AUTOMATIC MODULATION CLASSIFICATION FOR FLEXIBLE OFDM-BASED OPTICAL NETWORKS

Hai-Chau Le and Chien-Trinh Nguyen

Posts and Telecommunications Institute of Technology, Hanoi, Vietnam

Abstract: Orthogonal frequency division multiplexing (OFDM) technology, a multi-carrier digital modulation technology, has been widely implemented in optical networks thanks to the effective provision of dispersion compensation for optical paths. To provide bandwidth-abundant and flexible optical path services, OFDM-based optical networks may need to support several modulation formats, i.e., BPSK, QPSK, 8-PSK, and 16-QAM, and deploy them adaptively. Recently, automatic modulation classification (AMC) has become a promising solution for wireless networks to identify accurately the modulation formats of the received OFDM signals. In this paper, we propose an effective AMC using deep learning (DL) for flexible and adaptive OFDM-based optical networks. The proposed DL-based AMC is able to classify four typical modulation schemes such as binary phase-shift keying (BPSK), quadrature PSK (QPSK), 8-PSK, and 16-quadrature amplitude modulation (QAM) in dynamic network conditions. Numerical experiments are performed to verify the effectiveness of the developed solution. Our developed solution offers significantly high accuracy, 95.83+%, even with a low SNR, says 4 dB, and its performance is improved when the SNR is enhanced.

Keywords: Deep learning, optical network, Orthogonal frequency-division multiplexing, modulation format, modulation classification.

I. INTRODUCTION

Nowadays, optical transport networks have emerged as one of the key networking technologies for next-generation networks thanks to the capability of provisioning cost-effective, dynamic, and heterogeneous bandwidth-abundant flexible optical path services [1]–[4]. Orthogonal frequency division multiplexing (OFDM) technology, which can not only improve the spectral utilization efficiency but also enhance transmission performance with the deployment of adaptive high-order modulation formats per OFDM subcarrier while efficiently dealing with fiber dispersion compensation, has been widely adopted in next generation optical networks [5], [6]. Next generation optical networks have been expected to be reconfigurable, dynamic, adaptive, spectrum grid-free, and modulation format-free [1], [7]–[9]. Such advanced features offer a significant enhancement of the network flexibility, efficiency, and performance, more intelligent, effective, and sophisticated network solutions need to be developed [7], [10], [11]. Next-generation optical networks need to be equipped with intelligence to interact and adapt to network environments [5], [12], [13].

One of the key intelligent network solutions is to enable signal receivers to identify automatically the modulated signals, known as automatic modulation classification (AMC) in order to realize efficient, adaptive, and flexible optical networks in which the signal modulation and bandwidth are determined dynamically based on the network states [13], [14]. Parameter synchronization between transceivers is a highly challenging task for flexible, adaptive/ automated optical systems [9], [15], [16]. Limitation in exchanging parameters, i.e., modulation format and data rate, between a transmitter and a receiver usually causes an inefficient usage of available resources. Therefore, the receiver needs to have such an intelligent mechanism, i.e., AMC, to detect the necessary parameters of the transmitter to optimally make use of resources and enhance the network performance. Automatic modulation classification enables the receiver to identify the modulation format of the received signal without any prior knowledge of the transmitted signal parameters such as symbol rate, channel state information, ... [14], [17]. Furthermore, recent advances in machine learning (ML) including deep learning (DL) have shown a great improvement in state-of-the-art results and led to a widespread application in many fields especially in communication systems. Many works introduced for deep learning-based AMC of OFDM systems mainly focus on wireless communication systems using OFDM [18]–[25]. Some works on DL-based AMC in optical wireless systems have been developed [5], [16], [26]. However, to the best of our knowledge, there is still a lack of study about deep learning solutions for modulation classification in optical transport networks. Different from the wireless environment, optical transport networks using optical fiber link has higher transmission quality but requires more accurate modulation classification.

