



Wireless modulation classification based on Radon transform and convolutional neural networks

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Abstract

Convolutional Neural Networks (CNNs) are efficient tools for pattern recognition applications. They have found applications in wireless communication systems such as modulation classification from constellation diagrams. Unfortunately, noisy channels may render the constellation points deformed and scattered, which makes the classification a difficult task. This paper presents an efficient modulation classification algorithm based on CNNs. Constellation diagrams are generated for each modulation type and used for training and testing of the CNNs. The proposed work depends on the application of Radon Transform (RT) to generate more representative patterns for the constellation diagrams to be used for training and testing. The RT has a good ability to represent discrete points in the spatial domain as curved lines. Several pre-trained networks including AlexNet, VGG-16, and VGG-19 are used as classifiers for modulation type from the spatial-domain constellation diagrams or their RTs. Several simulation experiments are presented in this paper to compare different scenarios for modulation classification at different Signal-to-Noise Ratios (SNRs) and fading channel conditions.

Keywords Deep learning · Convolutional Neural Networks (CNNs) · Radon Transform (RT) · Modulation classification · Pre-trained networks

1 Introduction

Modulation of the transmitted signals is one of the fundamental steps in the transmission chain of wireless communication systems. In adaptive modulation systems, the

modulation type is varied in each transmission in response to the SNR to enhance the Bit Error Rate (BER) performance. Modulation classification is an important step in the receiver chain of several wireless communication applications, e.g. electronic surveillance systems, and electronic

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warfare. Different traditional methods have been used for modulation classification.

In Al-Makhlaway et al. (2012) and Keshk et al. (2015), Mel-Frequency Cepstral Coefficients (MFCCs) have been used as features and Neural Networks (NNs) and Support Vector Machines (SVMs) have been investigated as modulation classifiers for Orthogonal Frequency Division Multiplexing (OFDM) systems. Higher-order statistics have also been used. Higher-order moments have been utilized in Abu-Romoh et al. (2018). The main advantage of relying on such statistical features is their robustness to noise. Nevertheless, estimating these higher-order statistics endures large computational complexity. Another study introduced different types of images called contour stellar images for modulation classification (Lin et al. 2017). Signal identification can be implemented on different scales. It can be applied for Single-Carrier (SC), OFDM, single-antenna and Multiple Input Multiple Output (MIMO) systems (Eldemerdash et al. 2016).

For modulation classification, Feature-Based (FB) and Likelihood-Based (LB) methods have been investigated. The FB methods depend on feature selection and detection methods to provide sub-optimal performance, which results in reduced complexity and reduced sensitivity to model mismatches (Dobre et al. 2007). Most of the FB methods require frequency synchronization. Generally, they depend on the extraction of robust features and the design of the classifier. On the other hand, the LB methods depend on the likelihood function of the modulated signal, and they rely on Bayesian estimation of the modulation type considering prior information such as noise and channel models (Xu et al. 2010). Usually, they have high computational complexity and are not suitable for highly dynamic environments. Machine learning, especially pattern recognition, played a major role in the classification of the modulation type. Both K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) classifiers have been applied for modulation classification (Aslam et al. 2012; Peng et al. 2017), and Medium Access Control (MAC) protocol classification (Hu et al. 2014).

Deep Learning (DL) is a new type of machine learning. It has gained an increased interest in recent years and has achieved a remarkable success in classification tasks, mainly due to its high-performance capability achieved by the large number of involved hidden layers. It is used in several application fields such as computer vision (Jean et al. 2016), bioinformatics (Min et al. 2017), economics (Nosratabadi et al. 2020), security (Liu et al. 2020), and natural language processing (Wu et al. 2016). For modulation type classification based on DL, some studies have been reported e.g., (Mendis et al. 2016; Ali et al. 2017; Wang et al. 2017; O'Shea et al. 2018). Recently, DL models have been proposed for modulation classification without requiring prior information such

as the channel model (Lin et al. 2017; Jiang et al. 2020). In Zhang et al. (2020), a CNN was used to classify 11 different modulation types in the RadioML2016.10A dataset, with an accuracy exceeding 70%. To improve the accuracy, DL models such as Recurrent Neural Networks (RNNs) (Lin et al. 2017) and fusion methods have been utilized.

In wireless communication applications, DL has several advantages compared to traditional classifiers. A shortcoming of DL techniques is the need for large training datasets. However, in wireless communication settings, we can make use of the high transmission rate to obtain the necessary datasets. This is specifically true if we consider limited possibilities of transmission patterns, which is the exact case with adaptive modulation, when the modulation is confined to a set of well-defined modulation types.

