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An End-to-End Demodulation System Based on Convolutional **Neural Networks**

Ruobing Zhao¹, Jiao Wang² and Jianging Li^{2*}

¹Southwest China Institute of Electronic Technology, Chengdu, China ² School of Electronic Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China Email: 717466321@qq.com; misology@foxmail.com; lijg@uestc.edu.cn

Abstract. The demodulation of digital signal plays a key role in the communication system. The traditional demodulator is usually realized by special hardware platform, which has the disadvantages of high cost and long development cycle. In this paper, we propose an end-toend digital signal demodulator based on convolutional neural network (CNN). It consists of an encoder and a decoder, in which the encoder encodes the input symbol sequence and maps the signal features to the hidden layer space. Then, the decoder decodes the features of the hidden layer space to obtain the demodulation result of the input sequence. The proposed algorithm can automatically learn how to demodulate the received signal without manually extracting the features. Compared with the traditional demodulator, the proposed CNN demodulator has better bit error rate (BER) performance.

Keywords. Convolutional neural network; demodulation; end-to-end.

1. Introduction

A typical digital communications receiver includes a radio frequency (RF) front end, a band-pass filter, a low noise amplifier, automatic gain control, a demodulator, etc. The demodulator is the key device in the receiver, it is responsible for processing the intermediate frequency signal and recovering the baseband signal, its effect is directly related to the performance of the communication system. Traditional demodulator must obtain accurate channel state information (CSI) before demodulation, and then use coherent demodulation algorithm for demodulation and symbol decision. However, it is difficult to obtain real-time accurate CSI in large-scale multiple input multiple output (MIMO) antenna, high mobility and high frequency scenarios. Therefore, it is of great significance to design a demodulator which does not depend on the channel state information and has a low bit error rate.

Recently, due to the rapid development of computer hardware, machine learning has been developed accordingly. Deep learning is a kind of machine learning, whose advantage lies in the formation of more abstract high-level features by combining lower-level features, thus simulating the cognitive mechanism of human brain, and automatically discovering the distribution patterns hidden in the data. Compared with the forward neural network, deep learning not only has faster training rate and better performance, but also has strong robustness. Since neural networks were proposed, researchers have been exploring their applications in the field of communication. At present, many researches have successfully applied neural network to channel estimation [1], modulation recognition [2-4], coding recognition [5, 6], communication system simulation [7] and adaptive filtering [8]. Take the paper [9] for example, CNN was used to analyze the cyclic spectrum of modulated signals, so as to achieve the purpose of modulation recognition. This method makes full use of the ability of CNN to

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extract image features. It provides a new idea for the application of neural network in the field of communication.

Based on deep learning technology, this paper proposes a digital signal demodulation scheme based on convolutional neural network. Compared with the traditional log likelihood ratios (LLR) demodulation algorithm, the proposed algorithm does not need to use specific hardware and can be simply modified to adapt to different modulation modes. In order to verify the effectiveness of the proposed algorithm, we generate binary phase shift keying (BPSK) and quadrature phase shift keying (QPSK) data sets in additive white gaussian noise (AWGN) channels respectively, and compare their performance with the existing demodulation schemes.

2. Related Works

In recent years, many deep learning-based methods have been widely used in digital demodulation. Nakayama et al. [10] proposed a neural network amplitude shift keying demodulator that integrates wideband noise suppression, pulse waveform shaping and decoding into a neural network and self-organizes these functions through a learning process. Cheng et al. [11] took a sample corresponding to a symbol period in the baseband signal as the input of the neural network, which was mapped to binary symbols using the neural network. Onder et al. [12] used three-layer multilayer perceptron (MLP) for multiple phase shift keying (MPSK) demodulation and presented simulation results of channels with white Gaussian noise and multi-channel channels. In addition, Wang et al. [13] proposed two deep learning-based demodulator, namely, deep belief network-support vector machine demodulator and adaptive boosting demodulator.

