Abstract—Modulation recognition using deep neural networks has shown promising advantage over conventional algorithms. However, most existing research focuses on single receive antenna. In this paper, modulation recognition with multiple receive antennas using deep neural networks is investigated and four different architectures are introduced, including equal-gain CNN, multi-view CNN, 2-dimensional CNN and 3-dimensional CNN. Each architecture is constructed based on a ResNet and tuned to the extent that its performance does not further improve when the network size and parameters change with a given dataset. These architectures are then compared in terms of classification accuracy. Simulation results show that 3-dimensional CNN yields the overall best performance, while the equal-gain CNN leads to the lowest performance. Further, both 2-dimensional CNN and 3-dimensional CNN, which jointly extract features from multiple receive antennas with different feature encoding, outperforms either equal-gain or multi-view CNN, which fuses extracted features from each antenna. This indicates that utilizing inherent structures within deep neural networks to jointly extract features from different antennas can achieve better performance than the schemes that combine individually encoded features from each antenna, and extending the dimension of CNN from two to three can enhance feature extraction capabilities in the context of modulation recognition.

Index Terms—Deep learning, modulation recognition, multiple antennas, convolutional neural network.

I. INTRODUCTION

Modulation recognition has been widely investigated over the past decades based on likelihood-based (LB) or feature-based (FB) approaches [1]–[4]. Inspired by the remarkable success of deep neural networks in computer vision and natural language processing [5] [6], modulation recognition using deep neural networks, also called deep modulation recognition, has shown promising performance improvements over conventional methods and attracted increasing research interests.

O’Shea first introduced a convolutional neural network (CNN) in modulation recognition and showed potential advantage of learning features by deep neural networks over that using carefully designed expert features [7]. In [8], recurrent neural network (RNN) was used to exploit temporal sequence characteristic of modulated signals. Several deep architectures based on CNN and RNN were examined and analyzed in [9]. A CNN based unit classifier was proposed in [10] to accommodate varying input lengths. In [11], over-the-air radio machine learning dataset was generated using GNU Radio and USRP for deep modulation recognition. Representing received signal samples as images was proposed in [12] for modulation classification with CNN.

However, most existing research on deep modulation recognition considers the scenarios with one single antenna at the receiver [13]. In some radio propagation environments, modulation recognition suffers from channel impairments such as multipath fading, which could cause significant performance degradation, especially when the signal experiences deep fade at the receiver [11]. One of the most powerful techniques to mitigate the effects of fading is to use diversity-combining. Therefore, it is important to investigate deep neural networks for modulation recognition with multiple receive antennas.

In this paper, four different neural network architectures are introduced to perform multi-antenna modulation recognition, including:

- 2-Dimensional Convolutional Neural Network (2DCNN). The first architecture is the one that directly utilizes the most commonly discussed 2-dimensional CNN, by forming the signals from different antennas as inputs to different channels of the network.
- Equal-Gain CNN (EGCNN). Inspired by the equal-gain combining of diversity techniques, the second architecture is constructed by first training a CNN using single-antenna data, and then averaging over the network predicted distributions to obtain a most possible modulation type.
- Multi-View CNN (MVCNN). This was initially proposed for 3D shape recognition using view-based descriptors of 2D images, which combined information from multiple views of a 3D shape into a single and compact descriptor, and was shown to offer even better recognition performance [14].
- 3-Dimensional CNN (3DCNN). It extends the most commonly used 2DCNN to 3D volume, where the dimension of the antenna corresponds to the dimension of the depth of the 3DCNN.

For better comparisons, a base network is used to construct the above four different architectures. In this paper, ResNet is chosen as the base network according to the following reasons: (1) Existing research on modulation recognition with single receive antenna has shown that ResNet is a suitable candidate [11]; (2) The ResNet is tuned such that when we further increase the network size or change network parameters, the modulation classification performance does not further
Modulation recognition performances of these deep architectures with different numbers of receive antennas are then compared and analyzed. Results show that the four architectures are effective in multiantenna modulation recognition, and the recognition performances increase as the number of receive antennas increases. Among these architectures, 3D-CNN yields the overall best performance, while EGCNN, which combines the individual CNN outputs with equal weights for each antenna, results in the lowest performance.

