlines the challenges faced by modulation recognition and future research directions. Finally, Section VI summarizes the entire paper. The structural layout of the article can be illustrated in Fig 1. For ease of reading, Table 1 summarizes the main acronyms used in this paper.

II. MIMO SYSTEM MODEL AND MODULATION RECOGNITION FUNDAMENTAL

MIMO systems employ multiple antennas at both the transmitting and receiving ends, with diversity and multiplexing techniques widely used in multiple antenna technology. These two techniques enable MIMO systems to transmit more user information within the same frequency band compared to traditional single-antenna systems while also ensuring service quality for each user. Furthermore, diversity and multiplexing techniques provide MIMO systems with advantages such as high channel capacity, high link reliability, wide coverage, and low power consumption.

TABLE 1. List of major alphabetic acronyms.

Abbreviation	Full Name
DL	Deep Learning
AMR	Automatic Modulation Recognition
SISO	Single-Input Single-Output
MIMO	Multiple-Input Multiple-Output
5G	5th Generation Mobile Communication Technology
6G	6th Generation Mobile Communication Technology
MIMO-OFDM	Multiple-input multiple-output Orthogonal Frequency Division Multiplexing
MIMO-STBC	Multiple-Input Multiple-Output Space-Time Block Coding
ML	Machine Learning
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
ZF	Zero Forcing
ICA	Independent Component Analysis
JADE	Jade Adaptive Differential Evolution
MDL	Minimum Description Length
CSI	Channel State Information
ANN	Artificial Neural Network
SVM	Support Vector Machine
PCA	Principal Component Analysis
MC	Modulation Classification
LB	Likelihood Bias
FB	Feature Bias
RFE	Recursive Feature Elimination
LSTM	Long Short-Term Memory
BPNN	Back Propagation Neural Network
CDBN	Convolutional Deep Confidence Network
MLP	Multilayer Perceptron
TWRCN	Two-Way Relaying Channel Network
DRCN	Deep Reconstruction and Classification Network
SC-MFNet	Series-Constellation Multi-Modal Feature Network
4D2DConvNet	Two-dimensional Convolution (2DConv) and Four-dimensional Convolution Network
SMOTE-DNN	Synthetic Minority Over-sampling Technique-Deep Neural Network
NB	Naive Bayes
KNN	K-nearest neighbor classifier
NI-SI	Noise-independent STBC
RN	Residual Network
DHL	Dendrogram-based Heterogeneous Learners
MMFFN	Multi-Modality Features Fusion Network
MCNN	Multi-Channel Convolutional Neural Network

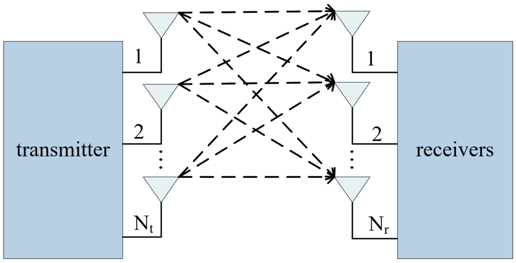

FIGURE 2. Structure of MIMO system.

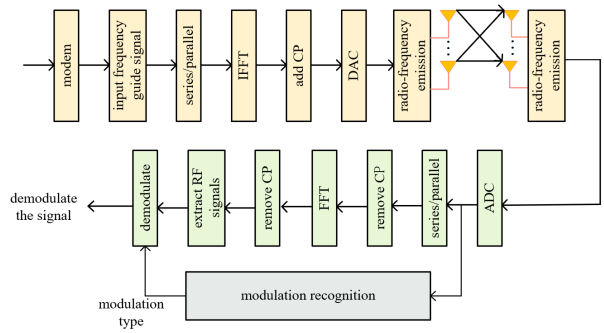

FIGURE 3. Structure of MIMO-OFDM system.

A. MIMO SYSTEM MODEL

N_t transmitting antennas at the broadcasting end and N_r receiving antennas at the receiving end make up the MIMO system of $N_t \times N_r$. The fundamental concept of MIMO communication, which is illustrated in Fig. 2, is that each antenna at the receiving end can receive the signals transmitted by all N_t transmitting antennas, that is, the signals transmitted by various transmitting antennas are superimposed on one receiving antenna, and the outgoing signals are recovered through signal detection and other methods.

We assume that the MIMO channel is a flat fading time-invariant channel, then the received signal at the nth sampling time can be expressed by Equation (1)

$$Y(n) = HX(n) + N(n). \tag{1}$$

where H denotes the channel matrix of size $N_t \times N_r (N_t \geq N_r)$, and the elements in matrix H obey a zero-mean and unit variance of the circularly symmetric complex normal distribution. The elements $h_{j,i}$ in H denote the path gain between the ith transmitting antenna and the j th receiving antenna, namely

$$H = \begin{pmatrix} h_{1,1} & \cdots & \cdots & h_{1,N_r} \\ \vdots & & & \vdots \\ h_{N_t,1} & \cdots & \cdots & h_{N_t,N_r} \end{pmatrix}. \tag{2}$$

$Y(n) = [Y_1(n), Y_2(n), \cdots, Y_{N_r}(n)]^T$ is the received signal vector, which is obtained by Nyquist sampling without phase and frequency offsets; $X(n) = [X_1(n), X_2(n), \cdots, X_{N_t}(n)]^T$ is the nth transmitted signal vector; and $N(n) = [N_1(n), N_2(n), \cdots, N_{N_r}(n)]^T$ is an additive Gaussian noise whose elements obey a normal distribution with zero mean and variance.

More research is being done on MIMO-OFDM systems, space-time block code MIMO-STBC systems, and massive MIMO systems, in addition to general MIMO systems. Consequently, we shall explore the MIMO-OFDM, MIMO-STBC, and massive MIMO systems.

B. MIMO-OFDM SYSTEM

We consider a MIMO-OFDM system with N_c subcarrier, N_t transmit antenna, N_r receive antenna, and M OFDM symbol. It is assumed that the channel is a multipath frequency-selective Rayleigh fading channel. The entire MIMO-OFDM system is shown in Fig. 3. In accordance with the data presented in Fig. 3, The receiver is equipped with a modulation identification module that automatically determines the modulation type of the MIMO-OFDM signal. The input bits at the transmitter are encoded by the system through a pre-established digital modulation technique, resulting in the generation of symbols. Subsequently, these symbols are inserted alongside the guide frequency, organized into frequency bins of equal spacing through a series-parallel mechanism, and transformed into numerous orthogonal overlapping sinusoids in the time domain by means of a fast Fourier inverse transform (IFFT) accompanied by an extra cyclic prefix (CP). In several OFDM systems, known guide frequency symbols are included to aid in channel estimation and equalization. Given the complex data of the modulated signal on the nth subcarrier $x_{n_t}[n, m]$ transmitted by the nth antenna, the kth baseband signal for the mth OFDM symbol can be written as Equation (3)

$$s_{n_t}[n, m] = \sum_{n=0}^{N-1} x_{n_t}[n, m] \, e^{j2\pi nk/N}, \quad 0 \leq k \leq N-1. \tag{3}$$

where $N = \eta \times N_c$ is the number of IFFT points and η is the oversampling factor. Then, the length L_{cp} of the CP information is prefixed to prevent inter-symbol interference problems with neighboring OFDM symbols. This step can be expressed by Eq. (4)

$$S_{n_t}[m, k] = \begin{cases} s_{n_t}[m, k+N], & -L_{cp} \leq k \leq -1 \\ s_{n_t}[m, k], & 0 \leq k \leq N-1. \end{cases} \tag{4}$$