An important challenge for wireless communication is the manual feature selection, which is completely solved by the automated extraction of features that is inherent in DL (Al-Makhlaway et al. 2020). In Eltaieb et al. (2019), contour stellar images with different colors have been used for modulation classification. These images are used as inputs for the CNN to identify the modulation types and their orders. Pre-trained CNNs including AlexNet, ResNetv4, VGG-16, and GoogLeNet-v2 have been used for modulation classification (Eltaieb et al. 2019). Radon Transforms (RTs) of constellation diagrams have been used with Singular Value Decomposition (SVD) for blind optical modulation classification in Eltaieb et al. (2019). In Al-Makhlaway et al. (2020), a scheme based on DL was proposed to deal with modulation classification in the presence of Adjacent Channel Interference (ACI). This scheme depends on the generated constellation diagrams for the received signals.

In this paper, we depend on CNNs for modulation classification. These CNNs work on constellation diagrams for the classification task. To enhance the accuracy of modulation classification in Al-Makhlaway et al. (2020), we use the RTs of the constellation diagrams for different modulation types as inputs for the CNNs. Seven types of modulation are considered in the classification process. These types are BPSK, QPSK, 8PSK, 16PSK, 8QAM, 16QAM, and 32QAM. AlexNet, VGG-16, and VGG-19 are used as classifiers.

2 Problem formulation

Following a general wireless transmission chain, the analog signal is firstly converted into a baseband signal, at the transmitting end, through the consecutive processes of sampling, quantization, and encoding. Then, this signal is transmitted over a certain frequency band to the receiving end. The received signal is given by:

$$r(t) = s(t) + n(t) \quad (1)$$

where $s(t)$ is the transmitted signal, $r(t)$ is the received signal and $n(t)$ is the Additive White Gaussian Noise (AWGN). The signal $s(t)$ can be expressed as:

$$s(t) = A_m \sum_n a_n g(t - nT_s) \cos[2\pi(f_c + f_m)t + \phi_0 + \phi_m] \quad (2)$$

where A_m is the modulation amplitude, a_n is the symbol sequence, T_s is the symbol period, f_c is the carrier frequency, f_m is the modulation frequency, ϕ_0 is the initial phase, $g(t)$ is the line code function, and ϕ_m is the modulation phase.

In digital wireless communication systems, representation of the amplitude and phase of the received signal is done efficiently with the aid of the constellation diagram of that signal. The receiver divides the received signal $s(t)$ to obtain the in-phase (I) component and quadrature (Q) component that are orthogonal to each other (Goldsmith 2005). The transmitted signal can be represented in terms of the two orthonormal I/Q basis in the form of $a + jb$, which is called a constellation point.

3 Radon transform (RT)

The RT is an integral transform that maps a function $f(x, y)$ defined on one plane to another function $W(d, \theta)$ on a different plane (Radon 1986). This transform was first introduced by Radon (1917), who provided a formulation for the inverse transform as well.

The RT is obtained with the following equation (Wikipedia 2005):

$$W(d, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(d - x \cos(\theta) - y \sin(\theta)) dx dy \quad (3)$$

where $f(x, y)$ is the constellation diagram image, x and y represent the coordinate point, θ is the angle of projection, d is the normal from the origin to the line of projection, $W(d, \theta)$ is the RT image, and $\delta(\cdot)$ is the Dirac delta function. The collection of all values of this integral in a single matrix is the RT. The angle of projection is taken from 0 to $\pi/2$ due to the symmetry property of the RT. Figure 1 shows the constellation diagrams and their RTs for different modulation types at different SNRs.

4 Constellation diagram classification with DL

The DL is used in several scientific fields. It depends on multiple layers of neurons for operation, where the output of a specific layer is fed into the consecutive one (Abu-Romoh et al. 2018). Each layer is prepared for extracting a huge amount of data. Deep neural networks depend on learning a large amount of features from the data in order to identify patterns (Peng et al. 2018), without the need for manual feature extraction. A network can collect simple features, through multiple nonlinear transformations in order to generate more complex features, autonomously (Meng et al. 2018). In the literature, there exists a group of well-designed pre-trained CNNs that can be used through transfer learning to execute new identification and classification tasks. In the following sub-sections, we list the pre-trained CNNs that we will apply on our datasets.

4.1 AlexNet

AlexNet is used in various applications with a huge and deep architecture. It includes a large number of neurons up to 650 thousands and 60 million parameters. It was implemented to classify 1.2 million images from 1000 groups. It contains five convolutional layers as well as three fully-connected layers with a 1000-channel softmax layer. To enhance the performance and decrease the time of training, Rectified Linear Units (ReLU) are adopted as neurons with non-saturating nonlinearity (Krizhevsky et al. 2012). The ReLUs are connected to fully-connected and convolutional layers. If we add a randomization mechanism to the first two fully-connected layers, the speed of convergence can be doubled.