The main contributions of this paper are:

- Four different deep architectures are first introduced for modulation recognition with multiple receive antennas.
- Performances of these architectures are examined and shown to be effective for multi-antenna modulation recognition.
- We show that 3D-CNN leads to the best performance, which indicates that utilizing inherent structures within deep neural networks to jointly extract features from different antennas can obtain better performances than those combining individually encoded features.

The rest of this paper is organized as follows. In Section II, system model is given, and deep architectures for multi-antenna modulation recognition are described in Section III. In Section IV, simulation results are given and analyzed. Finally, conclusions are discussed in Section V.

II. SYSTEM MODEL

A. Signal Model and Representations

Suppose that signals are sent from a transmitter, and our goal is to determine the modulation type of the signals using a receiver with \( N_r \) antennas. Given the transmitted signal \( s \), the equivalent baseband received signal \( r \) can be expressed as:

\[
    r = Hs + n
\]

where \( H \) is a complex-valued \( N_r \times 1 \) vector where its \( n_r \)-th element denotes the complex channel coefficient between the transmitter and the \( n_r \)-th receiving antenna. \( n \) denotes the additive Gaussian noise.

Within one observation interval, \( N \) signal samples are collected from each antenna to form a \( 1 \times N \) complex-valued vector, which is further decomposed into a \( 2 \times N \) matrix, where the first and second row correspond to the in-phase and quadrature components, respectively. For more efficient training, we normalize the power of these vectors. Signal samples from different antennas are then collected to form a \( N_r \times 2 \times N \) matrix.

Let \( x^{(i)} \) denote the three-dimensional matrix collected in the \( i \)-th observation interval, and \( y^{(i)} \) be its corresponding label denoting the transmitted modulation type. Then \( (x^{(i)}, y^{(i)}) \) forms one training example, and training examples from randomly different time instants with identical observation durations are collected as datasets for the training and testing of neural network models.

B. Deep Learning Based Modulation Recognition

The optimization of supervised deep learning process can be formulated as finding the parameters \( \theta \) of a neural network that significantly reduce a cost function \( J(\theta) \), which can be written as:

\[
    J(\theta) = \mathbb{E}_{(x,y) \sim \text{data}} L(f(x; \theta), y) \tag{2}
\]

where \( L(\cdot) \) denotes the loss function, \( f(x; \theta) \) is the neural network predicted output when the input is \( x \), and \( y \) denote the target output. \( \hat{y}_{\text{data}} \) is the empirical distribution. In our experiments, the cross-entropy loss is chosen as the loss function, and Adam optimizer [16] is used for minibatch optimization.

III. DEEP ARCHITECTURES FOR MULTI-ANTENNA MODULATION RECOGNITION

In this section, we introduce four different deep architectures for multi-antenna modulation recognition.

For better comparisons of different architectures, we use the same base network to construct these networks. ResNet is chosen as the base network because: (1) ResNet can reduce the effect of degradation of deeper networks; (2) It has been shown to be effective for modulation recognition with single antenna. The ResNet is tuned such that when we further increase the network size or change network parameters, the modulation classification performance does not improve, given the single-antenna dataset. In this way, a 34-layer ResNet is obtained, which consists of 1 convolutional (Conv) layer, 16 residual blocks, and a fully-connected (FC) layer. Each residual block consists of two convolutional layers and batch normalization (BN) [17] operations, as illustrated in Fig. 1. Softmax function is used to normalize the output distributions.

A. 2-Dimensional Convolutional Neural Network

One straightforward way is to utilize the general 2DCNN. The received signals from different antennas are fed into the 2DCNN as different channels, in a similar way as that of the RGB data of images. In this way, signal features from
different antennas are merged in the first convolutional layer by the operation of adding up the 2D convolution results of different channels.