To increase the outer band radiation of the subband signals, a filter with sinusoidal impulse response needs $f[k]$ to be applied, and this process can be described by equation (5).

$$y_{n_t}[m, k] = \widetilde{S}_{n_t}[m, k] \otimes f[k]. \tag{5}$$

where represents the convolution. Under the assumption of symbol timing and carrier frequency OFDM synchronization, the OFDM signal received by the R_T antenna at the receiver on a MIMO channel with frequency-selective multipath Rayleigh fading can be expressed by Equation (6)

$$Z_{r_t}[m, k] = y_{n_t}[m, k] \otimes h_{n_t, r_t}[m, k] + \delta[m, k], 0 \leq k \leq L_s - 1. \tag{6}$$

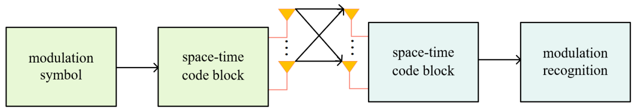

FIGURE 4. Structure of MIMO-STBC system.

where $\delta[m, k]$ denotes the additive Gaussian white noise, $L_s = L_{cp} + N$ is the OFDM signal length, and h_{n_t,r_t} is an element of the $N_r \times N_t$ channel matrix corresponding to the pulse.

C. MIMO-STBC SYSTEM

N_t transmit antenna and N_r receive antenna the MIMO-STBC system is explored in this research, and the system's topology is depicted in Fig. 4. In an STBC MIMO system, the transmitter first performs spatiotemporal block encoding of the v group to be sent symbol $s_v = [s_1, s_2, \cdots, s_K]^T$ of length K to obtain a transmission matrix $X(\mathrm{s}_v)$ of $N_\mathrm{t} \times L$, where L is also called the length of $X(\mathrm{s}_v)$, and each symbol in e is a non-Gaussian random variable with a mean of 0 and is independently and equally distributed. $C(\mathrm{s}_v)$ reaches the receiving end after passing through channel H, and the signal on N_r receiving antennas is represented as (7).

$$Y_v = HX(s_v) + N_v. \tag{7}$$

where Y_v represents the $N_r \times L$ -dimensional receiving matrix, element $h_{q,p}$in H is a Gaussian variable with a mean of 0 and a variance of 1, N_v represents a $N_r \times L$ -dimensional Gaussian white noise matrix, N_v and $X(\mathrm{s}_v)$ are independent of each other, and the mean of each element in N_v is 0 and the variance is σ_n^2.

D. MASSIVE MIMO SYSTEM

Massive MIMO technology offers a qualitative increase in antenna count as compared to MIMO technology. Hundreds of thousands of antennas can be used in a huge MIMO system. As seen in Figure 5 above, these antennas are positioned and assembled centrally using massive MIMO array technology to create a large-scale antenna array. Using a large antenna array allows the signal to be dynamically adjusted in both horizontal and vertical directions, focusing the energy more precisely on the individual user and lowering inter-cell interference. This increases the rate at which system spectrum resources are utilized overall and supports spatial multiplexing between multiple users. Massive MIMO antenna arrays simultaneously offer array gain and diversity gain, which greatly raises efficiency.

E. BASIC THEORY OF MODULATION RECOGNITION

Communication modulation recognition refers to the process of determining the modulation method used in the transmitted signal in the presence of noise and interference without prior knowledge of the modulation information and parameters. It involves identifying the modulation method of each type of signal in a signal set containing a mixture of different types of signals.

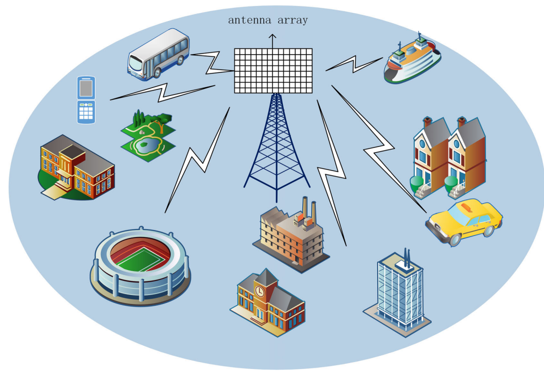

FIGURE 5. Schematic diagram of massive MIMO system.

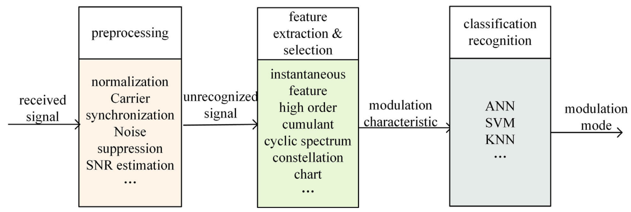

FIGURE 6. Block diagram of communication signal recognition process.

1) OVERALL PROCESS OF MODULATION SIGNAL RECOGNITION

The preprocessing of communication signals, the extraction and selection of signal features, and the classification and identification of signal modulation types make up the typical three steps, and the recognition process is shown in Figure 6. After receiving the signal, preprocessing operations are applied, and different preprocessing methods are chosen for various recognition tasks. Signal preprocessing aims to provide data that is more conducive to analysis and processing. As signal preprocessing significantly impacts the feature extraction for communication signal modulation recognition, the presence of noise in the signal severely affects the recognition accuracy of communication signal modulation patterns. Therefore, designing algorithms with better noise-resistant performance for preprocessing the raw signal is crucial for the subsequent modulation recognition classifier based on deep learning.

In the modulation recognition process, the extracted features are input into a classifier for identification, a crucial step. The computational complexity has a crucial impact on the final recognition performance. Initially, due to technological limitations, manual classification by experienced professionals was required. With the application of automatic modulation recognition methods in this field, automated classification methods have gradually replaced manual approaches. With the rise of machine learning (ML) technology, modulation recognition methods based on

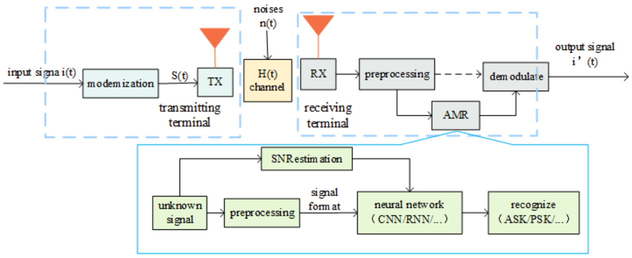

FIGURE 7. Block diagram of deep learning-based modulation recognition process.

ML have become popular. This method involves inputting preprocessed signals into designed classifiers, with commonly used classifiers including SVM, DT, KNNS, HMM, etc. However, ML-based AMR methods are not suitable for communication scenarios with massive data. Therefore, this method is no longer applicable.To address modulation recognition in scenarios with massive communication data, some scholars have started incorporating deep learning (DL) technology into AMR in recent years. Commonly used deep learning networks include Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Residual Neural Networks (ResNet), and a series of combined neural networks. The process of modulation recognition based on deep learning is illustrated in Figure 7. As deep neural networks classify and recognize different communication modulation patterns mainly by autonomously learning the features of input signals, selecting preprocessing features that significantly differentiate between different communication modulation patterns is crucial for communication modulation recognition methods.