4.2 Deep VGGNet

With the success of CNNs in image classification, an effective and simple design for CNNs was investigated, namely VGG (Simonyan et al. 2014). The VGG-16 and VGG-19 networks are composed of 16 and 19 layers, respectively. The VGG network is larger than the AlexNet. It depends on a stack of 3×3 filters. The concurrent placement of 3×3 filters eliminates the need for large-size filters. The exploitation of small-size filters grants an advantage of low computational complexity by decreasing the number of parameters. The VGG network complexity is reduced by inserting 1×1 convolution masks in between the convolutional layers. An inserted mask targets learning a linear set of the resultant feature maps.

To tune the network, after each convolutional layer, max-pooling is implemented, and padding is performed to preserve the spatial resolution. The VGG achieves particularly

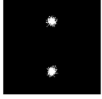

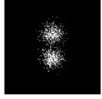

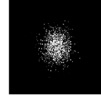

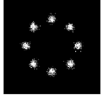

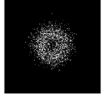

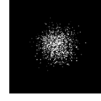
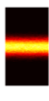
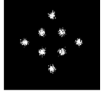

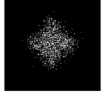

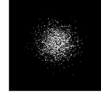



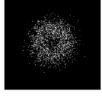
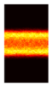

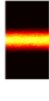
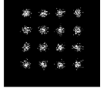

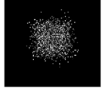








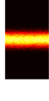
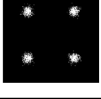

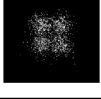

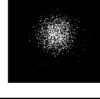

SNR	20 dB		5 dB		-5 dB	
Modulation type	Constellation diagram	RT	Constellation diagram	RT	Constellation diagram	RT
BPSK						
8PSK						
8QAM						
16PSK						
16QAM						
32QAM						
QPSK						

Fig. 1 Constellation diagrams and their RTs for different modulation types at different SNRs

good results for localization problems and image identification tasks. High computational cost is the essential restriction associated with the VGG network, even with the use of small-size filters. This is mainly attributed to the use of about 140 million parameters (Khan et al. 2020).

The VGG-16 network contains three fully-connected layers and thirteen convolutional layers. Two combined 3×3 convolution masks have a field of 5×5 . By using more layers, the expressiveness of features is increased. The integrated layers are followed by the ReLU layer with either a max-pooling or average pooling operation. Pooling layers result in a decrease in the spatial dimensions of features, and hence they enhance the classification performance. The final output layers are fully-connected layers.

The VGG-19 network is characterized by its simplicity as it utilizes 3×3 convolution masks that are mounted on top to increase depth. Max-pooling layers are used to decrease the volume size of data. In the training phase, for feature extraction, convolutional layers are used. Max-pooling layers are associated with the convolutional layers to decrease the feature dimensionality. In a convolutional layer, 64 kernels

are used for feature extraction from the input images. To prepare the feature vector, fully-connected layers are used. The 10-fold cross-validation is applied in the testing phase depending on the softmax activation.

5 Simulation experiments

In this paper, we have used CNN models for modulation classification in wireless communication systems. The communication system with modulation classification is illustrated in Fig. 2. We used seven types of modulation including BPSK, QPSK, 8PSK, 16PSK, 8QAM, 16QAM, and 32QAM. We used a CNN with three convolutional layers as a classifier. In addition, we investigated the utilization of pre-trained networks such as AlexNet, VGG-16, and VGG-19 as modulation type classifiers. The inputs of these classifiers are the RTs of the constellation diagrams. We generated more than 15,000 images of constellation diagrams for different modulation types at different SNRs. For the training phase, the RTs are used to enhance the accuracy of