Contact author: Hai-Chau Le
Email: chaulh@ptit.edu.vn
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In this paper, we study the automatic modulation classification problem in flexible OFDM-based distance-adaptive provisioning optical networks. We propose an efficient automatic modulation classification solution that exploits deep learning to identify accurately four typical modulation formats including BPSK, QPSK, 8-PSK, and 16-QAM without prior knowledge about the modulated signals or channel statistics for a flexible OFDM-based optical network. The performance of the developed DL-based AMC solution is estimated by using numerical simulations. The obtained results imply that our proposed DL-based AMC method provides a significantly high accuracy even with a low SNR, more than 95.83% with the SNR of 4 dB. The AMC performance is also enhanced as the transmission quality, SNR, is better.

II. DEVELOPED AUTOMATIC MODULATION CLASSIFICATION BASED ON DEEP LEARNING

A. *OFDM-based Optical Network with Deep Learning-based Automatic Modulation Classification*

In our work, we consider an OFDM-based optical network that employs an automatic modulation classification with deep learning to detect the modulation format of the received signals adaptively and automatically. The network is assumed to adopt the distance-adaptive modulation mechanism with four typical modulation formats, i.e., BPSK, QPSK, 8 phase shift keying (8-PSK), and 16-QAM, of the optical signals. For simplicity, it is assumed that no spectrum conversion is equipped and the optical link loss is mainly dominated by fiber loss.

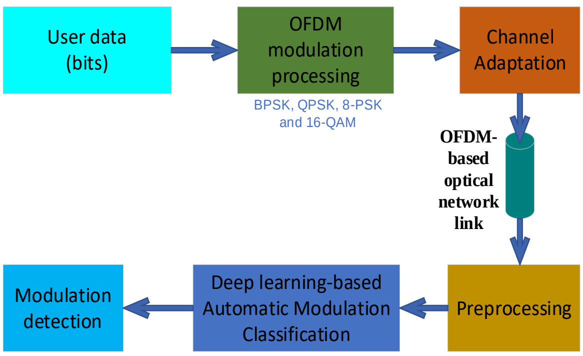

Fig. 1. DL-based AMC scheme for flexible OFDM optical network

Figure 1 shows the system architecture of a flexible OFDM optical network utilizing the proposed DL-based AMC scheme. The developed deep learning-based automatic modulation classification scheme for detecting the modulation formats of the received signals in noncooperative OFDM systems. User data is converted into appropriate optical OFDM signals by OFDM modulation and transferred through optical fiber links in the investigated optical network. Here, note that each sub-carrier is assumed to implement the same modulation mode. The deep learning model will be trained by using simulation data and is applied to recognize the modulation formats of the received OFDM signals after preprocessing.

B. *Proposed DL-based AMC Model*

The proposed deep learning-based AMC model consists of: 1) processing the input signal through sub-networks, 2) extracting relevant features, and 3) making a classification decision based on these features. Figure 2 illustrates our developed deep learning-based AMC architecture. The developed model is capable of adapting to signals with various characteristics by implementing SubNetworks for each filter size (FFT size). It leverages convolutional neural networks (CNNs) and fully connected layers to learn and classify modulation schemes automatically. In this approach, CNNs comprise a special type of layers that use convolution operations to extract useful representations from the input data. The automatic modulation classification model includes three components: (1) filter layers, (2) convolutional layers, and (3) fully connected layers.