B. Equal-Gain Convolutional Neural Network

EGCNN is inspired by diversity techniques in wireless communications, where one receive antenna is considered as one branch and each branch uses a CNN to individually extracts features. The decision on the modulation type is made based on outputs of CNNs from all branches, where each branch is weighed with the same factor. Note that maximum ratio combining is not considered here, since we are interested in the scenario where additional estimation such as channel state information is not required. Also, these CNNs share the same parameters and have the same structure, i.e., the base network in Table I.

The output of the \( k \)-th CNN is a \( M \times 1 \) vector denoted as \( \hat{p}_k \), where \( M \) corresponds to the total number of modulation types, and its \( m \)-th element, \( \hat{p}_{km} \), can be seen as the predicted possibility of the \( m \)-th modulation type from the \( k \)-th receive antenna.

The predicted distributions from different antennas are summed with equal weights to obtain the global estimate of modulation type. Let \( \hat{p}(m) \) denote the estimate of the \( m \)-th modulation format, given by

\[
\hat{p}(m) = \sum_{k=1}^{N_r} \hat{p}_{km} / N_r
\]

The decision on the modulation format can be reached by choosing the index \( m^* \) that maximizes \( \hat{p}(m) \), given by

\[
m^* = \arg\max_m \hat{p}(m)
\]

C. Multi-View Convolutional Neural Network

MVCNN was proposed for 3D view-based shape recognition, which combined information from multiple views of a 3D shape into a single and compact shape descriptor, and was shown to be quite effective in 3D shape recognition [14]. By taking received radio signals from one antenna as one view of a 3D object, MVCNN can be utilized to perform multi-antenna modulation recognition. The architecture of MVCNN used in this paper is illustrated in Fig. 2.

To realize the MVCNN in our considered scenario, the base network, i.e., the ResNet in Table I is splitted by a view pooling layer into two parts: CNN1 and CNN2. Features from individual antennas are first extracted by CNN1, and then the view pooling layer is employed to fuse these features from different receive antennas. Operations of the view pooling layer are similar as conventional pooling layers in CNN, e.g., max pooling or average pooling. The difference lies in that the view pooling operations, as shown in Fig. 2 are carried out across dimensions of receive antennas. Features fused by view pooling layer are then passed through CNN2, where the information obtained across multiple antennas are further processed to reach the output of MVCNN, a vector consisting of empirical conditional probability of modulation type.

Note that all the \( N_r \) branches of MVCNN, i.e., CNN1, share the same parameters. In this way, different locations of the view pooling layer determine different network architectures and could lead to different modulation recognition performances. So the location of view pooling layer and pooling operations need to be carefully designed. In this work, we test the performance of MVCNN with different locations of view pooling layer and with different view pooling operations including max and average pooling. Results show that, the best performance is obtained by locating the view pooling layer just before the FC layer of the base ResNet and by using max-view-pooling for feature fusion across antennas, where the max-view-pooling is an element-wise maximum operation across different receive antennas.

D. 3-Dimensional Convolutional Neural Network

Considering the potential in better representations with 3DCNN as compared to 2DCNN, we extend 2D convolution to 3D volume for modulation recognition of radio signals received with multiple antennas. Different from 2D convolution, as shown in Fig. 3 the 3D convolutional filter moves in 3 directions (depth, height, width) to gain a 3-dimensional feature map, where the depth is used as feature index for the dimension of receive antennas.

| Layer         | Kernel Size | Stride | Output Size |
|---------------|-------------|--------|-------------|
| Input         | 7           | 2      | 512         |
| Conv          | 3           | 2      | 256         |
| Tanh          | 3           | 1      | 64          |
| Max Pooling   | 3           | 2      | 1          |
| Residual Block * 3 | 3       | 2      | 64          |
| Residual Block * 4 | 3       | 2      | 256         |
| Residual Block * 6 | 3       | 2      | 64          |
| Residual Block * 4 | 3       | 2      | 256         |
| Average Pooling | 16      | 1      | 512 \times 1 \times 1 |
| FC, Softmax   |             |        | 20          |

Fig. 2. The architecture of MVCNN for multiple-antenna modulation recognition.

