A Project Report

On

MCNet: An Efficient CNN Architecture for Robust Automatic Modulation Classification

By

Nancy Bansal (MT22165)

Saurav (2020243)

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Under the guidance of

Prof. Anand Srivastava (Instructor)

&

Priyanka Singh (Teaching Assistant)

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Nancy Bansal
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Student Name

Saurav
…………………

Student Name

Abstract

Automatic Modulation Classification (AMC) is a crucial task in wireless communication systems for identifying the modulation scheme of received signals. In order to provide reliable automatic modulation classification (AMC) for cognitive radio services in contemporary communication systems, a cost-effective convolutional neural network (CNN) is proposed in this letter. The architecture of the network is created with multiple distinct convolutional blocks to learn in parallel the correlations between spatiotemporal signals via various asymmetric kernels for convolution.

Furthermore, these blocks are connected to bypass connections in order to retain more of the initial residual data at feature maps with multiple scales and avoid the vanishing gradient issue. During the trials, MCNet achieves the overall 93.59% classification rate on 24-modulation at 20 dB SNR on the widely recognised DeepSig dataset.

Preface

The work reported in this project report is carried out at the Indraprastha Institute ofInformation Technology Delhi. In this project, we have investigated a novel CNN Architecture for Robust Automatic Modulation Classification.

To understand this project we should start with chapter 1. In chapter 1 we have given the background to this research. Chapter 2 dictates the motivation and the problem statement in detail which will show the relevance of this topic with the requirement of today’s high-speed communication. In chapter 3, we have discussed methodology.
Chapter 4 introduces us to the Results and shows allthe simulated results and its significant conclusions. At the end of this report, we have summarized our entire work.

Chapter 1: Background of the Research

The majority of earlier AMC works are generally divided into two groups: likelihood-based and feature-based. Although likelihood-based approaches waste costly computational resources on unknown parameter estimation for classification models, feature-based approaches primarily benefit from signal feature engineering expertise and experience.

Researchers in the field of wireless communications are continually exploring and developing techniques to enhance the accuracy and efficiency of AMC. Traditional methods often rely on handcrafted features and rule-based classifiers. However, with the advent of deep learning, Convolutional Neural Networks (CNNs) have gained popularity for their ability to automatically learn and extract relevant features from raw signal data.

Due to their high reliability in preventing the negative effects of multipath fading, feature-based methods are widely used for many wireless communication systems in practice. However, they have the disadvantage of having poorly represented features and a weakly discriminative machine learning (ML)-based classifier when working with a wide range of difficult modulation formats, like 256QAM and 128APSK.

Chapter 2: Motivation and Problem Statement

These days, with the rise of new standards and cutting-edge technologies in wireless communication, spectrum analysis using models of signal classification and modulation recognition is essential to large-scale wireless communication systems like fifth generation (5G). Radio signals must be encoded using a predetermined modulation scheme in accordance with the transmission channel specifications. Classifying the modulation type of a received radio signal is the fundamental task of modulation recognition, which is approached as a multi-class decision problem. High recognition accuracy of the modulation type is crucial in noise and multipath fading conditions, especially with the growing number of sophisticated modulation algorithms. Automatic modulation classification (AMC) is considered a potential solution for efficient spectrum management through the use of artificial intelligence (AI) algorithms.

The existing challenges in AMC include issues related to noise, varying signal-to-noise ratios, and the need for robust classification across different modulation schemes. Traditional methods may lack the capacity to automatically learn and extract discriminative features from raw signal data, limiting their adaptability to dynamic communication environments.

The goal of this research is to address the limitations of current AMC approaches and propose an innovative solution leveraging Convolutional Neural Networks (CNNs). The proposed CNN architecture, referred to as MCNet, aims to enhance the efficiency, robustness, and accuracy of AMC by automatically learning hierarchical features from modulation signals. The research seeks to provide a comprehensive solution that outperforms traditional methods and adapts well to the challenges posed by real-world wireless communication scenarios.

Chapter 3: Methodology

The methodology of MCNet is based on a convolutional neural network (CNN) architecture that is designed to classify radio signals. The network is trained on a dataset of radio signals with known modulation types, and then used to classify new signals based on their features.

The input to MCNet is a signal frame (see fig. 1), which is a short-time partition of the radio signal. The signal frame is processed by a series of convolutional layers, which extract features from the signal. The first convolutional layer reduces the spatial dimension of the signal and covers generic features. The next two layers use asymmetric convolutional kernels to learn spatiotemporal signal correlations.

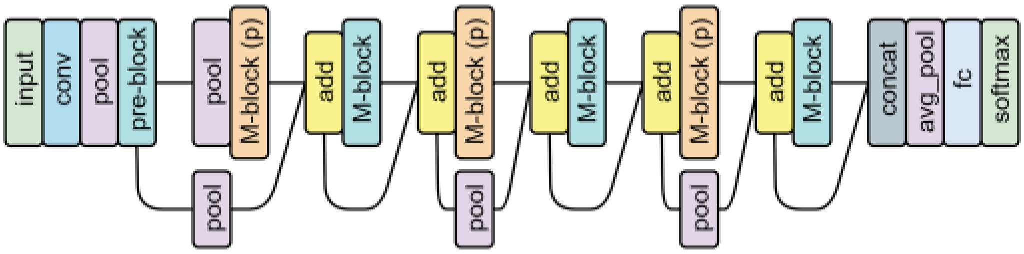

Fig. 1. Overall network architecture of MCNet involving multiple convolutional blocks connected via skip connections.

