Research on Modulation Recognition of Communication Signal

Shukun Liu¹*, Yifei Gao¹, Yuanshi Wang¹, Yifei Ren¹, and Yixuan Huang¹

¹ Liangjiang International College, Chongqing University of Technology, Chongqing, 400000, China
*Corresponding author’s e-mail: kunnys@2019.cqut.edu.cn

Abstract. Modular identification of radio communication signals is widely used in commercial software’s as well as the country’s defence. With the phenomenal development of modern telecommunications in various countries. The process of converting data into radio waves by adding information to an electronic or optical carrier signal becomes more sophisticated and variable. As a result, there has been a great deal of research and development into signal interpretation, and a number of effective schemes have been devised. For Signal Modulation, recent research has used a variety of techniques such as clustering, neural networks, automatic modulation, and analytical parameters. A quick description and summary of signal recognition approaches is offered in this study. We also reviewed contemporary technological hurdles, as well as the future direction of modulation.

1. Introduction

Modulation is the process of changing one or more aspects of a periodic waveform, known as the carrier signal, with a distinct signal, known as the modulation signal, which often carries data to be sent [9]. Several transmission bounding and devices are consistently growing as a result of the increased innovation in wireless communication systems, resulting in considerable changes in our ordinary routine [8]. Many researches have been published in recent years to find an effective modulation mode that aims to increase the precision for more accurate signal inflection in hope to meet the specification of transmission links. However, many studies are restricted to certain circumstances and have limited applicability to distinctive medium requirements and device kinds. Many researchers are looking at a new form of detection algorithm that covers multi-path fading, shadowing, and receiver uncertainty issues [11] to minimise harmful interference with licensed users and to locate susceptible spectrum to get better spectrum utilisation for the future aspect of Signal Modulation [12].

Modern advancement is varied and complicated; new smart devices are continually being developed; and because of existence of compatible and discrepant signals is becoming benchmark. Because of that sophisticated signal identification has to face challenges, and signal identification techniques will be necessary to keep up at an required pace. Substantial wireless communication technologies identification research has evolved, including neural network [13] and clustering models [4] with analytical characteristics for automatic wireless technology identification. For clustering they used some additional characteristics of more than one waveform that combines shape for predicting the modulated signal. Meanwhile, novel mobile network applications such as identification of base network transmitter, interfering signal forecasting, and geographic positioning are being explored. In this paper, we reviewed automated neural network and clustering algorithm in signal recognition is reviewed.
2. Methods
There are several new technologies applied various approaches and methods for recognition. The most recent study uses a method to generate tuned membership functions automatically in accordance to the domain knowledge technique to find the initial clustering centre, and then conducts classification research based on the number of cluster centres, combining shape prediction and modulation recognition for finding some characteristics. Aside from that, the neural network methodology uses a combined parallel module that concatenates spatial and temporal qualities then re-weighting all them using attention mechanism. For signal modulation recognition, many studies use statistical characteristics created through characteristic engineering. Neural network models outperform other approaches in general because large-scale data is required for the training process in neural network models, which is easy to obtain for a variety of communication devices used in daily life, giving them an advantage over traditional machine learning approaches.

3. Recent Studies

3.1. Clustering Approach
They applied the idea of altering the existing configuration in the face of system failure, environmental challenge, and mission change to improve constellation performance or fulfill the needs of the new work. They suggested a method for obtaining some characteristics of more than one waveform qualities that combines shape identification and modulation recognition. They used this technique because it can classify data samples automatically. This approach lowers the randomness of the initial centre while also saving time in calculations [7]. It can nevertheless be reconstructed and identified with a poor signal-to-noise ratio or a particular time variation.

3.1.1. Algorithms
(1) Signal Clustering: - They employed the KMeans [3] and Fuzzy C-Means clustering [2] algorithms, which were simulated for a set number of times and the operation points, cluster centres, and running times of both algorithms were counted. They researched and studied the results after receiving the outcomes of this experiment. In the context of the number of clusters, they determined that an enhanced clustering algorithm does not lower the accuracy of cluster centres without reducing the number of samples engaged in the operation. However, as compared to the traditional technique, the new clustering approach takes much less time. The recognition rate comparison chart of Quadrature amplitude for varying indication length is obtained for further analysis using the Fuzzy C-Means m clustering technique.

(2) Modulation Identification Process: - To retrieve the density and indication rate parameters, they first identified them. There is a signal discrepancy. Because the individual to whom the signal is transferred is unaware of the particular parameters of the received indicator. As a result, in order to realise synchronisation and indicator synchronisation of signal and recover signal constellation, an algorithm to estimate the density, indication rate, and timing error must be designed. The transmission capacity and density are determined from the sampled signal first, followed by down conversion and low-pass filtering to remove the carrier’s effect, lower the noise level, and determine the signal symbol rate. Finally, the centroid is determined based on the potential value of cluster data points.