2) MODULATION SIGNAL DATA PREPROCESSING

Due to the shared statistical properties between the transmitted and received signals in the SISO system, it becomes feasible to ascertain the modulation type of the received signal through direct extraction. The inclusion of the MIMO channel in a MIMO system will modify the statistical characteristics of the received signal, necessitating the elimination of the channel's impact before extracting the features in order to restore the transmitted signal. The ICA and ZF algorithms are currently employed by most researchers to restore the received signal. Below, you will find a comprehensive introduction to both the ZF algorithm and the ICA algorithm.

a: ICA ALGORITHM

The sent signal can be recovered using the ICA technique since it is statistically independent and the received signal is a linear mixture of the transmitted signal and noise. Three separation techniques that are frequently employed in ICA under MIMO systems were compared in the literature. Among these, the Joint Approximate Diagonalization of Eigenmatrices (JADE) approach in ICA has a reduced bit error rate when the data is tiny and requires smaller data sizes. Furthermore, there's no need to change the settings while the calculation is running. Some academics recover the broadcast signal using the JADE technique. The number of transmitting antennas, or information sources, must be known in order to use the JADE algorithm. To solve this problem, Tianqi et al. [92] estimated the transmitting antenna number based on the MDL criterion to estimate the process.

(1) Find the autocorrelation matrix of the received signal y(k)

$$Y = E[y(k)y^H(k)]. \tag{8}$$

where H stands for conjugate transpose.

(2) Perform eigenvalue decomposition for Y and arrange the obtained eigenvalues in descending order.

(3) The MDL algorithm is used to estimate the number of transmitting antennas.

$$\hat{N}_t = \arg\min_n \left\{ -\lg \left[\frac{\prod_{i=n+1}^{N_t} \lambda_i^{1/(N_t-n)}}{\sum_{i=n+1}^{N_t} \lambda_i/(N_r-n)} \right]^{K(N_t-n)} + \frac{n(N_r-n)+1}{2} \lg K \right\}. \tag{9}$$

where $n = 0, 1, \cdots, N_r - 1$, λ_i represents the$i$characteristic value, and K represents the number of symbols on a single antenna.

After estimating the number of transmitting antennas, it is necessary to do the signal-whitening processing. The first N_t eigenvalues form a diagonal matrix D, and the corresponding eigenvectors form a matrix F. Take the mean of the remaining $(N_t - N_r)$ eigenvalues $\tilde{\lambda}$, so that the noise variance is estimated at $\hat{\sigma}_n^2 = \tilde{\lambda}$. Make

$$B = D - \hat{\sigma}_n I. \tag{10}$$

where $I$is the identity matrix of $N_t \times N_r$ -dimension. The whitening matrix V is represented by

$$V = B^{-1/2} F^H. \tag{11}$$

Then the whitening signal can be expressed as

$$q(k) = V \cdot r(k). \tag{12}$$

After whitening, the dimension of the signal is reduced from $N_r \times 1$ to $N_t \times 1$, thus reducing the amount of subsequent computation. After the above pre-processing, the JADE algorithm can be used to restore the sent signal. The separation process of the JADE algorithm is as follows: First, the high-order cumulant matrix C of $q(k)$ is calculated, and then the singular value of C is decomposed to calculate the N_t eigenvalues of the maximum modulus and the corresponding eigenmatrix $\{\phi_i, U_i | 1 \leq i \leq N_t\}$; The matrix set $A^e = \{\phi_i, U_i | 1 \leq i \leq N_t\}$ is approximated diagonally jointly, and the separation matrix$X$can be obtained after operation. The recovered transmission signal can be expressed as

$$\hat{s}(k) = X \cdot q(k). \tag{13}$$

b: ZF ALGORITHM

In MIMO systems, the presence of a large number of antennas affects communication performance. Using ZF equalization technology can improve the classification performance under perfect CSI and imperfect CSI because ZF equalization can improve the signal-to-noise ratio of the received signal under perfect CSI or imperfect CSI (the channel estimation error is limited). The received signal, equalized by ZF, can be written as

$$\hat{R}(n) = ZF(\hat{H})R(n). \tag{14}$$

where $ZF(\hat{H}) = \hat{H}^{\dagger} = (\hat{H}^H\hat{H})^{-1}\hat{H}^H$ is the equalization matrix, where $(\hat{H}^H\hat{H})^{-1}\hat{H}^H$ is denoted as the pseudo inverse operation of $\hat{H}$. In addition, $\hat{H}$ is the estimated channel matrix. In this paper, we consider perfect CSI cases (i.e., $\hat{H} = H$) and imperfect CSI cases (i.e., $\hat{H} \neq H$).

3) PERFORMANCE EVALUATION METRICS FOR MODULATION RECOGNITION

Accuracy Metrics: In evaluating the performance of modulation recognition models, the considered accuracy metrics include the highest accuracy, average accuracy, and the variation of accuracy with signal-to-noise ratio (SNR). The highest accuracy represents the peak performance a model can achieve, typically obtained at a high SNR value. The average accuracy reflects the overall performance level of the model across all tested SNR levels. The variation of accuracy with SNR illustrates how model performance changes under different SNR conditions, usually presented visually.

Model Complexity and Training Time: The complexity of a model is primarily indicated by the number of learning parameters, while training speed is represented by training time and epochs. Designing models with fewer learning parameters and faster training speeds that can achieve high recognition accuracies is indicative of superior performance.

Confusion Matrix: The confusion matrix provides a straightforward representation of classification errors among different modulation types. With the vertical axis representing true labels and the horizontal axis representing predicted labels for N modulation classes, the confusion matrix is an NN matrix. It is a direct visual method to reflect the overall classification performance of a model.

Model Generalization: Most deep learning models for Automatic Modulation Recognition (AMR) are trained using data generated under specific channel conditions. For practical application, these models are expected to exhibit generalization and robustness, performing well across different datasets at the experimental level.

III. TRADITIONAL METHODS OF MIMO SYSTEM MODULATION RECOGNITION

Early attempts of modulation recognition mainly depended on manual tasks carried out by knowledgeable specialists. It was difficult to assure correctness because of the significant degree of subjectivity resulting from the final judgment's subjective nature. Many academics have currently put out pertinent algorithms for the problems with AMR in MIMO systems. The two main categories of traditional modulation recognition algorithms are feature-based and likelihood-based algorithms. In this part, we offer a thorough overview of these two classic recognition procedures.

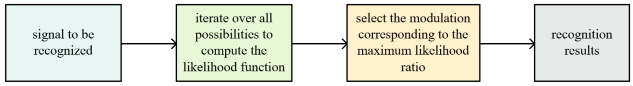

FIGURE 8. Flowchart of the likelihood modulation identification method.

A. LIKELIHOOD-BASED MODULATION RECOGNITION ALGORITHM

Likelihood-based modulation recognition algorithms require the calculation of likelihood functions for the signals of all candidate modulation modes and then make classification decisions based on the maximum values of these functions. As can be seen, the likelihood functions of the potential modulation schemes must be calculated for the likelihood-based modulation recognition algorithm to work. Figure 8 illustrates the method's flow. Consider the probability function being used for a specific modulation, where R stands for the received signal vector, for the modulation mode, and H for the channel matrix. Maximizing the likelihood function is the modulation identification process's most likely outcome, and Eq. (15) can be used to define the final modulation identification result.

$$\hat{\varphi} = \arg\max_{\varphi \in \Theta} (\Lambda(R/\varphi, H)). \tag{15}$$

where $\hat{\varphi}$ denotes the estimated modulation and $\Theta = \{\varphi_1, \varphi_2, \cdots, \varphi_n\}$ denotes the candidate modulation that maximizes the likelihood function.

