Blind Identification of LDPC Code based on Deep Learning

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***Abstract*—In cognitive radio or military communications systems, the receiver usually needs to blindly identify which LDPC code has been adopted by the transmitter. Existing methods for blind LDPC code identification suffer from high computational complexity. This paper proposes a deep learning based LDPC code identification algorithm. According to the algorithm, the received LDPC encoded sequence is treated as a text sentence, and a special convolutional neural network (CNN), TextCNN, is utilized to understand the sequence and infer which code is adopted. Two types of LDPC codes, namely quasi-cyclic LDPC and spatially coupled LDPC, are considered. Simulation results show that, the proposed algorithm is able to accurately identify both types of LDPC codes no matter whether an extra convolution code exists or not.**

Keywords—LDPC code, code identification, TextCNN

I. INTRODUCTION

Adaptive modulation and coding (AMC) [1] is an effective technique to increase the utilization rate of spectrum resources. In AMC, the transmitter adaptively adjusts the parameters of transmission, e.g., coding scheme, according to the channel state information, and the receiver has to identify which channel code has been adopted by the transmitter to decode the received signal correctly. In conventional communications systems, these parameters are usually shared though a control channel, which inevitably consumes extra channel resources. Moreover, in cognitive radio and military communications systems, such a control channel hardly exists because the transmitter and receiver do not cooperate with each other [2]. Therefore, it is necessary for the receiver to blindly identify the channel code adopted by the transmitter.

Various channel codes have been suggested for wireless communications, and the low density parity check (LDPC) code attracts great attention as its performance is very close to the Shannon limit. LDPC code was firstly proposed by Gallager in 1962 [3], and was determined as the data channel coding scheme for 5G enhanced mobile broadband scene in 2018. The task of LDPC code identification has been investigated in [4-7]. In [4], the average likelihood difference (LD) of parity checks is utilized to identify LDPC code. In [5], the unknown encoder and time-delay are blindly estimated using the average log-likelihood ratios (LLRs) of syndrome a posteriori probability. Literature [6] proposes a blind LDPC identification system, including an expectation-maximization estimator for signal amplitude and noise variance, an LLR estimator for syndrome a posteriori probabilities, and a maximum average LLR detector. In [7], a bind frame synchronization method based on maximum a posteriori probability is used for identification of LDPC code. Note that these methods are all based on LD or LLR, and suffer from high computational complexity.

In recent years, deep learning (DL) technology has been regarded as a powerful tool and widely applied in the fields of image classification [8-9], natural language processing (NLP) [10], and speech recognition [11]. Convolutional neural network (CNN) is one of the most popular networks in DL [12]. It contains convolutional computation and has a deep structure that can be conducted in both supervised and unsupervised learning. TextCNN is a special CNN proposed in 2014 [13]. Due to its simple structure and good performance, it is widely used in NLP such as text classification.

Although DL has been flourishing everywhere, its superiority in channel code identification is fully discussed. Recently, literature [14] suggests using TextCNN to blindly identify convolution code. However, blind identification of LDPC code based on DL has not been studied yet.

This paper concentrates on identifying LDPC code by use of DL. The LDPC encoded sequence is treated as a text sentence, and the task of LDPC code identification is converted into a problem of text recognition that can be easily conquered via TextCNN. According to the proposed algorithm, the received sequence is firstly preprocessed into word vectors to form a sentence matrix. Then the sentence matrix is understood by TextCNN to determine which LDPC code is adopted in the sequence.

The rest of this article is organized as follows. Section II formulates the problem. Section III proposes the blind DL based LDPC code identification algorithm. Section IV gives and analyzes the experimental results. Section V summarizes this paper.

II. PROBLEM FORMULATION

Having received an encoded bit sequence $\mathbf{r} = (r_1, \cdots, r_N)$, where N represents the length of received sequence, the aim is to identify which channel code $C_k (1 \le k \le K)$ is used in the sequence from a candidate channel code set represented by $\Theta = \{C_1, C_2, \cdots, C_K\}$, where K represents the number of types of channel codes.

The candidate set in this paper comprises two types of LDPC codes, namely quasi-cyclic LDPC (QC-LDPC) and spatially coupled LDPC (SC-LDPC). Our idea is to exploit DL networks to identify these LDPC codes.

A. QC-LDPC Code

QC-LDPC code is a kind of LDPC code based on cyclic code. It is composed of multiple cyclic submatrices, each of which has the same size but different displacement factors. The structure of its check matrix is shown in (1).

$$H_{QC}=\begin{bmatrix} H^b_{(0,0)} & H^b_{(0,1)} & \cdots & \cdots & H^b_{(0,q-1)} \\ H^b_{(1,0)} & H^b_{(1,1)} & \cdots & \cdots & H^b_{(1,q-1)} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ H^b_{(p-1,0)} & H^b_{(p-1,1)} & \cdots & \cdots & H^b_{(p-1,q-1)} \end{bmatrix} \quad (1)$$

where $H^b_{(i,j)}$ represents the (i,j)th cyclic identity matrix or all-zero matrix, and b refers to the number of cyclic right shifts of each submatrix $H^b_{(i,j)}$.

