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Identification of advanced optical modulation format and estimation of signal-to-noise-ratio based on parallel-twin convolutional neural network

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In this paper, we design a parallel-twin convolutional neural network (PT-CNN) deep learning model and use the signal constellation diagram to realize the identification of six advanced optical modulation formats (QPSK, 4QAM, 8PSK, 8QAM, 16PSK, 16QAM) and signal-to-noise-ratio (SNR) estimation. The influence of PT-CNN with different layers and kernel sizes is investigated and the optimal network model is chosen. Simulation results demonstrate that the proposed method has the advantages of not requiring manual feature extraction, having the ability to clearly distinguish the six modulation formats with 100% accuracy when SNR of the received signal sequences is higher than 12 dB. In addition, the high-accurate SNR estimation is realized simultaneously without increasing additional system complexity.

Keywords: deep learning, PT-CNN, constellation diagram, modulation format identification, SNR estimation.

1. Introduction

Global broadband data services and advanced Internet applications pose great challenges on the current optical networks. Besides laying more fiber-optic channels or exploiting denser wavelength multiplexing, some advanced optical modulation formats with higher spectral efficiency or better noise tolerance have become one of the most promising solutions for enhancing performance of the existing fiber-optic communication systems. For example, Chen *et al*. [1] showed 56-GB/s/λ C-band DSB IM/DD PAM-4 40 km SSMF transmission. Li *et al*. [2] demonstrated a higher tolerance to beat interference noise by using PSK-manchester modulation format. Ziyadi *et al*. [3] achieved optical channel de-aggregator of 30-Gbaud QPSK and 20-Gbaud 8PSK data. Masato *et al*. [4] demonstrated single-channel 15.3 Tbit/s transmission over 150 km by employing 64QAM coherent Nyquist pulse with a spectral efficiency of 8.3 bit/s/Hz. Chen *et al*. [5] reported a 4 294 967 296 ultra-dense QAM based Y-00 quantum stream cipher system, which carries a 160 Gb/s 16-QAM signal transmitting over 320 km standard-single-mode-fiber. Various modulation formats are playing significant role in different scenario and link conditions. Future optical networks are expected to have better adaptation and flexibility to new modulation formats.

At the early stage, it relied on experts to identify the modulation format by observing parameters of the detected signals. This approach will not be suitable for the ever-increasing and dynamic service requirements due to its slow response and inaccuracy. With the development of signal processing algorithms, automatic modulation identifications are proposed. By employing Bayesian decision-theory, likelihood-based methods were used to construct proper judgment criterion according to the statistical characteristics of signals [6]. This approach can provide the optimal solution, but cannot work without the prior knowledge about the actual signal model and channel conditions. Comparatively, the implementation of feature-based modulation classification is easier [7]. By extracting discriminative features of the received signals, such as spectrum features, cumulants and moments, the type of signal modulation formats can be identified based on the appropriate classifiers. However, hand-crafting features may not work well in new modulation formats at low signal-to-noise ratio (SNR) conditions.

Recently, data-driven deep learning techniques have been utilized to present superior results of the automatic modulation format identification for optical communication systems. For instance, ZHANG *et al.* [8] reported an identification technique by using an artificial neural network (ANN) to extract amplitude histogram features. But the method is effective only for classifying M-QAM signals. In Ref. [9], features extracted from the received signals' Stokes space constellations are injected into the deep neural network (DNN) for modulation format classification. In Ref. [10], modulation formats were successfully distinguished based on the two-dimensional in-phase quadrature histogram features and a convolutional neural network (CNN). However, methods reported in Ref. [9, 10] can only identify the modulation formats of polarization division multiplexing (PDM) signals. In Ref. [11], eye diagram images were input into CNN for recognizing the different modulation formats. But, eye diagram is highly sensitive to timing alignment of the received signal sequence, which needs additional hardware reprocessing units.

In this paper, we design a parallel-twin-CNN (PT-CNN) deep learning model and use the signal constellation diagram to realize the identification of six modulation formats: QPSK, 4QAM, 8PSK, 8QAM, 16PSK, 16QAM. Compared with the methods reported above, the proposed method has the advantages of not requiring manual feature extraction, having the ability to identify the constellation with the same modulation order and achieving the SNR estimation.