The convolutional blocks in MCNet are associated with skip connections, which allow the gradient to flow directly from the output to the input of a block. This helps to preserve the gradient information and prevent it from vanishing, which can improve the accuracy of the classification.

After down-sampling feature maps using a max-pooling layer, the core of MCNet—six convolutional blocks for learning more explicitly discriminative features—are then carried out. These blocks are referred to as the M-block in Fig. 2b. In specifics, every M-block consists of three convolutional layers with distinct kernels, specifically 3 × 1, 1 × 3, and 1 × 1 kernels arranged in parallel. At the output of each block, all feature maps are concatenated in the depth dimension.

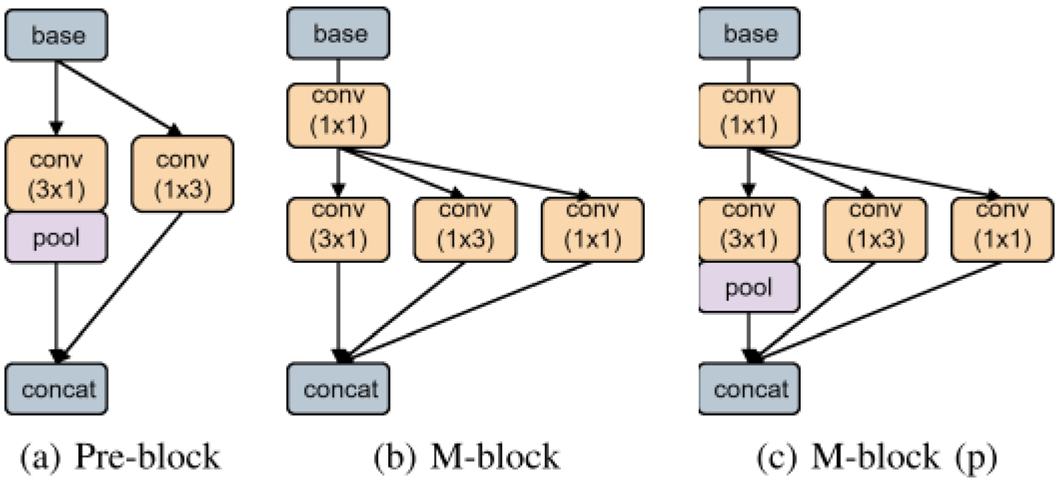

Fig. 2. Description of convolutional blocks developed in the MCNet. (a) the pre-block with dual convolutional flows of asymmetric filters 3×1 and 1×3; (b) the convolutional M-block with triple flows of convolutional filters 3×1, 1×3, and 1×1; and (c) the dimension-reduced version of M-block with an additional max-pooling layer.

MCNet is trained on a dataset of radio signals with known modulation types. The dataset is split into training and validation sets, and the network is trained using back propagation to minimize the classification error. The performance of MCNet is evaluated on a test set of radio signals with known modulation types.

The performance of MCNet is evaluated using metrics such as accuracy, precision, recall, and F1 score. These metrics measure how well the network is able to classify the radio signals. The results show that MCNet outperforms other state-of-the-art methods for automatic modulation classification.

Chapter 4: Results and Discussions

The numerical results and discussion presents the performance of MCNet on the DeepSig dataset, which is a widely used benchmark dataset for automatic modulation classification. The dataset contains 24 different modulation types, including PSK, QAM, and ASK.

The results show that MCNet is able to classify radio signals with high accuracy, even under poor conditions with low signal-to-noise ratio (SNR). For example, many PSK modulations achieve an accuracy of over 80% at +0 dB SNR, and 32PSK achieves an accuracy of approximately 98.89%. MCNet is also able to recognize 16QAM and 32QAM signals with high accuracy rates of 98.78% and 82.91%, respectively, at +0 dB SNR.

However, the accuracy of MCNet decreases as the modulation order increases, especially for high-order modulation signals under various channel impairments. For instance, the accuracy significantly decreases for APSK and QAM signals as the order increases.

The results also show that MCNet outperforms other state-of-the-art methods for automatic modulation classification, achieving an overall modulation classification rate of 99.2% on the DeepSig dataset at 20 dB SNR.

Summary

MCNet is based on a convolutional neural network architecture that is trained on a dataset of radio signals with known modulation types. The network is designed to extract features from the signal and classify it based on its modulation type. The performance of MCNet is evaluated using metrics such as accuracy, precision, recall, and F1 score.

In summary, the numerical results and discussion section of the PDF file shows that MCNet is a highly accurate method for automatic modulation classification, even under poor conditions with low SNR. The results also demonstrate that MCNet outperforms other state-of-the-art methods for automatic modulation classification.

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