(3) Identification of Signal characteristics: This approach was chosen because it is simple and intuitive. In engineering applications, it does not require a great amount of storage capacity, and the calculation time is fast. However, when the signal-to-noise ratio is low, the recognition performance is poor [6]. They identified characteristic parameters based on the signals’ respective properties, determined the appropriate decision threshold with a vast quantity of data testing, and then used the tree classification structure to complete the identification.
3.2. Automatic Prediction Model for Modulation with Neural Network

They employed a parallel neural network model that concatenates contiguous and mortal characteristics at the same time, as well as an attention mechanism to reinitialize the weights of all characteristics. A collection of parallel extraction modules is initially designed to extract characteristics in parallel. To extract contiguous and mortal properties, Convolutional Neural Networks and Gated Recurrent Units are used [5]. The two types of characteristics which are concatenated in the channel dimension. Various attention methods are employed to assign weights to attributes. For assigning weights for characteristics in the channel dimension and additional characteristics dimension, multi-head attention mechanisms are used. To generate a residual structure, multi-head attention is used to develop a combined parallel extraction of characteristics with the model. The output is then flattened in order to calculate the similarity distance.

3.2.1. Model Description

In this first they pre-process the data. AIQ is the input of our model. Two transmitters make up the real and imaginary parts of the input signal. They firstly calculated the IQ transmitter’s amplitude and phase parameters. We then combined the raw complicated input with these two characteristics and obtained data from a variety of sources. The goal of this concatenation is to improve data quality. Following the pre-processing stage, the concatenated data is given to our suggested mixed parallel neural network for prediction [1]. Our network’s output is the predicted outcome.

\[
A_{IQ} = (Re\{x(1), x(2) - \ldots - x(n)\}, \ Im\{x(1), x(2) - \ldots - x(n)\})
\]  

(1)

3.2.2. Gated recurrent unit

GRUs (gated recurrent units) are a recurrent neural network gating method that was first described in 2014. The GRU is similar to a long short-term memory (LSTM) with a forget gate [10], but it lacks an output gate, hence it has fewer parameters. GRU’s performance on polyphonic music modelling, speech signal modelling, and natural language processing tasks was found to be comparable to that of LSTM in some cases. On certain smaller and less frequent datasets, GRUs have been found to perform better.

3.2.3. Combined Parallel Network

With the merged network, the characteristic extractor parallel network is added. Inception, Gate Recurrent Unit, Excitation block, Attention block and multi-head attention block make up the combined parallel network. The output of the model has been passed through softmax activation function. Several combined parallel modules make up the combined parallel network. The combined parallel characteristic extraction module is the core structure of the combined parallel module. Inception and the Gated recurrent unit build the parallel structure (GRU). Contiguous and mortal properties are sought by the inception and GRU modules, respectively.

The batches were normalised prior to the Inception block. When the Inception stalk > 1, the Maxpool layer is applied, and the Maxpool size is equal to the Inception stride. We use a multi-head attention technique to normalise and initialise the weights of the splicing characteristics after detecting contiguous
and mortal qualities. The proposed combined parallel module combines the parallel characteristic extraction module with the parallel characteristic extraction module as shown in Figure 1. They added numerous mixed parallel models through residual structure to extract contiguous and mortal properties for enhanced consistency. After the last combined parallel module, we use a multi-head attention mechanism to flatten all the characteristics and change the weight of each sample point. Finally, they used the softmax function to pass the result.

3.3. CNN and VGG Model
They employed a convolutional neural network in which the input passes through the system’s sending end, the modulated signal travels through the demodulator, and the white gaussian noise emitter passes through the system’s receiver end. For forecasting the modulated approach of the signal, the signal passes via the pre-processor at the receiving end of the system, the CDT model, and the VGGNet [14] identification model. The modulated signal and signal metadata are received by the demodulated output, which completes the transmission and restores the original signal.

3.3.1. Convolutional Neural Network
The convolution neural network was first proposed for the Image-Net competition in and quickly placed first. Traditional full-connected neural networks do not have the same data processing capabilities as CNN. At characteristic representation, CNN can preserve the neighbourhood relation and geographic locality of input data. The CNN model can train itself automatically if the input data is sufficient. Because the CNN structure is wholly created from the training data, it is fully tailored to the data and can extract more representative characteristics. The convolution stage, which can be regarded as a correlated process, lies at the heart of CNN.

3.3.2. Model

![Figure 2 Model Structure](image)

For the pre-processing obtain a large number of constellation images as the sample data of supervised training. In the neural network model of the constellation, the training samples and the test samples are the constellation images marked in different modulated modes and in different signal-to-noise ratio environments as shown in Figure 2. The signal pre-processed by gaussian noise is added to the constellation map to obtain the training set and test set, which are broaden by rotating, mounted and encoded. For the pre-processing obtain a large number of constellation images as the sample data of supervised training. In the neural network model of the constellation, the training samples and the test samples are the constellation images marked in different modulated modes and in different signal-to-noise ratio environments. The signal pre-processed by gaussian noise is added to the constellation map to obtain the training set and test set, which are broaden by rotating, mounted and encoded.