When determining the modulation mode of the received signal, it is crucial to consider various unidentified communication factors at the receiver, including the channel matrix. Different methods of identifying modulation based on likelihood can be classified into three types: those that rely on average likelihood ratios, those that rely on generalized likelihood ratios, and those that rely on mixed likelihood ratios. The modulation recognition algorithm, which relies on the average likelihood ratio, must consider the unknown parameters as random variables with known probability density functions and subsequently solve the mean value of the likelihood function of the variable. Similarly, the modulation recognition algorithm, which relies on the generalized likelihood ratio, considers the unknown parameters as fixed quantities, solves the estimated value of the parameters under multiple assumptions, and replaces the likelihood function to estimate the likelihood ratio. Lastly, the modulation recognition method, which relies on the mixed likelihood ratio, considers a portion of the unknown. The mixed likelihood ratio-based modulation identification method employs the generalized likelihood ratio approach to

TABLE 2. Comparison of parameter volume calculations.

Author	Year	Methods	Advantage	Disadvantage
Choqueuse KYLC et al [24]	2009	Algorithms based on average likelihood ratios and mixed likelihood ratios	High recognition accuracy	Modulation recognition is difficult for both transmitting and receiving antennas
Kanterakis E et al [25]	2013	Low-complexity hybrid likelihood ratio algorithm	Low complexity	The signal noise is independent and does not meet the actual communication scenario
Zhu et al [26]	2014	An expectation-maximization algorithm based on a mixed likelihood ratio	The number of transmitting antennas must be less than or equal to the number of receiving antenna	The complexity is high and does not apply to actual communication scenarios
Turan M et al [27]	2015	A new decision theory based on the likelihood function	High performance at medium to low signal-to-noise ratio	Algorithms are too complex

determine the highest likelihood estimate, considering certain unknown parameters as predetermined values. The average likelihood ratio method is used to calculate the average value of the probability density function, which takes into account some of the unknown parameters as random variables.

In 2020, Shah and Dang [28] proposed a low-complexity maximum likelihood-based modulation recognition method for Space-Time Block Code (STBC) Multiple-Input Multiple-Output (MIMO) systems. The authors initially utilized Zero Forcing (ZF) technique to modify the typical average likelihood ratio function. The modified likelihood function, independent of the number of transmit and receive antennas, exhibits lower computational complexity compared to other likelihood-based Automatic Modulation Recognition (AMR) algorithms, while maintaining high classification accuracy. Moreover, it demonstrates robustness against high Channel State Information (CSI) error variance. In 2021, Pathy et al. [29] designed a tree-based modulation recognition algorithm for asynchronous MIMO-Orthogonal Frequency Division Multiplexing (OFDM) systems. The algorithm involves the following steps: preprocessing the received signal to compensate for timing offsets, calculating high-order cumulants of the frequency-domain signal as critical features, and determining the likelihood ratio of the signal based on these critical features as the classification threshold to achieve modulation recognition. Experimental results indicate that this algorithm can perform AMR even in the presence of unknown frequency, timing, and phase offsets, without the knowledge of CSI. In this paper, we summarize the research results of the likelihood function-based modulation identification methods for MIMO systems in Table 2.

Based on the preceding introduction, it is evident that likelihood-based modulation identification techniques prioritize the development of the likelihood function, which is typically associated with the quantity of transmitting and receiving antennas, thereby resulting in significant computational intricacy. In spite of this, the likelihood-based approach requires knowledge of the channel state information, which is not feasible in a completely blind communication system; thus, the likelihood-based modulation identification approach is not suitable for the current communication system.

B. FEATURE-BASED MODULATION RECOGNITION ALGORITHM

The first step in applying conventional feature-based AMR algorithms for MIMO systems is to recover the sent signal from the received signal during the signal preprocessing stage by employing equalization and blind channel estimating techniques. After each transmitted signal's statistical properties (including higher-order moments and cumulants) are retrieved for modulation recognition, the statistical features are used to make classification decisions. Figure 9 shows the steps involved in this procedure. Feature-based AMR algorithms for MIMO systems can be broadly divided into two main categories according to how features are processed: decision-fusion-based and feature-fusion-based techniques.

1) DECISION FUSION-BASED APPROACH

The decision fusion algorithm utilizes feature vectors extracted from each estimated transmit signal to train the appropriate classifiers, such as artificial neural networks (ANNs) and support vector machines (SVMs), in order to estimate the modulation scheme of each transmit signal. The choices made by each classifier are subsequently combined to generate the ultimate classification and identification

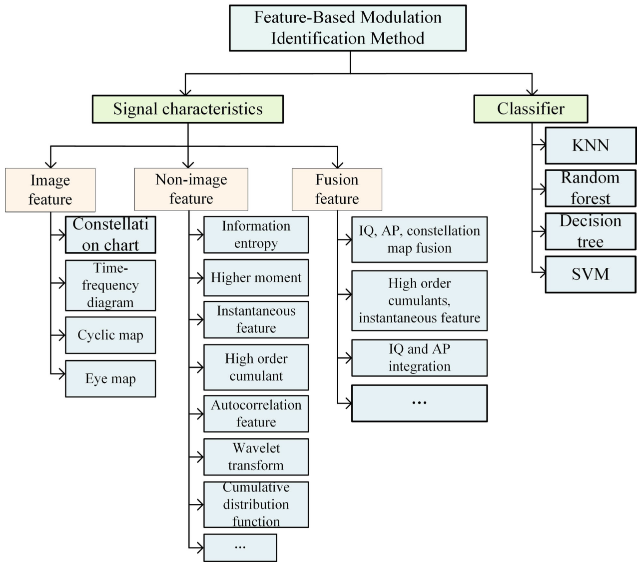

FIGURE 9. Flowchart of feature-based modulation recognition algorithm.

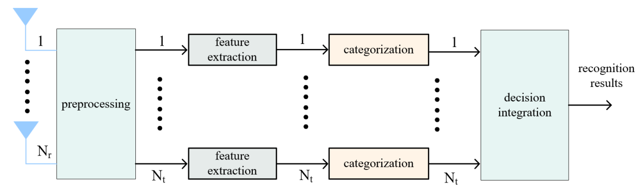

FIGURE 10. Decision fusion-based modulation identification method in MIMO systems.

determination regarding the modulation mode of the received signal. Fig. 10 can be used to demonstrate the decision-fusion-based AMR approach. At present, the research results of decision fusion-based modulation identification approaches are as follows: In 2012, Hassan et al. [30] suggested a modulation identification algorithm based on decision fusion to address the issue of modulation identification in MIMO systems when spatial fading correlation is present. The authors employed multiple higher-order cumulants of the transmitted signals as distinguishing characteristics and trained an artificial neural network (ANN) as a classification system with a backpropagation algorithm, and then the decision vector generated by the classifiers of multiple ANNs was combined and utilized for ultimate decision-making. Through experiments, the algorithm has been shown to have high recognition accuracy within a reasonable range of signal-to-noise ratios for cases with and without CSI knowledge at the receiver side. In 2014, Kharbech et al. [31] proposed a decision fusion-based AMR algorithm for MIMO systems, which takes the various higher-order cumulants of the estimated transmit signals as discriminative features and uses an ANN for classification, and then the average Bayes rule is utilized as a decision fusion rule. The algorithm works mainly on time-varying channels, where a sliding window technique is used to counter the effect of fading on the transmitted signal. It has been shown that

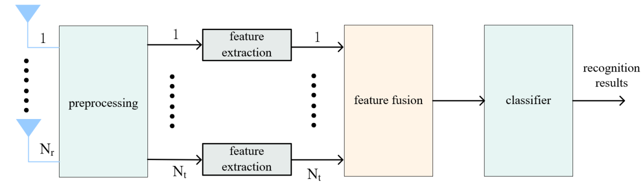

FIGURE 11. Feature fusion-based AMR algorithm in MIMO systems.

the algorithm improves the classification performance but increases the computational complexity due to the use of the sliding window technique in the algorithm.