2. Operating principle and model structure

2.1. Model structure

The proposed PT-CNN framework for identifying modulation format and estimating SNR of the received signal is illustrated in Fig. 1.

CNN has been proven to be a very effective model for image processing. For our specific tasks of signal modulation format identification and SNR estimation, CNN_i ($i = 1, 2$)

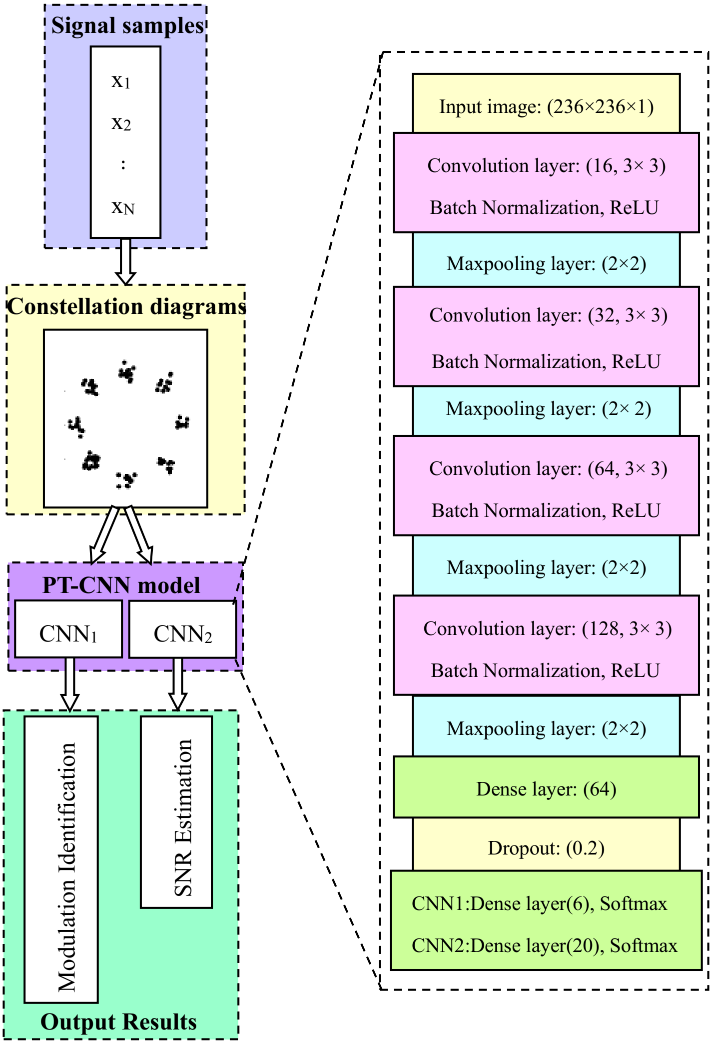

Fig. 1. PT-CNN framework for identifying modulation format and estimating SNR.

is designed to contain four convolution layers and two fully-connected layers. Each convolution layer uses a set of kernels with fixed size 3×3 to extract the proper features from the input image. Batch normalization and ReLU nonlinear activation are added after each of the convolution layer. The pooling layers are set as the max pooling in order to keep the most important features. All the pooling layers have the fixed size 2×2 and strides of 2, so as to reduce the size of feature maps to half. The fully-connected layers transfer the output of previous layers into the one-dimensional vector. For CNN_1, the dimension of output vector from the last fully-connected layer is set as 6, which is equal to the types of modulation formats. For CNN_2, the dimension of output vector from the last fully-connected layer is set as 20, so as to consistent with the number of SNR.

2.2. Datasets

The constellation diagrams are obtained by mapping both the in-phase (I) components and quadrature (Q) components of the received signal sequences. Due to both, the amplitude and phase information provided, constellation diagrams show more features compared with eye diagram or amplitude histogram. The resolution of each signal constellation is set as 236×236. Then, the received signal power is normalized to make its real part and imaginary part in the range of [–10, 10], which prevent the samples from falling outside the drawing area. In order to eliminate the influence of color and shape of the scatter points, dot points with fixed size are used and the gray constellation diagrams (in "png" images) are generated. The datasets come from six types of modulation formats and each type of the modulation format is generated by 1000 independent realizations. The additive white Gaussian noise is assumed to interfere in the transmission channel, which results in the received signals showing different SNR from –4 to 15 dB with a grid of 1 dB. A total of 6000 samples are obtained, 90% of which is randomly selected for training, the rest 10% of which is remained for validating the performance. Each sample is denoted by (x, y_1, y_2), where x indicates the constellation image, y_1 is the label indicating the modulation format, y_2 is the label denoting the SNR. Figure 2 shows some of the created constellation images for the six modulation formats. As the modulation order increases, the cluster of signal symbols becomes more indistinguishable.