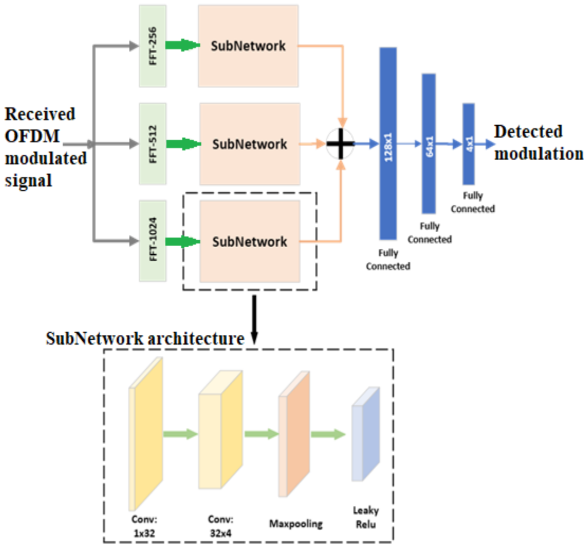

Fig. 2. Deep learning-based AMC architecture

- *Input data:* The input to the deep learning-based AMC model is an OFDM signal that needs to be classified into one of four designated modulation formats. This signal is typically a received communication signal, and it can be in the form of complex-valued data.
- *SubNetworks:* Deep learning model of the automatic modulation classification employs sub-networks to handle the signals with different characteristics. Each sub-network is responsible for processing the input signal with a specific filter size (FFT size) for feature extraction. The SubNetworks include four layers as follows.
  - ✓ *First layer:* input channel number is 1, the output channel number is 32 feature maps, kernel-size and padding are (2, 1) and (1, 0) respectively;
  - ✓ *Second layer:* number of input channels is 32, the output is 4 feature maps, kernel size is (2, 2) and padding is (1, 1);
  - ✓ *MaxPooling layer:* window size of 2x2, stride of 2 and padding of (1x1) are used;

✓ *Activation:* LeakyReLU is implemented.

❖ *Feature extraction:* Each sub-network, represented by the SubNetwork class, applies a common CNN architecture for feature extraction. The architecture includes convolutional layers, activation functions, and pooling layers. The input signal is processed through these layers to extract relevant features. The convolutional layers learn to identify patterns and characteristics in the signal.

❖ *Filtering:* After initial feature extraction using the common CNN architecture, each sub-network applies additional filtering to the feature representations. The filtering is performed using a filter from the FilterBank module, which is not provided in the code snippet. The specific filter applied depends on the FFT size of the sub-network.

❖ *Concatenation of features:* The outputs of all sub-networks are concatenated into a single feature vector. This feature vector contains information about the signal's characteristics as captured by different sub-networks.

❖ *Fully connected layers:* The concatenated feature vector is passed through a sequence of fully connected layers. These layers perform additional feature mapping and classification. They help the model learn and discriminate between different modulation schemes. The final fully connected layer has a number of output nodes equal to the number of modulation schemes that the model aims to classify.

❖ *Activation functions:* After each fully connected layer, the Tanh activation function is used. It introduces non-linearity and helps the network capture complex patterns in the data.

❖ *Classification:* The final output of the model is a modulation classification prediction. It indicates the most likely modulation scheme used in the input signal. The specific modulation scheme is determined based on the highest activation value among the output nodes of the last fully connected layer.

In fact, the developed model is trained with simulation data and can detect accurately four designated OFDM modulated signals including BPSK, QPSK, 8-phase shift keying (8-PSK), and 16-QAM, which are the most typical in optical transport networks. Details on the dataset generation for training and testing as well as network parameter initialization and optimization are explained in the next section.

III. NUMERICAL SIMULATIONS

In this section, we have simulated and evaluated the performance of the proposed deep learning-based AMC solution for a flexible optical OFDM network. Python framework with PyTorch library was utilized to generate the training and testing dataset for the simulation, build, and train the proposed model. To evaluate the performance of the developed DL-based AMC model, we employ major performance metrics including Accuracy, Sensitivity (Recall), Specificity, Precision, and F1-score. The Accuracy estimates the total performance of the deep learning model for classification, the Sensitivity and Specificity consider the accuracy of diagnosis for each modulation class, and the Precision measures the proportion of correctly predicted positive instances. At the same time, the F1-score is a geometric mean of sensitivity/recall and precision, this metric provides more meaningful results for imbalanced data sets. These performance metrics are determined as follows.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{FP+TN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$F_1\text{-}score = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \quad (5)$$

where *TP*, *TN*, *FN*, and *FP* respectively stand for true positive, true negative, false negative, and false positive.