2) FEATURE FUSION-BASED APPROACH

In the feature fusion-based technique, feature vectors are taken from the signal and fused into a single vector before being sent to the classifier for classification. The advantage of the feature fusion-based approach is that classification is required only once, which reduces the computational complexity. The feature fusion-based AMR algorithm in the MIMO system can be illustrated in Fig. 11. The findings of the present research on modulation recognition algorithms utilizing feature fusion are as follows: In 2010, Hassan et al. [32] and colleagues The authors proposed an AMR algorithm that uses feature-complementary fusion for MIMO systems. This algorithm uses various higher-order statistics of the estimated transmitted signals as distinguishing features and fuses them. However, since the algorithm cascades various features to form a fused feature vector, which improves the dimensionality of the feature vectors, the Principal Component Analysis (PCA) method is used for dimensionality reduction. Finally, the feature vectors are input into the neural network to complete the classification. The algorithm has demonstrated its ability to attain high recognition accuracy when the receiving side possesses complete knowledge of the CSI and coding information. Despite the challenge of having a thorough understanding of CSI and coding information on the receiver side in actual communication situations, this approach is not suitable for practical use. In 2014, a feature-based AMR algorithm was proposed in the work [33], [34]. The authors combined the features of the data found in the first-order and second-order correlation functions of the received signals and used a statistical test based on the likelihood of false alarms as a criterion for making decisions. MIMO systems with frequency-selective channels can make use of this technique. Bahloul and colleagues [42] suggested the implementation of a feature fusion-based modulation classification (MC) algorithm for multiple-input multiple-output (MIMO) systems. The transmitted signal stream is classified as a broad set of modulation types using two higher-order cumulants, without any prior knowledge of channel state information. To begin with, blind channel estimation and compensation are used to calculate the MT transmit signal flow from the linear combination of noise in the MT transmit signal flow. Furthermore, the estimation of the post-processing signal-to-noise ratio (PPSNR) for each of these

TABLE 3. Summary of advantages and disadvantages of traditional modulation recognition algorithms.

Methods	Advantages	Disadvantages
Modulation recognition method based on likelihood	Effective classification Well-established theoretical foundation Better performance at low signal-to-noise ratios	High computational complexity A priori information required Poor applicability
Modulation recognition method based on feature	Low computational complexity Good robustness to complex channel characteristics Low dependence on a priori knowledge	Reliance on large sample sizes Sensitive to the signal quality Complex identification system

streams is currently underway. Subsequently, the statistical characteristics for modulation classification are computed for every retrieved stream. An optimal soft decision fusion scheme is used in the last step of the proposed algorithm to decide the modulation type of the MIMO signal based on the PPSNR and the characteristics of all streams. They used a soft decision-fusion technique to find the classification results.

Considering the preceding introduction, it is found that feature-based modulation recognition methods are usually accomplished by using features of the signal and a machine learning framework of traditional classification algorithms. However, these algorithms require manual feature extraction and the design of suitable machine-learning classifiers to achieve better results. On the other hand, due to the complexity of communication systems nowadays, conventional feature-based modulation identification methods are no longer useful.

We illustrate the benefits and drawbacks of the Likelihood Bias (LB) and Feature (FB) recognition approaches, as shown in Table 3, based on the preceding pertinent introduction to these two techniques:

The emergence of deep learning in recent years has been a pivotal moment in resolving the issue of the inadequate precision of conventional modulation recognition. A multitude of scientists have endeavored to utilize deep learning algorithms in the realm of modulation recognition, and a plethora of remarkable outcomes have been attained. We have outlined the pros and cons of conventional modulation recognition techniques and deep learning-based modulation recognition techniques, as demonstrated in Table 4. In Section IV, we will concentrate on deep learning-based modulation recognition techniques.

IV. DEEP LEARNING-BASED MODULATION RECOGNITION FOR MIMO SYSTEMS

Deep learning is a powerful artificial intelligence technique capable of learning features from vast amounts of data and fitting nonlinear networks. As a result, it has found widespread applications in computer vision, natural language processing, and speech recognition, achieving considerable success. Traditional modulation recognition methods primarily rely on feature extraction and classifier design.

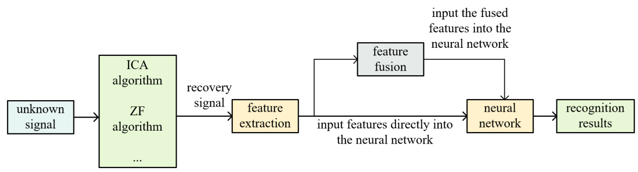

FIGURE 12. Deep learning-based modulation identification method for MIMO system.

However, these methods require manual feature extraction, and different modulation schemes necessitate the design of distinct classifiers, introducing certain limitations. Deep learning-based modulation recognition can automatically learn signal features, enabling automatic classification. This approach offers advantages such as high automation, strong robustness, and adaptability.

Modulation recognition algorithms of MIMO systems based on deep learning mainly include convolutional neural networks (CNN), multi-layer perceptron, and so on. The flow chart of the modulation recognition method based on deep learning in the MIMO system is shown in Figure 12. First of all, because the MIMO system contains N_t transmitting antennas and N_r receiving antennas, according to the characteristics of the wireless channel, each receiving antenna will receive the contents of different transmitting antennas. In order to facilitate the subsequent feature extraction, some scholars proposed applying ICA, ZF, and other algorithms to recover the received unknown signals and then carry out feature extraction. The extracted features are directly input into the neural network for modulation classification, or different features are fused, and the fused features are input into the neural network for modulation classification. In this section, we will provide a detailed overview of the application of deep learning to modulation recognition in MIMO systems.

A. MODULATION RECOGNITION ALGORITHMS FOR MIMO SYSTEMS

The accuracy of modulation recognition is affected by the channel. Due to the complexity and multipath effect of the channel in MIMO systems, the signal experiences the Keyhole effect, which means that there is a major transmission path (Keyhole) in the signal transmission path,

TABLE 4. Summarizes the advantages and disadvantages of traditional modulation recognition algorithms and modulation recognition algorithms based on deep learning.

Methods	Advantages	Disadvantages
Traditional modulation recognition algorithms	Well-established theoretical foundation Performs well at a low signal-to-noise ratio Easy to understand and implement	Features need to be extracted manually Cannot be used for complex modulation types and large data
Modulation recognition algorithm based on deep learning	Have strong expression and generalization abilities Adapts to unknown modulation types Automatic feature learning	Models are more black-box Requires large amounts of labeled data for training High computational resource requirements

resulting in a change in the transmission characteristics of the signal. This channel characteristic is a challenge for modulation classification tasks. To address this problem, Dileep et al. [36] proposed a deep learning-based automatic modulation classification method for MIMO systems. Specifically, a convolutional neural network (CNN) is used to process the received signals and perform modulation classification. The construction process of the dataset is first described, including the signal generation of different modulation methods and the modeling of the keyhole channel. Then, the paper designs a CNN model for extracting features from the received signals and performing modulation classification. This CNN model includes multiple convolutional and fully connected layers for learning the relationship between the time-frequency features of the signal and the modulation mode. To improve the classification performance, techniques of data enhancement and regularization are also introduced. Data augmentation increases the diversity of the data and improves the robustness of the model by randomly transforming and expanding the training data. Regularization techniques, on the other hand, are used to reduce the overfitting risk of the model and improve its generalization ability.