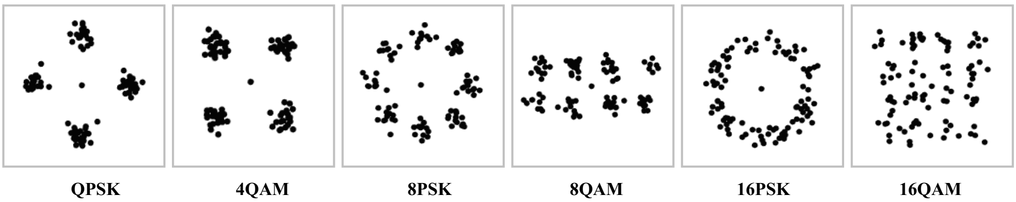

Fig. 2. Constellation images of the six modulation formats with some noise.

2.3. Training process

Datasets of the signal constellation diagrams are injected into CNN_i ($i = 1, 2$) network, which is respectively offline trained to obtain the optimal parameters according to the loss and accuracy. Identification of modulation format and estimation of SNR are processed simultaneously, each of which is divided into the two steps. In the first step, the 6000 samples are input into the PT-CNN network and mini-batch gradient descent are used for the offline training. According to Ref. [11–13], for modulation format identification based on eye diagram or histogram, the training samples for each type of modulation format are usually in the range of 1000–1600. Due to both I and Q components used, there are more features information in each sample of signal constellation diagrams. Therefore, 6000 samples are sufficient for offline training to indentify the six modulation formats in our model. The sparse cross-entropy loss between the predicted outputs and

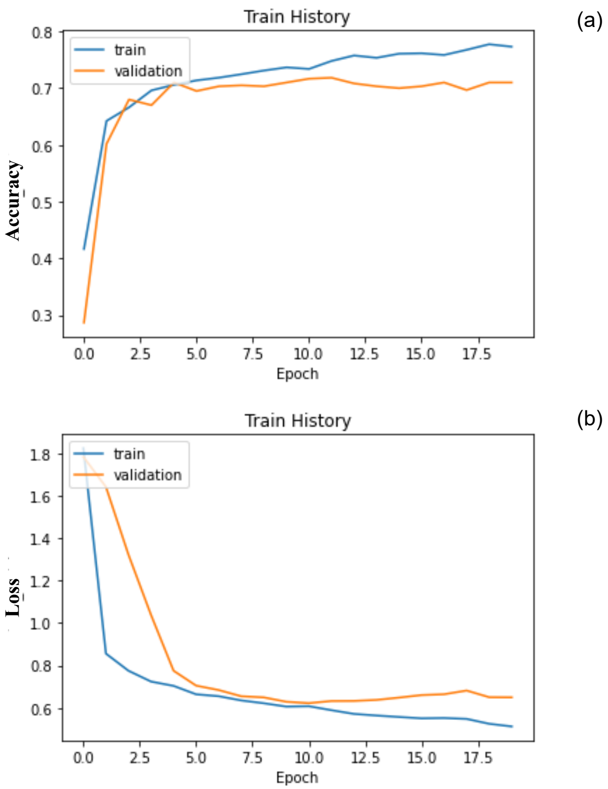

Fig. 3. (a) Accuracies and (b) sparse cross-entropy losses in the training step.

target labels are back-propagated to adjust the network parameters. The training step takes about 20 minutes on Lenovo laptop computer with NVIDA GeForce MX350 GPU. Accuracies and losses for both the train and validation datasets are monitored. Figure 3 illustrates that accuracy and sparse cross-entropy loss for the training data are improved continuously as the epochs increasing. But the validation accuracy and loss begin to deteriorate and the over-fitting begins to appear after 11 epochs.