A. Dataset

In our experimental simulation, the optical network flexibly supports distance-adaptive OFDM modulation assignment of established optical paths. In the network, optical paths can be modulated by one of four typical formats that are BPSK, QPSK, 8-PSK, and 16-QAM. In order to generate OFDM signals, user data (random bit sequence) is modulated by applying the OFDM technique. The modulated OFDM signals are transferred through an optical fiber channel and the channel characteristics are represented generally by the signal-to-ratio (SNR). For each modulation format, data was generated for a varying number of data subcarriers with FFT sizes of 256, 512, and 1024 and with SNR values in the range of 4 dB to 16 dB in steps of 4 dB. Moreover, each modulation format consists of 1000 examples for each of the subcarrier and SNR values. The data is split into 85% for training and 15% for validation. Here, note that each sub-carrier is assumed to implement the same modulation mode. IQ samples are generated via simulation data to train the model. Table I summarizes major dataset parameters.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Modulation format	BPSK, QPSK, 8-PSK and 16QAM
FFT size	256, 512 and 1024
Number of symbols per sample	2048
Number of samples	1000
Training and testing portions	85:15

B. Model Training

The model training is performed under the training dataset in which SNR values are 4, 8, 12, and 16 dBs for the epochs of 1, 5, and 10 respectively. Epoch means the entire dataset is passed forward and backward through the neural network only once. We applied the Adam optimizer with initial learning rates of 10^{-4},10^{-3}, $5x10^{-3}$, and 10^{-2} to figure out the best hyperparameters while the batch size is fixed at 1. Actually, the model architecture is independent of the sample number of input signals, the model is trained with the signal length of 2048 samples. Figures 3 and 4 describe the training loss and the overall accuracy obtained with the epochs of 1, 5, and 10 when the applied learning rate is 10^{-4}. For faster convergence and higher performance, the epoch of 5 and the learning rate of 10^{-4} are then selected for the performance estimation.

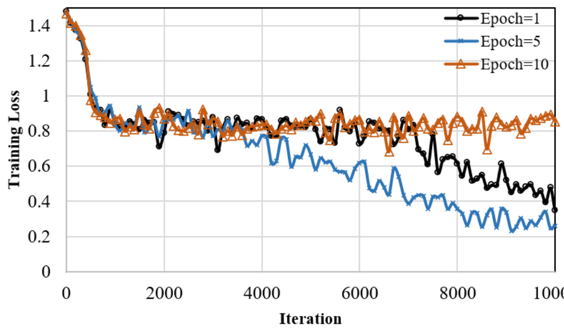

Fig. 3. Training loss concerning iteration

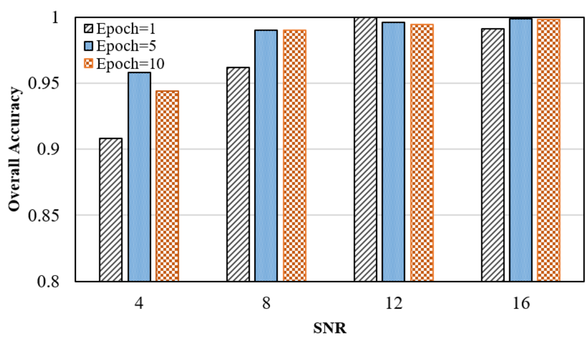

Fig. 4. Overall accuracy versus SNR with various epoch values

C. Experimental Results

Table II summarizes the average classification performance of the proposed AMC model in terms of accuracy, F1-score, sensitivity, specificity, and precision concerning the SNR. The results show that our developed solution can achieve significant high performance with an accuracy of more than 95.83% even at low SNR of 4 dB. The performance metrics are improved as the SNR is enhanced. This implies that the developed method can be applied effectively in various network conditions.