Fig. 3. The 3D convolutional filter moves in 3 directions (depth, height, width) to gain a 3-dimensional feature map, where the depth is used as feature index for the dimension of receive antennas.
Given the base ResNet in Table I, the convolution and pooling operations along the dimension of receive antennas need to be tuned. While the operations along the height and width dimensions stay the same as those in Table I, the best performance of 3DCNN is achieved when the 3D kernel size is set to 3 and the max pooling kernel size is set to 1 along the dimension of receive antennas.

IV. RESULTS AND ANALYSIS

In this section, we analyze and compare performances of the deep architectures for modulation recognition with multiple receive antennas.

Datasets in our experiments are generated using GNU Radio [18]. A square root raised cosine filter with a roll-off factor of 0.35 is used for pulse shaping. Transmitted signals experience independent and identically distributed Rayleigh fading, where the second moment of the Rayleigh fading coefficient is normalized to unit. Received signals are filtered and down converted to baseband, and are up sampled by a factor of 8. $N_r \times 2 \times N$ real samples are collected from $N_r$ receive antennas to form one example, where $N_r$ ranges from 1 to 8 and $N$ is set to 512 in our experiments. 1500 examples are generated for each signal-to-noise ratio (SNR) and each modulation type, whereby 1000 are randomly chosen for training, and the remaining are used for the test. There are 20 different modulation formats including both analog and digital modulation types, including: BPSK, QPSK, 8PSK, 16PSK, 16QAM, 32QAM, 128QAM, 256QAM, 16APSK, 32APSK, 64APSK, 128APSK, OOK, 4ASK, GMSK, FM, AM, DSB, SSB.

The classification accuracy versus SNR for 2DCNN, EGCNN, MVCNN, and 3DCNN with different numbers of receive antennas are presented in Fig. 4.

It is shown that, when the number of receive antennas increases, the classification accuracy increases accordingly. This coincides with the analysis in conventional modulation recognition for multiple receive antennas that modulation recognition performance can be improved by utilizing the spatial diversity. Note that performances of the four networks are identical for the case $N_r = 1$. This is because when the number of receive antenna is equal to 1, these four networks reduce to the same computational architecture. When $N_r$ increases from 1 to 8, the noise tolerance of these modulation classifiers is improved by around 10 to 15dB, and the classification accuracy is improved by roughly 20% to 25% when the SNR is around 0dB. This indicates that the proposed four

![2D Convolution](image1.png) ![3D Convolution](image2.png)

Fig. 3. An illustration of 2D and 3D convolution operation.

![Fig. 4](image3.png)

Fig. 4. Modulation recognition performances versus SNR with different numbers of receive antennas with the deep architectures: (a) 2DCNN; (b) EGCNN; (c) MVCNN; (d) 3DCNN.
deep architectures can make use of spatial diversity and are effective for the modulation recognition with multiple receive antennas. The classification accuracy versus $N_r$ for different architectures with given SNRs are plotted in Fig. 5. It is shown that 3DCNN results in the best performance, 2DCNN has better performance than MVCNN, and EGCNN performs the worst. This is reasonable because: (1) Although the channel coefficients are identically and independently distributed, at any particular instant of time, the fading coefficient for one channel is different from another. Accordingly, equally combining the outputs of convolutional neural network could not lead to the best performance. MVCNN uses a view pooling layer across receiving antennas followed by CNN, which can be interpreted as using a convolutional neural network to learn to combine features from different receive antennas. In this way, MVCNN can obtain better performance than EGCNN. (2) Both EGCNN and MVCNN first extract features of modulated signals from each antenna individually and then combine these features to perform modulation recognition, while 2DCNN and 3DCNN jointly extract features from multiple receive antennas with different feature encoding within their layers. In this way, 2DCNN and 3DCNN perform better than EGCNN and MVCNN. (3) The reason why the performance of 2DCNN is lower than that of 3DCNN is that 2DCNN merges the features of different antennas through multi-channel convolution in the first layer by the addition of convolutions, while 3DCNN retains features of different antennas in the first few layers, and merges these features through layer by layer downsampling (the 2-stride convolution in the 3DCNN model). This also explains the phenomenon that the gap between 3DCNN and 2DCNN increases as the number of receive antennas increases.