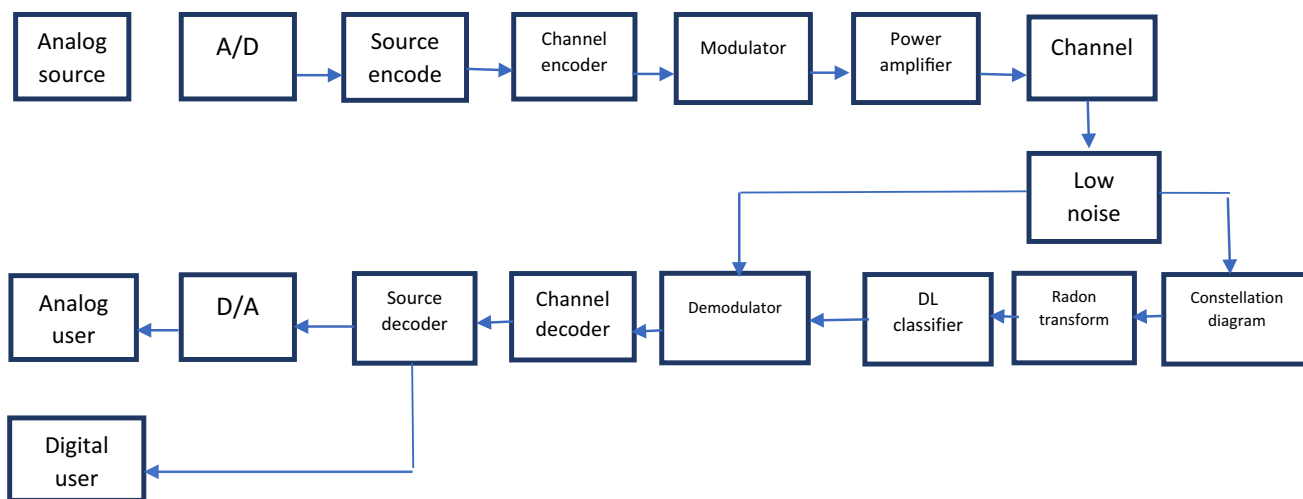


Fig. 2 The proposed communication system with modulation classification

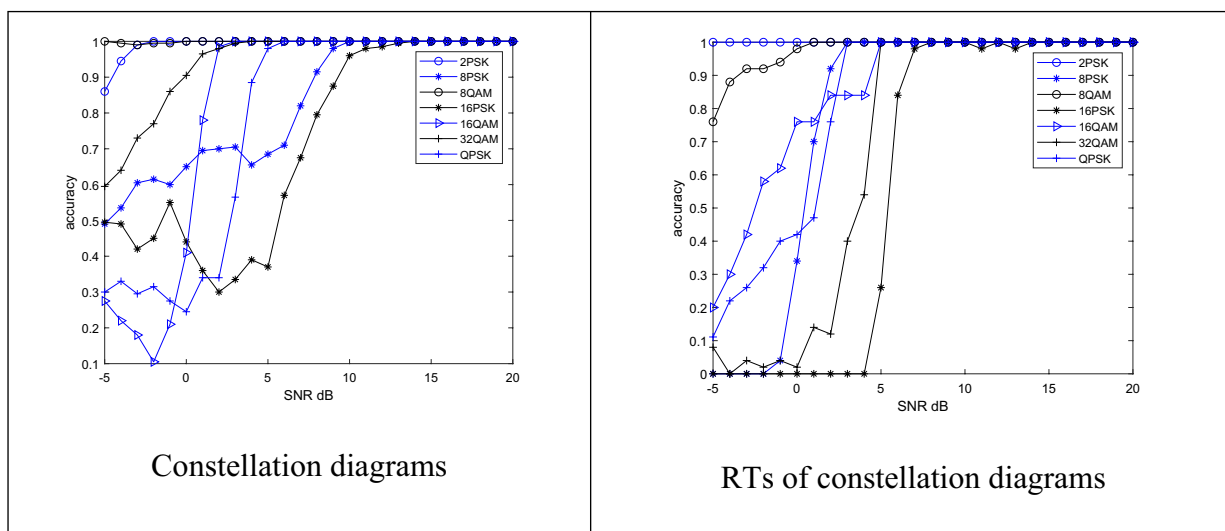


Fig. 3 Accuracy of CNN classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over AWGN channel

classification in the presence of AWGN and fading channel effects.

The CNN with three convolutional layers has been applied on the constellation diagram images and their RTs, and the results are shown in Fig. 3. We notice that with RTs of constellation diagrams for an AWGN channel, the classification accuracy reaches 100% at an SNR of 5 dB for different modulation types. For the classification of BPSK based on RTs, we achieve a good accuracy at - 5 dB SNR. At - 5 dB, the classification of 32QAM based on constellation diagrams achieves a good accuracy. For the AlexNet classifier, the accuracy is 100% for different modulation types at

an SNR of 10 dB from constellation diagrams as shown in Fig. 4. For VGG-16, 8QAM classification is performed with high accuracy at low SNRs as shown in Fig. 5. The accuracy reaches 100% for different modulation types when RTs are used at 5 dB, but the accuracy reaches 100% at 10 dB when the constellation diagrams are used. At an SNR of 5 dB, the accuracy is 100% for different modulation types with VGG-19, when the RTs are used as shown in Fig. 6.