In the above demodulation algorithms based on neural network, sampling points are input into the neural network according to the code cycle, and then the code of input vector mapping is judged. However, it is difficult to group the baseband data strictly according to the symbolic period, especially when there is frequency offset or sampling error, grouping sampling points according to a fixed number will bring great error. In order to solve this problem, Zhang et al. [14] proposed a convolutional neural network architecture based on time-sliding window input for binary PSK modulation signals, and optimized it with one-dimensional convolutional check demodulation complexity and error performance. They determine symbol categories by detecting the position of phase shifts in the modulation data. At the same time, the proposed structure can deal with carrier frequency offset and sampling frequency error by coordinating with the symbolic synchronization algorithm. However, this algorithm cannot demodulate multiple modulation modes at the same time. When the modulation mode is changed, it needs to re-model and the number of identified networks increases exponentially.

3. The Proposed Method

3.1. CNN

CNN is a kind of deep feedforward neural network, which is developed from back propagation (BP) neural network. It is widely used in visual image analysis, natural language processing and recommendation system. The network structure of CNN is composed of input layer, convolutional layer, pooling layer, full connection layer and output layer. CNN uses sparse connection, weight sharing, down sampling and other operations to reduce the computational complexity, so as to achieve the purpose of training deep network. In this paper, 1-D CNN is used to adapt one-dimensional digital communication signal data. Figure 1 shows a schematic representation of a one-dimensional convolutional operation. 1-D CNN is a special CNN, which is often used in the processing of one-dimensional signals, such as speech signals. Its input is a one-dimensional vector, so the convolutional kernel and characteristic graph of the network are also one-dimensional.

$$\mathbf{O}^{m} = f(\sum_{p=0}^{p-1} \omega^{p} i^{m+p} + b)$$
(1)

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Figure 1. A complete convolution operation.

where w^p is the *p*-th weight in the one-dimensional convolutional kernel, i^{m+p} is the (m+p)-th value in the input vector, O^m is the *m*-th value in the output vector, b is the offset, and f is the activation function.

3.2. Architecture of End-to-End Demodulation System

The network structure proposed in this paper is shown in figure 2, which consists of two parts: encoder and decoder. The encoder corresponds to the signal down sampling process, and the decoder corresponds to the feature graph up sampling process. The encoder consists of 7 convolutional blocks and 7 subsampling layers, and each convolutional block contains 2 convolutional layers with the size of 3×1 convolutional kernel and step size of 1. The decoder consists of 7 convolutional blocks and 5 up-sampling layers, among which, the convolutional block is the same as the convolutional block of the encoder. For the entire network, we used Leaky ReLU as the activation function. The Leaky ReLU function is an improved version of ReLU, as expressed in Equation (2). The Leaky ReLU function multiplies the input value when the input x<0 by a coefficient so that the gradient of the neuron is not 0 when the neuron is not active, avoiding the situation where the inactive neuron never activates.

$$f(x) = \begin{cases} ax, \ x < 0\\ x, \ x \ge 0 \end{cases}$$
(2)

In the Leaky ReLU definition of the excitation function, a is generally a very small coefficient, usually agreeing that 0 < a < 1. Compared with the ReLU function, the Leaky ReLU function retains the value of the negative axis so that the negative axis information is not lost, solving the problem that the ReLU function causes neurons to "die".



Figure 2. Structure of the proposed 1-D CNN demodulator.

The activation function for the final layer is softmax, which takes the maximum output probability for all categories as the final result. In addition, we add a batch normalization (BN) layer after each convolution layer. The BN layer has the ability to increase the learning rate so that the network converges faster without over-fitting.

3.3. Implementation Platform

The deep learning algorithm framework is based on Python 3.7.1, TensorFlow 2.3.0 and Keras 2.4.3, and the training/test data sets are randomly generated by MATLAB software. The whole system was trained and tested on a computer with an NVIDIA GTX 2080TI GPU and eight Intel i7-7700 CPUs.

4. Simulation Results

4.1. Experimental Dataset and Preprocessing

Figure 3 shows the schematic diagram of the end-to-end convolutional neural network demodulation system based on deep learning, which is mainly composed of the transmitter terminal composed of baseband modulation, baseband shaping filter and modulator, the transmission channel, and the receiver terminal including pre-processing and neural network decision. This part of data is mainly used to analyze the demodulation ability of CNN model under AWGN interference. The symbol rate f_d of the transmitter is 2.5 MBd, and the sampling rate f_s is set to be 10 Msps, i.e., there are 4 samples per symbol. Signal pulses were shaped by a root-raised cosine pulse shaping filter, roll-off values are uniformly distributed in the range of 0.1-0.5. The training signal-to-noise ratio (SNR) varies randomly in the range of 3-4 dB, and the test SNR varies in the range of -2-8 dB. In addition, the baseband signals in this paper are randomly generated, and the sequence length of each sample is 1024 symbols. Two thousand samples were generated for each SNR and modulation type.



