DOI: 10.54254/2755-2721/154/2025.TJ23004

Research on CNN-Based Satellite Communication Modulation Mode Recognition Technology

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Abstract: The identification of modulation mode constitutes a pivotal element within satellite communication systems. Its utilization is pervasive, manifesting in domains such as signal demodulation, resource allocation, and communication quality assessment. However, traditional methods of modulation mode identification are dependent on manual feature extraction, which is both time-consuming and less adaptable in complex environments. Recent advancements in deep learning technology, particularly Convolutional Neural Network (CNN), have introduced novel approaches and methodologies for the identification of radio signal modulation modes. This paper focuses on how deep learning techniques, particularly CNN, can improve the accuracy and efficiency of modulation mode recognition during satellite communications. It summarize key advances in dataset construction, network model design, training methods and optimization techniques. This paper also explores the potential application prospects of CNN technology in 6G communications, emphasizing its critical role in enhancing communication efficiency and service quality. The findings indicate that CNN has significant advantages in satellite communication modulation mode recognition, especially in improving recognition accuracy and robustness.

Keywords: Convolutional Neural Network (CNN), Modulation mode recognition, Satellite communication, Deep learning, 6G communication

1. Introduction

As global communication technology advances at an accelerated rate, satellite communication, as a pivotal medium of communication, assumes a substantial role in the global communication network. The Convolutional Neural Network (CNN), a significant branch of deep learning, has achieved notable advancements in image recognition, speech processing and related domains. For instance, the CNN-Transformer lightweight intelligent modulation recognition algorithm has been shown to enhance the accuracy and efficiency of modulation mode recognition by integrating CNN and Transformer architectures [1]. Furthermore, a modulation recognition method based on a Generative Adversarial Network (GAN) combined with CNN has also demonstrated robust performance in complex channel conditions [2]. These studies not only demonstrate the potential of deep learning in modulation mode identification, but also provide new directions for future research.

This paper systematically reviews the current research status of CNN-based modulation mode identification technology for satellite communications. It summarizes the advantages of CNNs in enhancing the accuracy and robustness of modulation mode identification through comparative

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analysis. The study provides a novel technical perspective for the field of satellite communication and serves as a valuable reference for developing 6G communication technology. By exploring the application of CNN technology in modulation mode identification, this paper provides both theoretical support and practical guidance for the further development of future wireless communication technology.

2. Overview of modulation methods in satellite communications

2.1. Common modulation methods for satellite communications

In satellite communications, modulation technology represents a pivotal aspect for signal transmission, converting digital signals into analog signals suitable for wireless transmission [3]. This paper introduces several common modulation methods.

The first of these is Amplitude Shift Keying (ASK), in which the amplitude of the carrier is changed to represent different digital signals. The principle is to map the amplitude change of the digital signal onto the carrier, and to transmit data by controlling the presence or absence or amplitude of the carrier. This method has low hardware requirements,making it suitable for low-speed data transmission. However, its performance is poor in noisy environments. Conversely, Frequency Shift Keying (FSK) is a method of representing different digital signals by altering the frequency of the carrier. A key advantage is its strong noise immunity, achieved by switching between two distinct frequencies to represent binary data, with the selection of the frequency being informed by the characteristics of the channel and the limitations of the bandwidth.

Phase Shift Keying (PSK) is another such method that can represent different digital signals by changing the phase of the carrier. Due to its high spectral efficiency and anti-interference capability, PSK is widely used in satellite communications. Notable examples of this include Binary Phase Shift Keying (BPSK) and Quad Phase Shift Keying (QPSK), both of which facilitate the transmission of additional data bits through the implementation of distinct phase alterations [4].

Developed from prior methods, APSK combines amplitude and phase modulation to transmit more data within limited spectral resources. It enhances spectral efficiency by using multiple amplitude and phase layers, although this increases complexity. Another notable method is Quadrature Amplitude Modulation (QAM), which employs both amplitude and phase variations to represent a greater volume of data. The transmission of data over multiple amplitude and phase combinations enables the achievement of higher data rates within a constrained bandwidth, though this is contingent on optimal channel conditions and the efficacy of the receiver.