2.4. Testing results

In the second step, another 1200 samples with the similar but independent distribution as the train datasets are used to test the performance of the proposed model. Although the training time is relatively long, the test time for the modulation format identification is only 5.8 ms for every sample, which is suitable for time-real online processing.

Figure 4 shows the influence of different network schemes on the identification accuracy of all modulation formats. From the comparison results demonstrated in Fig. 4(a), we can see that the identification accuracy is slightly higher for neural network with four convolution layers than the one with three convolution layers. In addition, for the convolution neural network with four layers, Fig. 4(b) illustrates that the identification

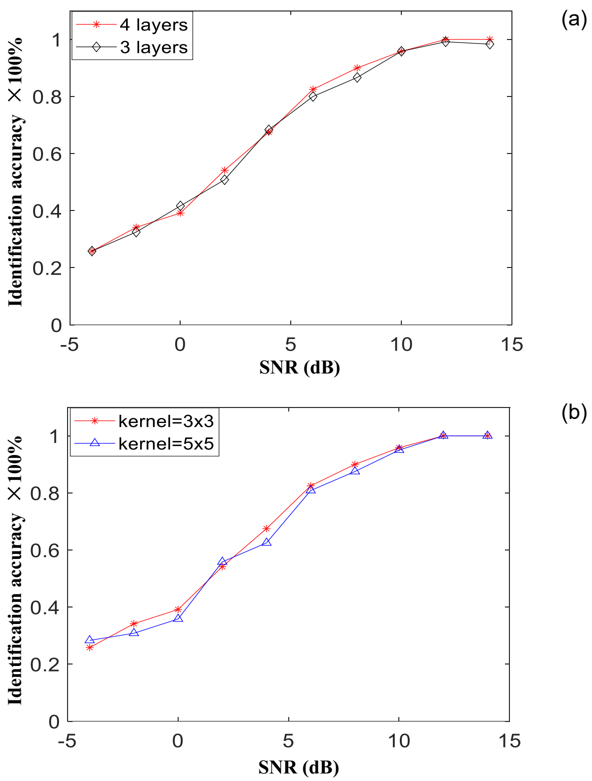

Fig. 4. Identification accuracy of all modulation formats for convolution neural network with (a) different layers and (b) kernel sizes.

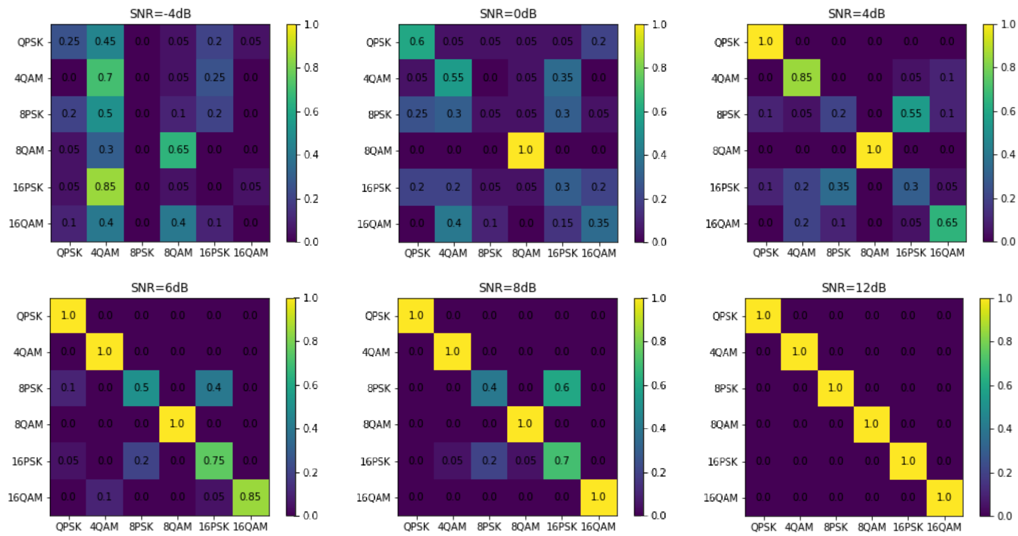

Fig. 5. Confusion matrices for modulation format identification for various SNRs.

accuracy can be further improved if kernel size 3×3 is chosen. The comparison results in Fig. 4 verify the optimal performance of our CNN_1 scheme.