For fading channel, the CNN classifier with RTs of constellation diagrams has higher accuracies than those with constellation diagrams only as shown in Fig. 7. At low SNRs, the classification accuracy of 16QAM is good with

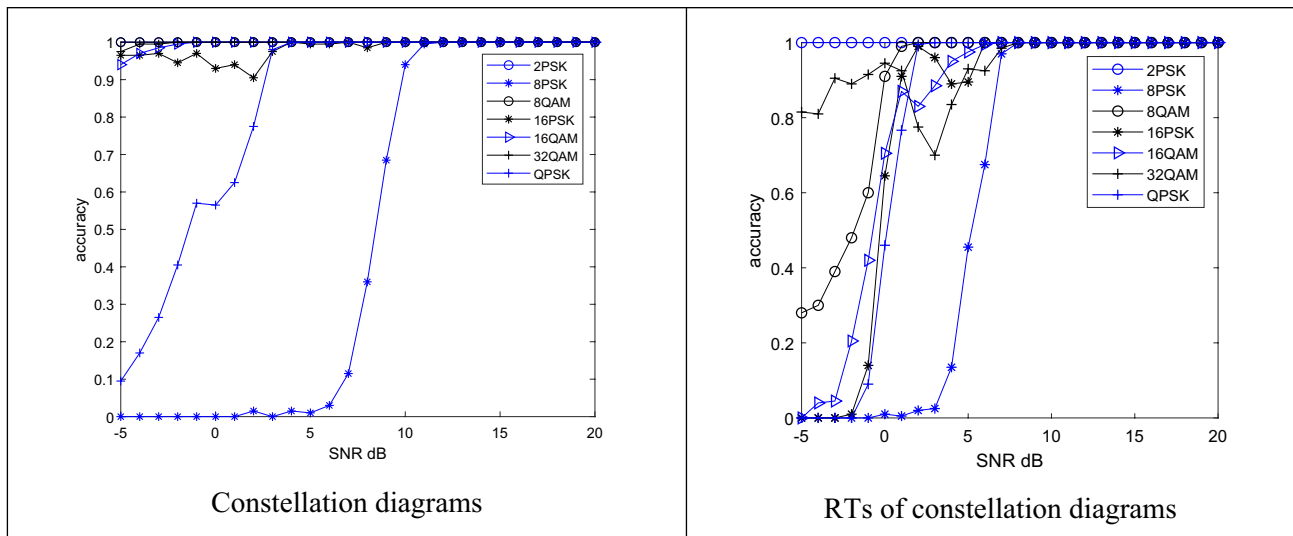


Fig. 4 Accuracy of AlexNet classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over AWGN channel

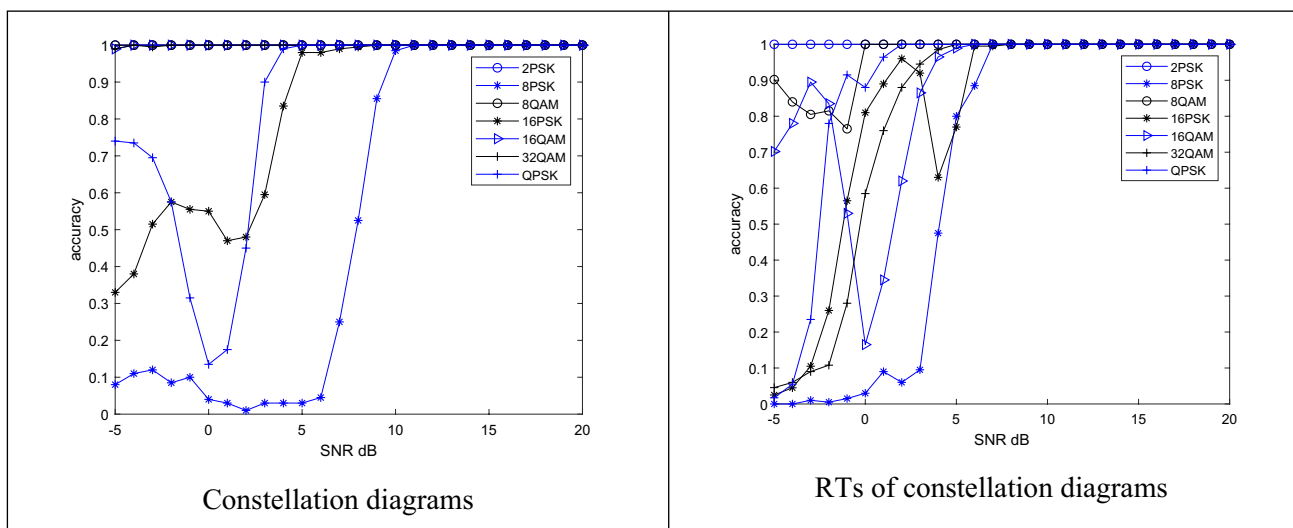


Fig. 5 Accuracy of VGG-16 classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over AWGN channel