2.2. Comparison of the characteristics of different modulation methods

With regard to power efficiency, PSK and APSK demonstrate superior performance, achieving higher data transmission rates with lower power requirements. Conversely, QAM exhibits elevated power demands in higher-order modulation, particularly in instances of poor channel conditions [5]. Furthermore, PSK and APSK demonstrate robust anti-jamming capabilities in complex channel environments, such as scenarios with multipath effects or noise interference, while ASK and FSK exhibit limited efficacy in this regard. However, due to lower hardware requirements, ASK and FSK are simple to implement, while APSK and QAM require higher hardware support and finer signal processing.

The application scenarios of these modulation methods are as follows: ASK and FSK are commonly used in low and medium-speed data transmission, such as satellite telemetry and satellite navigation. PSK is widely used in various fields of satellite communication, especially when the data transmission rate are required. Meanwhile, as more comprehensive modulation methods, APSK and QAM excel in satellite broadband Internet service, multi-carrier transmission.

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In conclusion, the judicious selection of modulation method for a given communication scenario is contingent upon a comprehensive evaluation of factors including spectrum efficiency, power efficiency, anti-interference capability, and implementation complexity, in order to ensure optimal performance and meet the specific requirements of the communication task at hand [3]. For instance, in scenarios where spectrum resources are scarce, APSK and QAM emerge as superior alternatives. Conversely, in contexts characterized by less stringent hardware requirements and enhanced anti-jamming capabilities, PSK stands out as a more optimal choice. It is evident that with the continuous development of communication technology, there will be the emergence of enhanced modulation techniques and novel modulation methods, thus providing enhanced performance and a more diverse array of options for satellite communication.

3. CNN and satellite communication modulation mode identification

3.1. Basic architecture of CNN and its advantages

Convolutional Neural Network (CNN) is a significant model in the field of deep learning, which has achieved notable success in domains such as image and speech recognition.The fundamental architecture of CNN typically comprises an input layer, multiple convolutional and pooling layers, a fully connected layer, and an output layer. The specific relationship between these layers is illustrated in Figure 1.

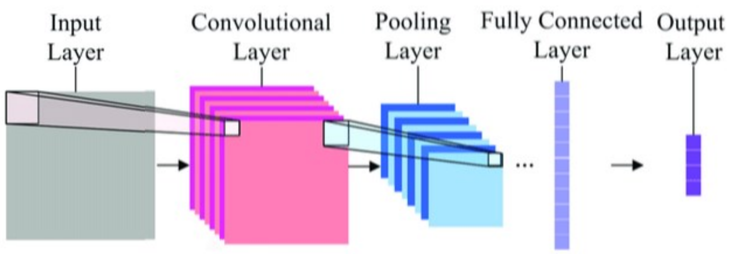

Figure 1: Structure of CNN [6]

Upon receiving the input signal, the convolutional layers automatically extract local features by performing convolutional operations on it through convolutional kernels. The pooling layers, conversely, are employed to reduce the spatial dimensions of the features. This reduction in dimension leads to a decrease in computation and, concomitantly, an augmentation in the model's generalization capability. Finally, the fully connected layer maps the features extracted by the previous layers to the output space, and the output layer outputs the classification results or regression values according to the specific task requirements [7].

In comparison with traditional approaches, CNN's primary advantage lies in its capacity for automatic feature learning from raw data, thereby reducing the necessity for manual feature extraction and enhancing recognition efficiency and accuracy. Furthermore, CNN exhibits superior generalization capabilities and robustness, maintaining high recognition performance in noisy environments.

3.2. Application process of CNN

The identification of satellite communication modulation modes is facilitated by CNN, which is capable of processing complex signal data and automatically learning the time-frequency characteristics of the signal. This enables the accurate identification of different modulation modes.

This capability allows for the accurate identification of different modulation modes. The application of CNNs involves four fundamental steps.

Initially, the satellite communication signals that have been collected must undergo preprocessing, a process that includes denoising, normalization and feature extraction, amongst other procedures. This is done to enhance the quality of the data, ensuring its suitability for the subsequent training of the CNN model. During the training process, the network parameters (e.g. convolutional kernel size, learning rate, etc.) can also be continuously adjusted to identify the most appropriate values corresponding to different input data. This optimization maximizes the model's performance and ultimately achieves the objective of accurately identifying different modulation modes [8].