V. CONCLUSION AND DISCUSSION

Different deep architectures for modulation recognition with multiple receive antennas have been introduced and compared, whereby each of them has been verified through simulations to be effective for the recognition task. Results show that 3DCNN yields the overall best performance, and EGCNN results in the lowest performance. This indicates that a deep neural network can be trained to jointly extract features of modulated signals from different antennas, and using the inherent structures within the neural network to jointly extract features from multiple antennas can obtain better performance than combining features individually extracted from each antenna.

VI. ACKNOWLEDGMENT

We would like to thank Professor Nuno Vasconcelos for his valuable comments and discussions on different deep architectures for modulation recognition.

REFERENCES

[1] A. K. Nandi and E. E. Azzouz, “Algorithms for automatic modulation recognition of communication signals,” IEEE Transactions on communications, vol. 46, no. 4, pp. 431–436, 1998.
[2] W. Wei and J. M. Mendel, “Maximum-likelihood classification for digital amplitude-phase modulations,” IEEE transactions on Communications, vol. 48, no. 2, pp. 189–193, 2000.
[3] Y. Yang and S. S. Soliman, “A suboptimal algorithm for modulation classification,” IEEE transactions on aerospace and electronic systems, vol. 33, no. 1, pp. 38–45, 1997.
[4] A. Swami and B. M. Sadler, “Hierarchical digital modulation classification using cumulants,” IEEE Transactions on communications, vol. 48, no. 3, pp. 416–429, 2000.
[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097–1105.
[6] R. Socher, “Recursive deep learning for natural language processing and computer vision,” Ph.D. dissertation, Citeseer, 2014.
[7] T. J. O'Shea, J. Corgan, and T. C. Clancy, “Convolutional radio modulation recognition networks,” in International conference on engineering applications of neural networks. Springer, 2016, pp. 213–226.
[8] D. Hong, Z. Zhang, and X. Xu, “Automatic modulation classification using recurrent neural networks,” in 2017 3rd IEEE International Conference on Computer and Communications (ICCC). IEEE, 2017, pp. 695–700.
[9] N. E. West and T. O'Shea, “Deep architectures for modulation recognition,” in 2017 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN). IEEE, 2017, pp. 1–6.
[10] F. Meng, P. Chen, L. Wu, and X. Wang, “Automatic modulation classification: A deep learning enabled approach,” IEEE Transactions on Vehicular Technology, vol. 67, no. 11, pp. 10760–10772, 2018.
[11] T. J. O'Shea, T. Roy, and T. C. Clancy, “Over-the-air deep learning based radio signal classification,” IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 168–179, 2018.
[12] S. Peng, H. Jiang, H. Wang, H. Alwageed, Y. Zhou, M. M. Sebdani, and Y.-D. Yao, “Modulation classification based on signal constellation diagrams and deep learning,” IEEE transactions on neural networks and learning systems, vol. 30, no. 3, pp. 718–727, 2018.
[13] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, “Survey of automatic modulation classification techniques: classical approaches and new trends,” IET communications, vol. 1, no. 2, pp. 137–156, 2007.
[14] H. Su, S. Maji, E. Kalogerakis, and E. Learned-Miller, “Multi-view convolutional neural networks for 3d shape recognition,” in Proceedings of the IEEE international conference on computer vision, 2015, pp. 945–953.
[15] I. Goodfellow, Y. Bengio, and A. Courville, Deep learning. MIT press, 2016.
[16] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.
[17] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” arXiv preprint arXiv:1502.03167, 2015.
[18] T. J. O’Shea and N. West, “Radio machine learning dataset generation with gnuradio,” in Proceedings of the GNU Radio Conference, vol. 1, no. 1, 2016.