TABLE II. OVERALL PERFORMANCE

SNR	Performance				
	Accuracy	F1-Score	Sensitivity	Specificity	Precision
4	0.9583	0.9580	0.9583	0.9583	0.9582
8	0.9900	0.9900	0.9900	0.9900	0.9901
12	0.9961	0.9961	0.9961	0.9961	0.9962
16	0.9989	0.9989	0.9989	0.9989	0.9989

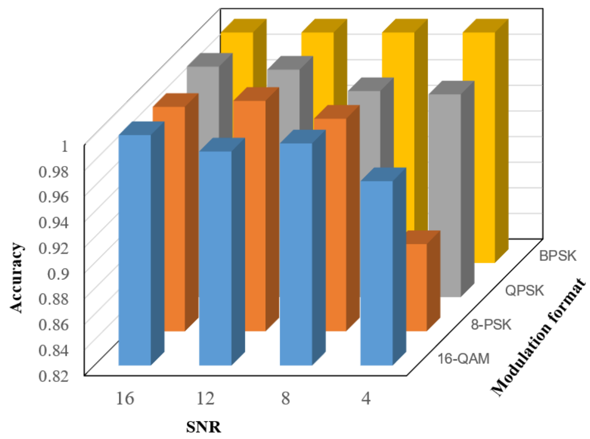

Fig. 5. The obtained accuracy for each modulation format when the epoch is set at 5

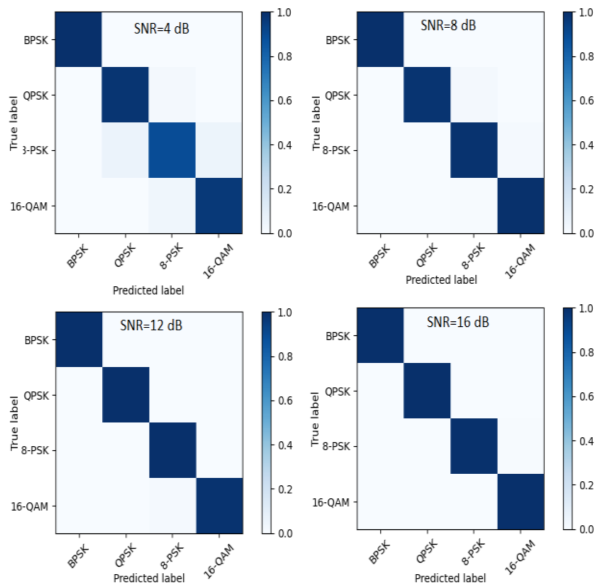

Fig. 6. Confusion matrix

TABLE III. PERFORMANCE OF EACH MODULATION CLASS

SNR	Modulation	Performance				
		Accuracy	F1-Score	Sensitivity	Specificity	Precision
4	BPSK	1.0000	1.0000	1.0000	1.0000	1.0000
	QPSK	0.9784	0.9617	0.9784	0.9806	0.9456
	8-PSK	0.8881	0.9121	0.8881	0.9809	0.9373
	16-QAM	0.9640	0.9564	0.9640	0.9830	0.9490
8	BPSK	1.0000	1.0000	1.0000	1.0000	1.0000
	QPSK	0.9809	0.9904	0.9809	1.0000	1.0000
	8-PSK	0.9860	0.9792	0.9860	0.9912	0.9724
	16-QAM	0.9934	0.9902	0.9934	0.9955	0.9870
12	BPSK	1.0000	1.0000	1.0000	1.0000	1.0000
	QPSK	0.9977	0.9988	0.9977	1.0000	1.0000
	8-PSK	1.0000	0.9922	1.0000	0.9948	0.9845
	16-QAM	0.9872	0.9935	0.9872	1.0000	1.0000
16	BPSK	1.0000	1.0000	1.0000	1.0000	1.0000
	QPSK	1.0000	1.0000	1.0000	1.0000	1.0000
	8-PSK	0.9953	0.9976	0.9953	1.0000	1.0000
	16-QAM	1.0000	0.9980	1.0000	0.9985	0.9959

Moreover, the classification accuracy comparison of the developed AMC model for each modulation format is illustrated in Figure 5 while the attained confusion matrices are shown in Figure 6. It is verified that better SNR offers higher classification accuracy and with the same SNR value, the classification becomes more effective as simpler modulation is applied. The detailed classification performance of the developed solution is explained in Table III. The obtained results show that the model easily identifies BPSK modulation with the highest performance while 8-PSK seems to be the least efficient classification. The classification performance enhancement even becomes better with a greater received signal-to-noise ratio, says better transmission performance achieved, higher reliability and accuracy are provided. This means that the proposed method offers great performance, especially for a high-quality transmission environment, and is able to classify a broad range of modulation classes including BPSK, QPSK, 8-PSK, and 16-QAM. Note that one of the limitations of the AMC using deep learning is that the model must be retrained if a new modulation set is deployed in the network.