Following the training phase, the model must undergo evaluation to ascertain its accuracy and robustness in identifying modulation modes. The evaluation metrics typically encompass accuracy, recall, and F1 score, among others, and the selection of appropriate metrics should be grounded in the specific context to ensure the selection of the most suitable ones or a combination thereof. Finally, the deployment stage is the final step in the process. At this point, the model must be able to swiftly and accurately identify the modulation mode of the signal. It must then be deployed to the actual application scenario in order to support the decision-making process of the communication system.

Following the completion of the fundamental process, CNN technology can be employed with great efficacy for the identification of satellite communication modulation modes, thereby providing intelligent support and services for the target communication system. It is evident that with the continuous development of 6G communication technology, the future application prospects of CNN in modulation mode identification will be more extensive.

3.3. Current research status of CNN in satellite communication modulation mode recognition

3.3.1. Established CNN-based recognition methods

This paper briefly introduces CNN-based recognition methods that have already gained some practical value by taking the following specific application scenarios as examples.

In the Internet of Underwater Things (IoUT) environment, some researchers have proposed a CNN model-based method for modulation identification of Optical Wireless Communication (OWC) systems, especially 64-QAM and 32-PSK. The method generates a dataset by simulating the transmission environment of underwater signals and utilizes the feature extraction function of CNN to achieve a high accuracy under different signal-to-noise ratio conditions (100%) and low test loss rate (1.82×10-6) [9]. Furthermore, an algorithm combining fractional low-order Choi-Williams distribution (FLO-CWD) and CNN has been proposed to address the problem of modulation pattern recognition of communication signals in impulsive noise environments. The FLO-CWD effectively suppresses the impulsive noise, while the CNN is responsible for extracting the features from time-frequency distributions and classifying them, which significantly improves the recognition performance [10].

With regard to the classification of interference signals, one study proposed a method for identifying suppressed interference signals based on a CNN model fusion. Specifically, the method utilizes a two-branch CNN and an improved MDS-CNN model fusion algorithm. This fusion algorithm improves the recognition rate to 93%, while also significantly reducing the time spent on training. As a result, the method is more suitable for areas requiring real-time applications [11]. Furthermore, for the small sample communication interference signal recognition method based on Deep Convolution Generative Adversarial Network-Convolutional Neural Network (DCGAN-CNN), it utilizes the generative adversarial property of DCGAN to expand the limited sample dataset and

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combines it with CNN for classification recognition. This effectively mitigates the problem of difficult recognition under small sample conditions and significantly improves the recognition rate [12].

3.3.2. Technological innovations and breakthroughs

In addressing the multi-scale feature fusion challenge in the modulation recognition of satellite communication signals, a Multi-Scale Recurrent Convolutional Neural Network (MSRC) model is proposed. This model integrates the dual-branching parallel structure, Res2Net, Long Short-Term Memory (LSTM), and the SE attention mechanism. The objective is to comprehensively capture the multi-scale characteristics of the signals and efficiently model the time series. The two-branch structure enhances the model's feature representation capability by extracting local and global features of the signal in parallel with convolutional kernels of different sizes. The LSTM network effectively models the temporal dependence of the signal and enhances the model's ability to recognize complex signals, and its specific operational process is illustrated in Figure 2. A comparison of existing models reveals that MSRC exhibits notable advantages in terms of recognition accuracy, parameter complexity, and training efficiency, particularly in the context of 16-QAM and 64-QAM modulation styles [13].

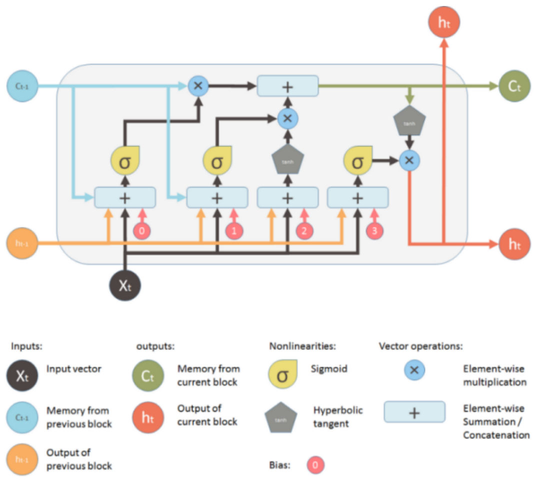

Figure 2: Schematic of LSTM network operation [14]