Lightweight devices have a restricted capacity for storage and processing because of their size and energy usage limitations. Furthermore, the complexity of deep neural networks, combined with their numerous parameters, restricts their use in MIMO systems. Wang et al. [37] propose an automatic modulation recognition method based on lightweight complex-valued residual networks and design a hybrid data enhancement method to compensate for the potential performance degradation caused by lightweight networks, which improves the accuracy of the method by at least 8%.

The traditional method of signal modulation detection relies heavily on the signal's spectral characteristics, but in high-noise settings, the spectral characteristics are easily interfered with, lowering the recognition accuracy. To improve the performance of signal modulation recognition, researchers have begun to explore the cumulant-based method. This method extracts features such as instantaneous amplitude and instantaneous frequency of the signal by analyzing the cumulative amount of the signal to achieve accurate recognition of the signal modulation mode. Following this, numerous academics adopted higher-order cumulative quantities as characteristics for modulation categorization [39], [40] and attained satisfactory outcomes. As deep learning progressed, certain academics merged deep learning with higher-level cumulants to investigate the novel AMR algorithm.

The cumulant aspects of the received signal are linearly differentiable by utilizing hyperplanes following the signal distribution properties of various modulation types. As a result, the modulation types are classified using a support vector machine (SVM), and weight vectors are utilized to determine the contributions of various cumulant properties. Given this, Zhou et al. [41] suggested a recursive feature elimination (RFE) algorithm based on support vector machines to decrease the size of features in MIMO systems and enhance classification effectiveness. A one-to-one multiclassification segmentation approach is employed to transform multiclassification into multiple binary classifications, and the combined weight vectors of all binary classifications are combined to get the overall weight vector. At each step, the features with the least weight are eliminated according to the overall weight vector. The SVM-RFE algorithm allows for the ranking of cumulant features, enabling the selection and utilization of specific cumulants based on their respective contributions to modulation identification.

For MIMO systems with less-than-ideal channel conditions, m-quadrature amplitude modulation (QAM) signals are identified in [43] using a classifier based on random graph theory. For undirected random graph classification, the method makes use of feature data from discrete Fourier transforms and sparse transforms. The approach obtains acceptable classification results using simulated data. A generalized CNN-driven technique for modulation identification in IoT systems was put forth by Zhang et al. [48]. In comparison to conventional CNN algorithms, the method is more robust and utilizes data in various noise situations. The findings demonstrate that the technology is more capable of classifying data than conventional CNN. Designing modulation identification techniques for MIMO systems has been the subject of extensive research. See, for instance, several pertinent review papers [49]. Khosraviani et al. [50] suggested an approach based on received data for identifying

TABLE 5. Modulation recognition algorithm of the MIMO system based on deep learning.

Author	Year	Model	Separation mode	Modulation recognition brief
Chikha et al [46]	2022	TWRCN	ZF	In the presence of Nakagami-m fading, the user modulation pairs for a given superimposed constellation are classified
Wang et al [38]	2020	CNN	ZF	With the help of CSI, ZF equalization technique is applied to reveal the fuzziness of the received signal to improve various AMC methods
Zhang et al [35]	2020	BPNN	ICA	The transmitted signal is separated from the received mixed signal by ICA algorithm, and then the modulation type of the signal is identified by a hierarchical neural network classifier
Wang et al [47]	2020	CNN	ZF	Each received antenna gives its recognition sub-result via CNN. The decision maker then determines the modulation type based on these sub- results and cooperative decision rules
Rahim et al [51]	2023	MLP	/	Each MLP receives the time-frequency characteristics of the received signal as input and outputs the corresponding modulation mode
Wang et al [44]	2020	DRCN	ZF	The labeled samples flow out of CAE for modulating signal reconstruction, and the labeled samples are fed to CNN for AMC, passing knowledge from CAE's coding layer to CNN's feature layer by sharing weights
Beknadj et al [45]	2024	KNN and DT	ZF	Using higher-order statistics as features for digital modulation identification to assess the performance of frequently utilized classifiers, namely k-nearest neighbor and decision tree.

digital modulation in MIMO systems, specifically targeting the segmentation of received data samples with higher statistics like cumulants. It is believed that the modulation type of the received sample corresponds to the modulation whose theoretical cumulant is in closest proximity to the average cumulant. A cumulative sum is calculated for every segment. A comparison is made between the average of the computed cumulants and the theoretical cumulants of different modulations. Existing approaches ignore the advantages of simultaneously considering the multimodality and complementarity of multiple-input multiple-output (MIMO) systems in a single DL framework. To address this issue, the literature [52] proposes an AMC algorithm based on a dual-mode multichannel configurable DL for MIMO systems with ideal channel state information and a forced-zero equalizer. The suggested DL framework comprises two concurrent multichannel convolutional layer structures, wherein one multichannel structure incorporates in-phase/quadrature (I/Q) as the initial modal information, while the other multichannel structure incorporates magnitude/phase as the subsequent modal information. The features taken from this parallel structure are processed by a Long Short-Time Memory (LSTM) layer to effectively extract the temporal information. At long last, the fully connected layer has finished the categorization. The simulation results showcase the framework's resilience, resulting in a 0.6% to 12% enhancement in average accuracy when compared to the current DL models. In Table 5, this study outlines the modulation recognition techniques that deep learning has recently applied to MIMO systems.