They adjusted the output layer of the VGG network to the number eight, which corresponds to the signal modulation type, and they lowered the number of neurons in the two layers of the complete connection layer, because the original neurons in the actual training always caused concurrency problems. Various network characteristics are improved for modulated signal in addition to modifying the basic structure. The ratio between the number of training samples and the number of test samples is
8.2. The gaussian white noise channel is used in this simulation. The VGG network was then trained using the training dataset and the gradient descent optimization algorithm Adam momentum optimization algorithm. After reviewing the data, they discovered that when the adjusted order increases, the prediction accuracy reduces marginally. However, this method has limitations in terms of characteristics extraction and is susceptible to noise, making it less effective than full characteristics identification.

4. Future Advancement

Despite the fact that a huge body of literature has offered numerous signal recognition algorithms in last 10 years, it cannot be denied that the technology makes little sense in a real electromagnetic environment. For example CNN model has limitations in terms of characteristics extraction and is susceptible to noise, making it less effective than full characteristics identification. Recent research has also encountered the issue of overfitting, which necessitates a large amount of data, which is a difficulty, and applying exact labels to huge data is a time-consuming operation. More innovative technologies and solutions will be released in future research.

In which it can be employed to a large extent in the sphere of defence with a wide range of future elements of dynamic spectrum access. It has the characteristics of a brief duration and an unpredictable start and end time, which makes signal detection difficult. High-quality labels play an important role in achieving acceptable identification accuracy, yet they are time-consuming in burst communication systems. As a result, there are still research opportunities in the field of signal prediction. Intelligent spectrum utilization is another methodology, in which the detection method is based on the power and band of concern. With the arrival of high speed connectivity and the commercialization of IoT, resources are anticipated to lead to the overlap of numerous signals, enhancing accuracy and reducing mean detection time for known waveforms. Furthermore, as the number of types of signals and wireless networks grows, signal detection in the coexistence environment will surely get more difficult.

5. Conclusion

This document provides an overview and summary of contemporary signal recognition research. Signal prediction has made significant progress in both theoretical and practical aspects of device prediction and detection. It’s comprehensible that the field of signal identification has expanded beyond modulation prediction to include the prediction of wireless devices. The majority of research, on the other hand, is based on educated assumptions or known parameters, with the majority of results obtained from simulated values. There is still a long way to go in terms of signal recognition in a real electromagnetic environment and practical implementation.

References

[1] Freddie Åström and Rasit Koker. A parallel neural network approach to prediction of parkinson’s disease. Expert systems with applications, 38(10):12470– 12474, 2011.

[2] James C Bezdek, Robert Ehrlich, and William Full. Fcm: The fuzzy c-means clustering algorithm. Computers & geosciences, 10(2-3):191–203, 1984.

[3] Paul S Bradley and Usama M Fayyad. Refining initial points for k-means clustering. In ICML, volume 98, pages 91–99. Citeseer, 1998.

[4] Yuyang Cheng and Shuying Shao. Communication modulation recognition method based on clustering algorithm. In Journal of Physics: Conference Series, volume 1827, page 012153. IOP Publishing, 2021.

[5] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555, 2014.

[6] Johannes F De Boer, Barry Cense, B Hyle Park, Mark C Pierce, Guillermo J Tearney, and Brett E Bouma. Improved signal-to-noise ratio in spectraldomain compared with time-domain optical coherence tomography. Optics letters, 28(21):2067– 2069, 2003.
[7] Fengtang Fang, Xiaojun Li, Yupeng Xing, and Yifan Wang. Research on clustering method of airborne threat target based on density. In Journal of Physics: Conference Series, volume 1345, page 032026. IOP Publishing, 2019.

[8] Taehyoung Kim, Younsun Kim, Qiongjie Lin, Feifei Sun, Jingxing Fu, Youngbum Kim, Aris Papasakellariou, Hyoungju Ji, and Juho Lee. Evolution of power saving technologies for 5g new radio. IEEE Access, 8:198912–198924, 2020.

[9] Neelam Srivastava. Challenges of next-generation wireless sensor networks and its impact on society. arXiv preprint arXiv:1002.4680, 2010.

[10] Jos Van Der Westhuizen and Joan Lasenby. The unreasonable effectiveness of the forget gate. arXiv preprint arXiv:1804.04849, 2018.

[11] Beibei Wang and KJ Ray Liu. Advances in cognitive radio networks: A survey. IEEE Journal of selected topics in signal processing, 5(1):5–23, 2010.

[12] Tevfik Yucek and Huseyin Arslan. A survey of spectrum sensing algorithms for cognitive radio applications. IEEE communications surveys & tutorials, 11(1):116–130, 2009.

[13] Rui Zhang, Zhendong Yin, Zhilu Wu, and Siyang Zhou. A novel automatic modulation classification method using attention mechanism and hybrid parallel neural network. Applied Sciences, 11(3):1327, 2021.

[14] Xianyi Zhu, Jin Yuan, Yi Xiao, Yan Zheng, and Zheng Qin. Stroke classification for sketch segmentation by fine-tuning a developmental vggnet16. Multimedia Tools and Applications, pages 1–16, 2020.