constellation diagrams. With RTs of constellation diagrams, 32QAM achieves a good accuracy of classification at low SNRs as well. We notice that the accuracies are low compared to those obtained in the case of AWGN channels. For the AlexNet classifier, the accuracy is 100% at the SNR of 10 dB. Both 8PSK and QPSK achieve high accuracy of

classification at low SNRs as shown in Fig. 8. As shown in Fig. 9, 16QAM achieves a high accuracy of classification at low SNRs, when the VGG-16 classifier is applied. Figure 10 illustrates the accuracy for the VGG-19 classifier over a fading channel.

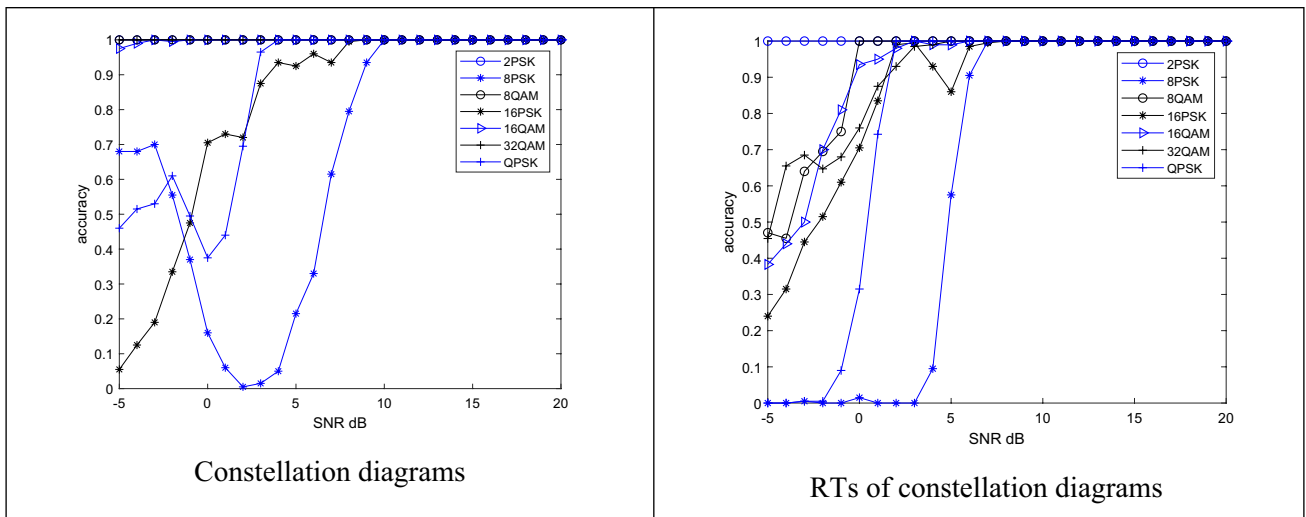


Fig. 6 Accuracy of VGG-19 classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over AWGN channel