B. MODULATION RECOGNITION FOR MIMO-OFDM SYSTEMS

Modern wireless communication systems use the well-known multicarrier modulation technology known as orthogonal frequency division multiplexing (OFDM). Long-Term Evolution Advanced (LTE/LTE-A), Worldwide Interoperability for Microwave Access (WiMAX), and high-speed Wireless Local Area Network (WLAN) standards like 802.11n all make use of OFDM in the 4G Third Generation Partnership Project (3GPP). It is a part of 5G New Radio (NR) cellular as well. The primary characteristic of OFDM lies in its capacity to convert frequency-selective fading into flat-fading channels. OFDM modulation methods have been selected as the primary transmission method for large data-rate systems [53] because of their high spectrum utilization and remarkable resistance to multipath interference. M-PSK and M-QAM are the prevailing modulation techniques employed in OFDM. In addition to 5G and wireless communications, the study of the MC of OFDM signals poses a significant research hurdle, with AI serving as the fundamental building block of the communication system [54], [55], [56], [57]. MC methods based on the statistical characteristics of received OFDM signals are studied in [58]. This approach utilizes mean, skewness, and kurtosis to differentiate between QPSK, 16-QAM, and 64-QAM modulation strategies. This technique does not perform well when it comes to timing and frequency synchronization errors. Regerence [59] delves into the discussion of the MC algorithm, which takes into account the magnitude moment. This approach makes use of the relationship between any two subcarriers to differentiate between 16-QAM and 64-QAM modulation schemes. The classification of M-PSK/M-QAM modulation schemes is achieved through the utilization of the nonparametric Kolmogorov-Smirnov (KS)-based technique introduced in [61] and [62]. It functions effectively when there are established timing offsets, unidentified frequency and phase offsets, and noise channels that deviate from the Gaussian distribution. The majority of the aforementioned MC algorithms for OFDM signals are restricted to the established CSI and/or flawless synchronization scenarios. The utilization of discrete Fourier transform (DFT) and normalized higher-order cumulants [60] for blind modulation identification has also been explored in the classification of low-order digital modulation schemes for OFDM systems. The classification accuracy is not up to par and is affected by channel degradation. In [63], the authors developed a high-performance deep residual network (ResNet) with a three-hop residual stack (TRNN)-based MC algorithm for real-time OFDM signal classification under dynamically fading channel conditions. A methodology for indexed modulation MIMO-OFDM signal detection using deep neural networks was proposed by Altin G [64]. The deep learning model training and feature extraction enable accurate modulated symbol index detection with good robustness. In [65], active subcarriers and modulation orders are estimated using DNN for modulation detection in OFDM-IM systems. [66] investigates deep learning channel estimates for OFDM-IM-based hydroacoustic communication systems. A 3D convolutional network-based technique to categorize MIMO-OFDM modulations in received signals is proposed in [67]. The method learns the modulation patterns based on the assumption of unknown frequency selective fading channels and signal-to-noise ratio. Simulation results show that the method achieves a classification accuracy of about 95% at 0 dB SNR. This study lists the modulation recognition techniques that deep learning has recently been used to apply to MIMO-OFDM systems in Table 6. In terms of modulation identification for MIMO-OFDM systems, some research methods have achieved some results. For example, the method based on matrix decomposition can decompose the received signal matrix into a modulation matrix and channel matrix. In addition, the method based on the joint probability density function can utilize the statistical properties of the received signal for modulation identification. As for the modulation identification of MIMO-STBC systems, there are relatively few research methods, but some methods have made some progress. In the next section, the modulation identification methods in MIMO-STBC will be introduced.

C. MODULATION RECOGNITION FOR MIMO-STBC SYSTEMS

Although there is some research literature on modulation identification [28], [35], [47], [71] and STBC identification [72], [73] for MIMO communication systems, these studies only focus on modulation identification or STBC identification. Despite the fact that the received signal contains both modulation information and STBC information from the source, these two types of studies are carried out separately. Neglecting STBC to solely identify the modulation pattern results in interference with the information contained within the symbols; conversely, disregarding STBC to solely identify the modulation pattern hinders the recognition of STBC. This section concentrates on the modulation recognition technique employed in MIMO-STBC systems, despite the fact that there are certain restrictions in practical applications.

Hu et al. [74] suggested the implementation of a combined recognition technique for STBC and modulation. Firstly, the correspondence between the combination of STBC, modulation mode, and received signal trajectory image is analyzed, and the feasibility of the joint identification of STBC and modulation mode based on the trajectory image is demonstrated. To improve the differentiation of different STBs on the trajectory image under BPSK and the detailed information contained in the trajectory image, two improvement schemes for the trajectory image are given. Finally, the trajectory images are classified using the improved Lene T network. In [34], Alamouti (AL) employed the statistical properties of the correlation function to determine the modulation type of the received signal in their space-time packet code (STBC). This study lists the modulation recognition techniques that deep learning has recently been used to apply to MIMO-STBC systems in Table 7. In MIMO-STBC systems, due to the introduction of space-time coding, the signal features are more complex, and modulation identification is more difficult. In massive MIMO systems, the signal has a higher dimension due to the use of massive antenna arrays and also faces more interference and complex channel conditions. Although the modulation identification methods for MIMO-STBC systems and massive MIMO systems have yet to be further studied and developed, some methods have made some progress. The modulation identification methods for massive MIMO systems are described next.

D. MODULATION RECOGNITION METHODS FOR MASSIVE MIMO

Massive MIMO (m MIMO) communication has been recognized as a key and important technology to meet the expected demands of fifth-generation (5G) and beyond 5G systems. By deploying too many antennas at the base station, it provides huge potential for 5G systems. Thus increasing the possibility of using different modulations by different transmitters to reduce the BER as well as increase the data rate. It leads to the development of intelligent receivers that can efficiently classify and recognize accurately modulated and decoded data. To solve this problem, Huaji et al. [84] investigated an automatic identification method for modulation modes based on integrated classifiers. The authors analyzed the overall performance of integrated classifiers for several radio modulation signals. The accuracy level of the integrated classifiers is 93% to 98%, which is much higher than the accuracy level of other individual classifiers. The accuracy level proves its ability to classify and recognize modulation labels. The experimental results show that the proposed integrated classifier model outperforms other ML models. Wu et al. [85] introduced an innovative uplink BMR algorithm that incorporates deep learning to assist in the analysis of cyclic stationary features (CF) for blind modulation identification in large-scale MIMO systems. Initially, the researchers employed a minimum description length (MDL) approach combined with the complex fast independent component analysis (CFICA algorithm) to segregate multiuser signals with diverse modulation schemes from an unspecified number of transmitters. Subsequently, they utilized a convolutional deep confidence network (CDBN) to scrutinize the correlation between CF and modulation type, producing reliable modulation identification outcomes.

TABLE 6. Modulation recognition algorithm of the MIMO-OFDM system based on deep learning.

Author	Year	Model	Separation mode	Input signa	Recognition accuracy
Zhang et al [92]	2022	CNN	ICA	I/Q sequence and cyclic spectrum section diagram	90%(4 dB)
Wang et al [93]	2023	CNN	ICA	Cyclic spectrum and quadric spectrum	100%(10 dB)
An et al [68]	2022	SC-MFNet	ICA	I/Q sequence and constellation chart	/
Zhang et al [69]	2022	CNN	ICA	Q sequence	increased by 4.75%(-10 dB)
Zhang et al [70]	2023	CNN-LSTM	ICA	IQ sequence and cyclic spectrum	98%(2 dB)
Zou et al [89]	2023	Decision fusion	ICA	Fourth power spectrum, cyclic spectrum and higher order cumulants	99.4%(10 dB)
Ren et al [90]	2024	4D2DConvNet	/	IQ components	95%(8 dB)
Yang et al [91]	2024	SMOTE-DNN	/	normalized statistical dispersion of amplitude and high-order statistics	87.5%(0 dB)

TABLE 7. Modulation recognition algorithm of the MIMO-STBC system based on deep learning.

Author	Year	Model	Recognition accuracy	Modulation recognition method
Marey et al. [75]	2022	EM algorithm	/	Utilize soft information in conjunction with channel decoders to improve the recognition performance of the suggested algorithm
Zhang et al. [76]	2022	MMFFN	More than 90%(-9 dB)	A multimodal feature fusion recognition network serves as the foundation for proposed space-time block code recognition algorithm
Guy et al. [77]	2022	MCNN	/	The complete extraction of the in-phase and quadrature (IQ) channel formation of STBC signals is possible by utilizing the structure of numerous input channels
Tayakout H et al. [78]	2018	SVM/NB /KNN	96.3%(10 dB)	The suggested method for AMC was semi-blind and relied on a streamlined Distributed Space-Time Block Coding technique
Khosraviyani M et al. [79]	2019	(NI-SI) / (SI-TV)	/	The features that were taken out of the received data samples' cumulants are the foundation for the suggested algorithms
Dehri B et al. [80]	2019	Joint semi-blind CFO and channel estimation	More than 97.6%(-10 dB)	Combining techniques for pattern recognition with higher order statistics, which are utilized for feature extraction
Tayakout H et al. [81]	2022	ANN	/	Create a multi-layer ANN and train it with aspects of the incoming signals that correspond to higher-order statistics
Zhang L et al. [82]	2022	RN	68.5%∼ 99.9% (-10 dB∼ -3 dB)	Examine the best RN structure for STBC blind recognition
MOULAY et al. [83]	2024	DHL	99%(5 dB)	The dendrogram-based heterogeneous learners classifier were obtained via ascendant hierarchical clustering and by employing higher-order momentand higher-order cumulants as features

The efficacy of the proposed method was confirmed through simulation results.