Confusion matrix is a visual way to show the relation between the predicted results and the true values. In order to observe the test accuracy of modulation identification, confusion matrix is shown in Fig. 5. The predicted modulation format is displayed in each column and its true label is denoted in each row side-by-side. It can be seen that the identification accuracy of modulation format becomes better as the SNR increases. When SNR is higher than 12 dB, the accuracy in the confusion matrix is 100% and all the modulation can be clearly distinguished.

Due to the parallel feature of the proposed PT-CNN network model, CNN_2 is trained and tested simultaneously when the CNN_1 is working. Figure 6 shows the cor-

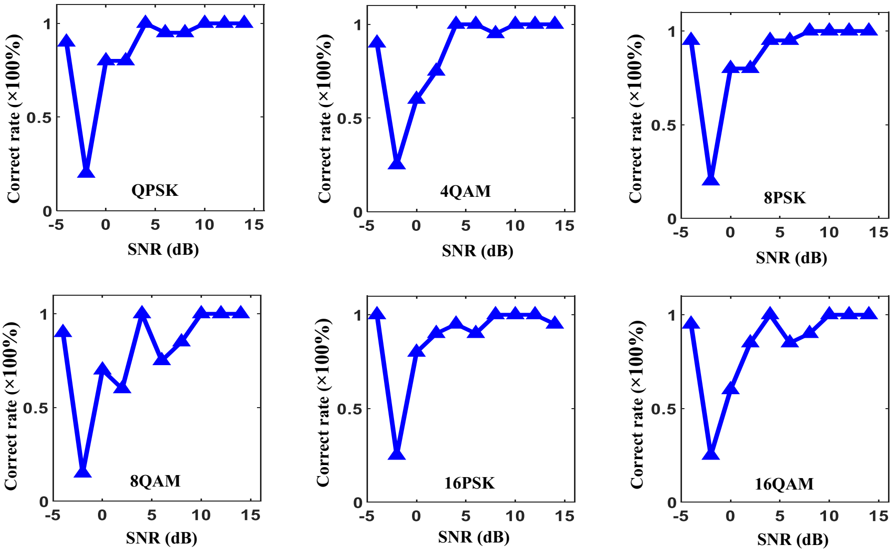

Fig. 6. Correct rate of the estimated SNR as the SNR varying.

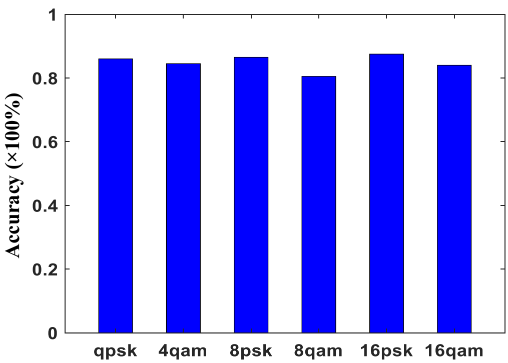

Fig. 7. Statistics histogram of SNR estimation for each modulation format.

rect rate of the estimated SNR at various SNR values. Except for constellation diagrams with SNR = –2 dB, the risk to misestimate SNR of all the modulation formats is very low. Figure 7 illustrates the statistics histogram of SNR estimation for each modulation format. Result demonstrates that over 80% high-accuracy of SNR estimation can be achieved for all the modulation formats within the SNR range [–4 dB, 15 dB].

3. Conclusion

In this paper, PT-CNN deep learning model is proposed to realize both the identification of six advanced optical modulation formats (QPSK, 4QAM, 8PSK, 8QAM, 16PSK, 16QAM) and the estimation of SNR. By mapping the in-phase (I) components and quadrature (Q) components of the received signal sequences, constellation diagrams are generated, pre-processed and used as the inputs to the PT-CNN. Then, PT-CNN is offline trained to extract the signal features and online tested to verify performance of the proposed method. Simulation results demonstrate that the accuracy in the confusion matrix is 100% and the six modulation formats can be clearly distinguished when SNR of the received signal sequences is higher than 12 dB. In addition, over 80% high accuracy of SNR estimation is achieved simultaneously without increasing additional system complexity.

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