IV. CONCLUSION

We have investigated modulation format classification that exploits deep learning techniques for flexible OFDM-based optical networks. We have proposed an efficient deep learning-based automatic modulation classification solution that is data-driven completely and does not need prior knowledge about the modulated signals or channel statistics for an OFDM-based optical network with four typical modulation formats, i.e., BPSK, QPSK, 8-PSK, and 16-QAM. Numerical simulations have been performed to verify the performance of the developed solution. The obtained experimental results demonstrate that the proposed method can be applied to automatically classify the modulated signals effectively without any prior knowledge of channel conditions.

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GIẢI PHÁP PHÂN LOẠI ĐIỀU CHẾ TỰ ĐỘNG CHO MẠNG QUANG LINH HOẠT DỰA TRÊN OFDM

Tóm tắt: Công nghệ ghép kênh phân chia tần số trực giao (OFDM) đang được triển khai rộng rãi trong mạng quang nhờ khả năng hỗ trợ bù tán sắc hiệu quả cho các tuyến quang. Nhằm cung cấp dịch vụ tuyến quang linh hoạt và băng thông cực lớn, mạng quang dựa trên kỹ thuật OFDM cần có khả năng hỗ trợ và triển khai một cách thích ứng nhiều khuôn dạng điều chế, ví dụ BPSK, QPSK, 8-PSK và 16-QAM. Trong thời gian gần đây, phân loại điều chế tự động (AMC) đang là một giải pháp đầy hứa hẹn cho các mạng không dây trong việc xác định chính xác các khuôn dạng điều chế của tín hiệu OFDM nhận được. Trong bài báo này, chúng tôi đề xuất một giải pháp phân loại điều chế tự động hiệu quả sử dụng kỹ thuật học sâu (DL) cho mạng quang sử dụng OFDM linh hoạt và thích ứng. AMC dựa trên DL được đề xuất có thể phân loại bốn khuôn dạng điều chế điển hình như khóa dịch pha nhị phân (BPSK), PSK cầu phương (QPSK), 8-PSK và điều chế 16-QAM trong các điều kiện mạng khác nhau. Phương pháp mô phỏng số được thực hiện để xác minh tính hiệu quả của giải pháp được phát triển và các kết quả đạt được cho thấy giải pháp AMC sử dụng DL được phát triển mang lại độ chính xác cao, trên 95,83%, ngay cả với SNR thấp, tức là 4 dB, đồng thời hiệu năng này cũng được nâng cao khi SNR được cải thiện.

Từ khoá: Học sâu, mạng quang, ghép kênh phân chia tần số trực giao, khuôn dạng điều chế, phân loại điều chế.

Hai-Chau Le received the B.E. degree in Electronics and Telecommunications Engineering from Posts and Telecommunications Institute of Technology (PTIT) of Vietnam in 2003, and the M.Eng. and D.Eng. degrees in Electrical Engineering and Computer Science from Nagoya University of Japan in 2009 and 2012, respectively. From 2012 to 2015, he was a researcher in Nagoya University of Japan and in University of California, Davis, USA. He is currently a lecturer in Telecommunications Faculty at PTIT. His research interests include optical technologies, network design and optimization, and future network technologies. He is an IEEE member.

Chien-Trinh Nguyen received the B.E degree from the University of Electro-Communications, Odessa, Ukraine in 1989, and the M.E. and Ph.D. degrees in 1999 and 2005 from the University of Electrical and Information Engineering, Tokyo, Japan. He joined the Research Institute of Posts and Telecommunications in Vietnam in 1990. He is currently Vice Dean of the Faculty of Telecommunications, Posts and Telecommunications Institute of Technology. Fields of interest include Next Generation Networks, QoS Assurance, QoS routing, traffic engineering, SDN, and Wireless Sensor Networks.