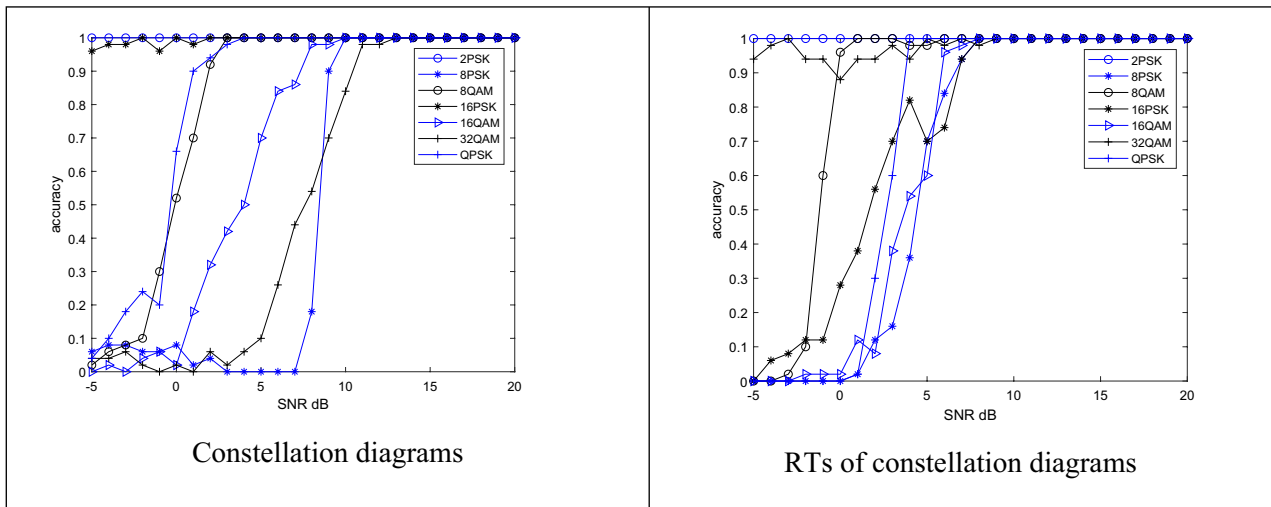


Fig. 7 Accuracy of CNN classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over fading channel

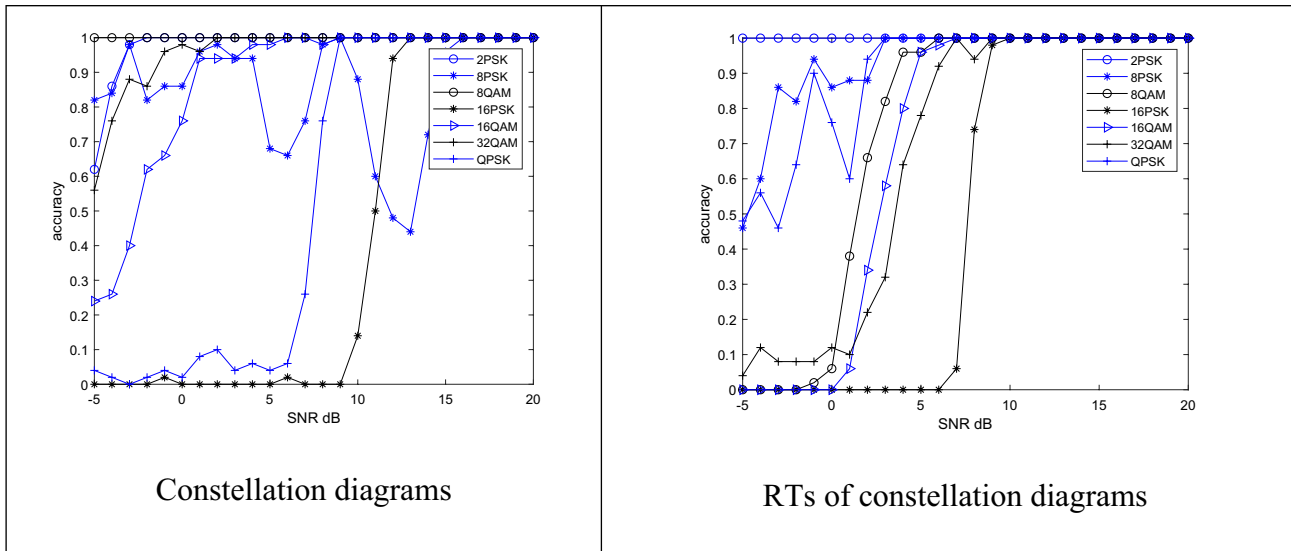


Fig. 8 Accuracy of AlexNet classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over fading channel