Liu et al. [86] considered that in real communication scenarios, additive noise usually exhibits non-Gaussian characteristics, and thus AMR methods developed for Gaussian noise cannot be well applied in practice. To solve this problem, the authors proposed a modulation identification classifier based on a single-sample KS test for MIMO systems with Cauchy-Gaussian two-parameter hybrid ground. Considering multiple receivers, to facilitate the computation and reduce the complexity of the algorithm, the authors combine the signals from different receivers and process them together as a set of data, then the orthogonal components of the data are used as the features, and finally, the KS test is used to compute the suitability of the theoretical distribution values with the empirical distribution values and finally complete the modulation classification and recognition. Experiments show that the method has a modulation recognition accuracy higher than 90% when the signal-to-noise ratio is greater than 10 dB.

In real communication scenarios, the labeled and unlabeled samples are large. In this case, it is almost impossible to realize the previously proposed deep learning-based AMC algorithms. Wang et al. [44] proposed a TL-based semi-supervised AMC (TL-AMC) method in zero-forcing-assisted multiple-input-multiple-output (ZF-MIMO) systems. With limited samples, TL-AMC outperforms CNN-based AMC, and TL-AMC achieves recognition accuracy at high SNR as well, similar to CNN-based AMC trained on a large number of labeled samples.

The modulation recognition methods applied to massive MIMO systems are fewer, and further research and development are needed. Deep learning has a wide range of application prospects in MIMO system modulation identification, which can help improve the performance and reliability of the system. In the future, with the continuous development of deep learning technology, its application in MIMO system modulation identification will be more extensive. In MIMO systems, automatic modulation identification is an important means to realize high-speed data transmission and improve system performance. However, automatic modulation identification in MIMO systems requires accurate identification and estimation of channel state information, which puts higher requirements on modulation identification algorithms. Currently, feature-based modulation identification methods, machine learning-based methods, and deep learning-based methods are applied, but there are still some challenges and problems.

V. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Despite recent advancements in DL-AMR models, numerous problems remain that need to be resolved in further studies. Generally speaking, the creation of the perfect robust classifier is still an open topic even with notable advancements and encouraging outcomes in earlier work. For example, some algorithms are restricted to a limited number of modulation schemes, while others require prior knowledge of the signal (e.g., carrier frequency, baud rate, timing offset, etc.). Furthermore, some algorithms are not appropriate for real-time applications due to their high computational cost. Others are predicated on idealized notions that hold false in real-world scenarios. Unlike real-world situations, certain classifiers have high signal-to-noise ratio (SNR) requirements.Consequently, in order to maximize the success of current DL-AMR research, focus must be placed on the extraction of critical features and the choice of classification criteria in low signal-to-noise ratio scenarios. The remaining part of this section will specifically highlight some unresolved issues and potential research directions.

A. MIXED SIGNAL SEPARATION

Mixed signal separation mainly includes methods based on independent component analysis (ICA), wavelet transform, singular value decomposition (SVD), etc. Mixed signal separation can reduce the noise mixed with signals with a low signal-to-noise ratio, which provides a basis for subsequent signal processing and analysis and has a significant impact on signal modulation recognition and classification. In MIMO systems, signals are mainly affected by ambient noise and space-time aliasing of signals from different transmitting antennas. The receiver receives mixed signals, and the modulation recognition of mixed signals is more difficult. Some scholars propose to use the ICA algorithm to separate the transmitted signals from the received mixed signals, extract the features of the separated transmitted signals, and use a neural network classifier to identify the modulation types of signals. Under the condition of 0 dB, the algorithm can achieve an average recognition rate of 90.71% for low-order modulated signals [35]. Therefore, the separation of mixed signals helps to improve the overall performance, and mixed-signal separation is the focus of future research.

B. FEATURE FUSION

The majority of deep learning-based modulation recognition techniques tend to focus on a single signal feature with superior recognition as the network input or modify the network architecture to extract more abstract features to enhance the accuracy of modulation recognition, without taking into account the interdependence between different transform domain features and different classifiers. Although Zhang et al. [87] proposed a modulation recognition method based on multi-mode feature fusion, which fuses features of different modes, multi-mode feature fusion can combine information from different feature perspectives, thus providing more comprehensive and accurate modulation recognition results and improving modulation recognition performance under different channel interference. However, the robustness of multi-mode feature fusion recognition methods is not good, so improving the robustness of existing modulation recognition methods is the focus of future research.

C. ESTABLISHING A STANDARDIZED SIGNAL DATASET

Researchers have produced a number of publicly accessible datasets, the most well-known of which is the Radio ML dataset, to assess and compare the effectiveness of modulation recognition techniques for various SISO systems. There are limited data sets for MIMO systems, however, they include RML2016.10a, RML2016.10b, RML2016.04.C, RML2018.01a, and HisarMod2019.1 [88]. Building reliable and sufficient signal data sets for MIMO systems is crucial for future study because of this.

D. COMBINING CHANNEL ESTIMATION WITH MODULATION RECOGNITION TASKS

After the above research, it was found that deep learning-based modulation identification methods applied to MIMO systems usually need to be combined with signal separation techniques, i.e., using Zero-breaking Equalization (ZF) or ICA algorithms to recover the desired transmit signals, and then extracting features of the recovered signals from different signal forms (e.g., IQ sequences, constellation diagrams, higher-order moments, higher-order accumulators, etc.), and then finally using deep neural networks to learn the features from the different features to complete the task. different features to learn, thereby accomplishing the modulation recognition task. However, it is worth noting that the use of the broken zero equalization (ZF) method to recover the signal requires knowledge of the channel matrix, but in the full-blind condition, the channel matrix information is not known, which requires a more accurate channel estimation, so it is promising to combine channel estimation with the modulation recognition task in future research.

E. BLIND CHANNEL ESTIMATION IS TRANSFORMED INTO ONLINE ESTIMATION

Considering the computational cost of signal processing brought by the massive MIMO system and the time of blind channel recognition, the next research needs to transform the batch blind channel estimation algorithm into an online estimation algorithm.

VI. CONCLUSION

Deep learning is gaining popularity in the field of AMR for MIMO systems, where research is still in its infancy, but remarkable results have been achieved. This paper describes the advanced modulation recognition algorithm of the MIMO system based on deep learning published in recent years. The system model and the basic theory of modulation recognition of the MIMO system and its derivative communication system are detailed. Then the traditional modulation recognition algorithm of the MIMO system is described, and the advantages and disadvantages of the traditional modulation recognition algorithm are summarized. The modulation recognition algorithms of the MIMO system based on deep learning are introduced, and the modulation recognition algorithms based on the MIMO-OFDM system, the MIMO-STBC system, and the Massive MIMO system are discussed. Finally, based on the review of modulation recognition algorithms, the unsolved problems and potential research directions of MIMO system modulation recognition are proposed, hoping to provide some references for future research.

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