In the domain of radar and communication signal modulation recognition, researchers have employed a preprocessing method that involves the intermediate frequency signal delay autocorrelation combined with time-frequency analysis to train the time-frequency information of the signal as the input of the CNN. The CNN model they developed enhances the ability to extract fine features of the signal by optimizing the convolution kernel size and the number of layers. The experimental results demonstrate that the method has high recognition accuracy for multiple modulated signals under different signal-to-noise ratio conditions. For instance, when the signal-to-noise ratio is 10 dB, the training and testing accuracies attain over 94% and 92%, respectively. This suggests a novel approach for signal modulation recognition in complex electromagnetic environments [15].

A modulation recognition algorithm based on Convolutional Neural Network Based on Time-Frequency Characteristics (TFC-CNN) has been developed. This algorithm converts the time-frequency characteristics of signals into image features as inputs to the CNN via short-time Fourier transform. It employs smaller convolutional kernels (e.g. 3×3 and 1×1) and global mean pooling layers, which serve to reduce the model parameters and enhance the timeliness of the model

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and the convergence speed. The TFC-CNN, as introduced in the study, enhances the transfer of feature information by means of channel superposition, thus effectively addressing the issue of gradient vanishing. This, in turn, improves the robustness of the model and provides a reference for future deep learning models that incorporate more signal features [16].

4. Challenges and future directions

4.1. Challenges in current research

The challenges currently faced by CNN-based modulation pattern recognition techniques for satellite communications can be categorized into several key areas.

First, the lack of transparency in the decision-making process of CNN models limits the intuitive understanding of their internal mechanisms, which in turn affects the credibility of these models. Second, CNN models require a large amount of computational resources during the training process, which not only increases the cost of the research, but also restricts their applications in resource-limited environments. Despite significant advancements in theoretical research, the practical implementation of CNN models remains constrained, and their reliability still needs thorough validation.

4.2. Future research directions

This paper argues that future research should prioritize enhancing the efficiency and interpretability of CNN models, while concurrently exploring their potential applications in 6G communications. Specifically, research could concentrate on developing more lightweight CNN models to reduce the demand for computational resources and make them more suitable for deployment in resource-constrained environments. With the development of 6G communication technology, optimization and innovation of deep learning models will also be key to improving the accuracy of modulation pattern recognition. Through continuous technological innovation and interdisciplinary cooperation, it is anticipated that CNN will assume a more significant role in 6G communication systems, providing substantial technical support for the development of global satellite communication networks.

5. Conclusion

It has been determined that the automatic extraction of critical features by CNN reduces the workload associated with manual feature extraction and enhances recognition efficiency. Furthermore, this paper explores the potential of CNN technology in 6G communication, offering novel insights into satellite communication and providing a valuable reference point for the development of 6G communication technology.

However, this paper is not very exhaustive in describing the specific implementation details of CNN-related models and algorithms, and it fails to fully reveal the prospects of their applications in emerging technology areas other than 6G communication. This may lead to the readers' lack of a clear understanding of the specific steps and key elements of the technological implementation. In addition, this paper is still deficient in exploring the limitations of CNN technology practice and fails to comprehensively cover the problems that CNN may encounter in practical applications. For instance, the discourse on the reliance of CNN models on extensive datasets, the substantial demand for labeled data, and the constraints in handling unstructured data is inadequate.

The development of 6G communication technology will undoubtedly lead to increased demands for modulation mode recognition technology. The crux of the issue will be whether future research can achieve breakthroughs in enhancing recognition accuracy and reducing computational

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complexity. One potential avenue for enhancement is the integration of CNN with other deep learning methodologies, such as Transformer and GAN, within hybrid models. This integration has the potential to yield substantial advancements in the accuracy and efficiency of modality recognition. In addition, researchers must direct their attention to new application scenarios in 6G communication, such as immersive communication and communication-aware integration, and explore the potential of modulation mode recognition techniques in these contexts. Through continuous innovation and optimization, the identification of modulation modes is poised to assume an increasingly pivotal role in future communication systems, providing substantial support for the development of global communication networks.

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