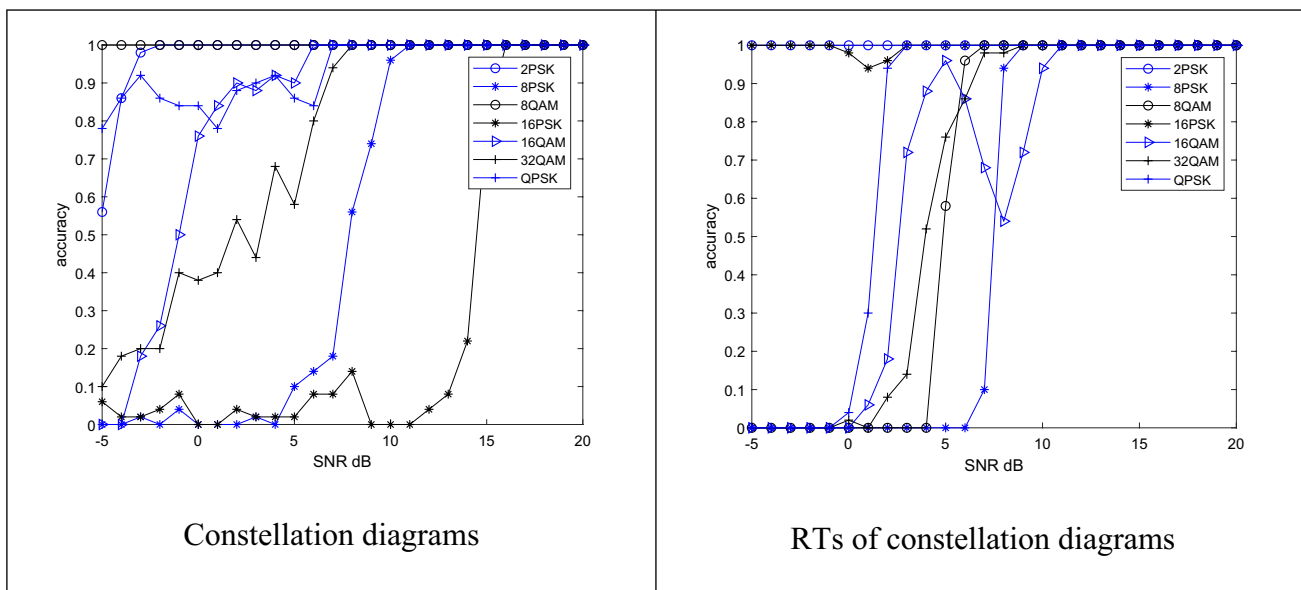


Fig. 9 Accuracy of VGG-16 classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over fading channel

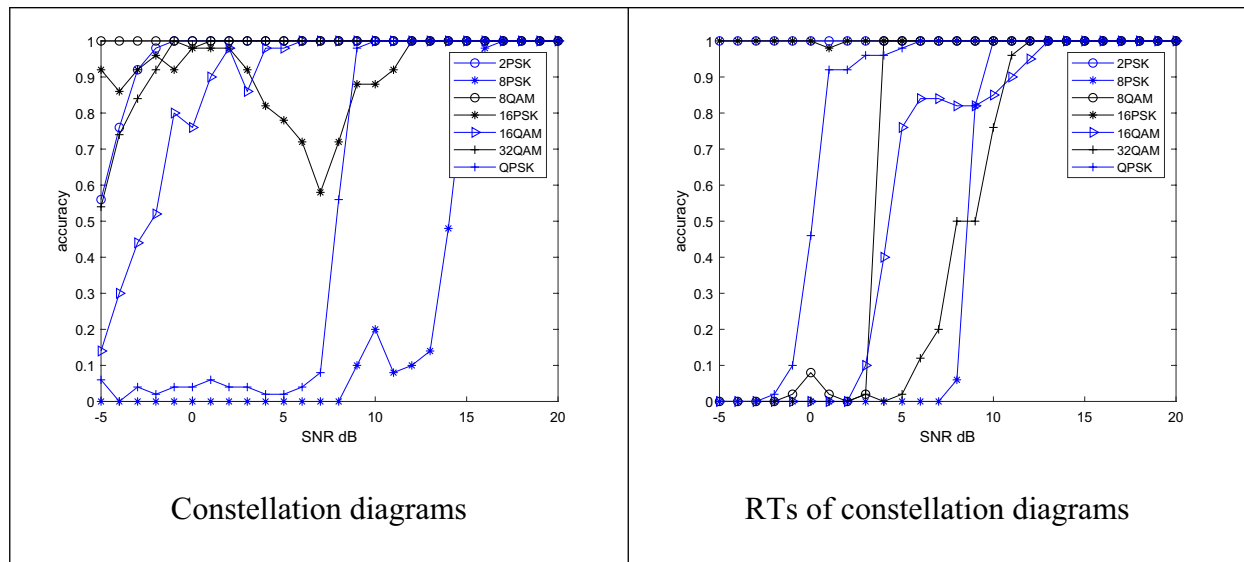


Fig. 10 Accuracy of VGG-19 classifier for constellation diagrams and RTs of constellation diagrams for different modulation types versus SNR over fading channel

6 Conclusion and future work

In this paper, we investigated the utilization of RTs of constellation diagrams for modulation classification with CNNs. The RTs of the constellation diagrams can enhance, for several modulation types, the performance of the classifiers and increase the accuracy to reach acceptable values at small values of SNR. The proposed classifier has been applied at different SNRs with AWGN and fading channels. In addition, we investigated the utilization of pre-trained networks such as AlexNet, VGG-16, and VGG-19 for modulation classification. These classifiers achieve good performance. Moreover, the fading channel reduces the accuracy of classification. We notice that the proposed CNN achieves higher accuracy than those of other classifiers at low SNRs. In the future plan, to enhance the accuracy of the classifiers, we can use other transforms to extract features from the constellation diagrams such as Gabor transform, and Speeded-Up Robust Feature (SURF) transform. In addition, the SVD can also be investigated with the RT, as it has previously succeeded in the classification of optical modulation formats.

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Availability of data and material Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Conflict of interest No conflict of interest.

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