Figure 3. System structure.

In order to ensure the uncorrelation of signal features and the consistency of data dimensions, data pre-processing is needed. And most neural networks require input data within the range of [-1,1] or [0,1]. In addition, in order to make the input data of neural network conform to the distribution of output data better, data pre-processing is indispensable. In this paper, the input data *x* is mapped to between [0,1], and the maximum value x_{max} is guaranteed to be mapped to 1, the minimum value x_{min} is mapped to 0, and the rest data are distributed between [0,1] according to the original distribution.

$$x_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

4.2. Training Complexity

When using CNN to demodulate the symbol sequence, the cross-entropy loss function is adopted.

$$L(\theta) = -\frac{1}{N_b} \sum_{i=0}^{N_b} y_i \log y_i + (1 - y_i) \log(1 - y_i)$$
(4)

where y_i represents the true probability distribution of the *i*-th training sample, and N_b represents the number of training samples in each training batch. Gradient descent is used to optimize the loss function in the training process.

$$\theta_{t+1} = \theta_t - \eta \Delta L(\theta_t) \tag{5}$$

where η represents the learning rate, the initial value is set to 0.001, and Δ represents the gradient operation.

The relationship between training loss value and iteration number is shown in figure 4. At the end of the iteration 100 times, the training loss value has almost stopped declining.



Figure 4. Training loss plot.

4.3. Performance Comparisons

Figure 5 shows the bit error rate curve of BPSK signal demodulation by the optimal 1-D CNN demodulator, soft demodulator computes the log likelihood ratios (LLR) and MLP demodulator. The SNR (Es/N0) of the test set ranged from -2dB to 8dB. As can be seen from figure 5, when the SNR is less than or equal to 0dB, the demodulator based on CNN is basically close to the bit error performance of the traditional soft demodulator, and both are better than the MLP demodulator. When the SNR is greater than 0dB, the bit error performance of CNN demodulator is better than that of traditional demodulator and MLP demodulator, and shows relatively stable performance. Compared with the traditional demodulator, the CNN demodulator does not need to rebuild the architecture in the process of demodulating BPSK and QPSK modulation signals, but only needs to retrain in the scene of corresponding modulation information to obtain the ability of the best statistical decision.



Figure 5. The demodulation performance of BPSK modulated signals.

Figure 6. The demodulation performance of QPSK modulated signals.

Figure 6 shows the demodulation error rate curves of QPSK signals with three different algorithms. Compared with BPSK demodulation, the demodulation error rate of QPSK signal is much higher. This is because QPSK is a quaternary phase modulation. Each symbol contains two bits of original information. Under the same channel conditions, the bit error rate will be higher. However, it can be

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seen from the figure that the CNN demodulator still has excellent performance. Only when the signalto-noise ratio is less than -1dB, the performance of the MLP demodulator is slightly better than the CNN demodulator and the traditional demodulator. When the signal-to-noise ratio is greater than -1dB, the demodulation effect of CNN is still better than the traditional demodulator and MLP demodulator, and the demodulation effect of MLP is close to the traditional QPSK demodulator.

5. Conclusion

In this paper, a multi-code demodulation algorithm based on full convolutional neural network is proposed, which requires neither complex signal pre-processing nor grouping of sampling points. The proposed demodulator is composed of an encoder and a decoder. The encoder corresponds to the signal subsampling process, and the decoder corresponds to the feature map up-sampling process. Compared with the traditional blind demodulation system, this system has high demodulation accuracy and does not need to manually extract features. The experimental results show that when the SNR is greater than 0dB, the demodulator of CNN is better than the bit error performance of traditional soft demodulator and MLP demodulator, and shows relatively stable performance. In addition, compared with the traditional demodulator, the convolutional neural network does not need to rebuild the architecture in the process of demodulating BPSK and QPSK modulation signals, but only needs to retrain in the scene of corresponding modulation information, so as to obtain the ability of optimal statistical decision.

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