In this paper, the QC-LDPC code chooses the basis matrix (BG) 2 under the 5G standard. The scatter plot of BG2 is shown in Fig. 1.

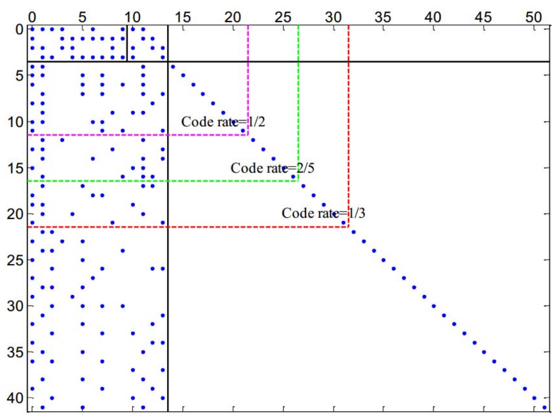

Fig. 1. Scatter plot of 5G LDPC code BG2.

B. SC-LDPC Code

SC-LDPC code is a kind of convolution LDPC code, which is able to approximate the Shannon limit in binary memoryless symmetric (BMS) channels when exploiting the belief propagation (BP) decoding algorithm. It is constructed by connecting several identical but unrelated grouped protograph LDPC codes through spatial coupling. The structure of its check matrix is demonstrated as (2).

$$H_{SC}=\begin{bmatrix} H_0 & & & & \\ H_1 & H_0 & & & \\ \vdots & \vdots & \ddots & & \\ H_{m-1} & H_{m-2} & \cdots & \ddots & \\ & H_{m-1} & H_{m-2} & \cdots & H_0 \\ & & \ddots & \ddots & H_1 \\ & & & \ddots & \ddots \end{bmatrix} \quad (2)$$

An SC-LDPC code denoted by (l,r,L) is constructed by coupling of the regular LDPC code with L degree distribution as (l,r) on the basis of the original regular LDPC code, where l represents the column weight of the code, r represents the maximum row weight of the code, and L represents the length of the spatial coupling chain.

C. DL Network

DL automatically extracts the features of the data and characterizes the data in an abstract form by use of deep neural network (DNN). DNN is also known as deep feedforward network, which is composed of an input layer, many hidden layers, and an output layer, as shown in Fig. 2.

The input layer is usually defined as the input of the raw data. For text data, it can be words or characters. For image data, it can be the original pixel values of different color channels. The hidden layers are located between the input layer and the output layer. The neurons of the hidden layers can be organized in various forms, such as pooling layer and convolution layer. The output layer is the output of the network, which is constructed according to the problem to be solved.

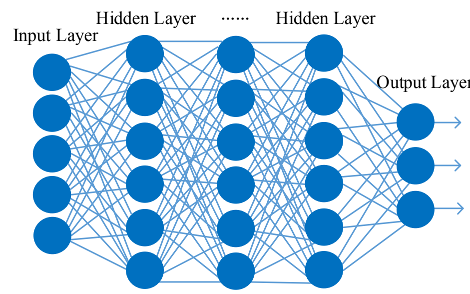

Fig. 2. Deep neural network.

III. LDPC Code Identification Based on DL

Since the received encoded sequence looks like a text sentence, this paper conquers the problem of LDPC code identification via DL based text recognition. Firstly, the received sentence is preprocessed into a sentence matrix. Then, the sentence matrix is understood by TextCNN to infer which LDPC code has been adopted in the sequence.

A. Data Generation and Preprocessing

For each channel code in the candidate set, $N \times R$ bits are generated and encoded with the code rate of R. Then the encoded bits are binary phase-shift keying (BPSK) modulated with unit power and polluted by an additive white Gaussian noise (AWGN) channel with the signal to noise ratio of $SNR = 10\log_{10}(1/\sigma^2)$, where σ^2 is the power of noise. After that, the polluted signal is received and demodulated with hard decision, producing a received bit sequence of N bits.

Similar to [14], the received sequence is divided into $N/4$ segments with the segment length of 4 bits. Each segment is regarded as a word and can be mapped into a word vector. All word vectors are combined to construct a sentence matrix that is further understood by TextCNN. Samples of the received sequences for both QC-LDPC and SC-LDPC are illustrated in TABLE I.

TABLE I.
Samples of Received Sequences at SNR = 2dB

Type	Received Sequence (N= 40)
QC-LDPC	1100 0000 1100 1111 0111 0101 1000 1100 1000 0010
SC-LDPC	0000 1100 0011 1111 0000 0111 0100 1000 0000 1111

B. Structure and Principle of TextCNN

The structure of TextCNN is shown in Fig. 3. The entire network consists of four parts: the embedding layer, the convolution layer, the pooling layer, and the fully connected layer.

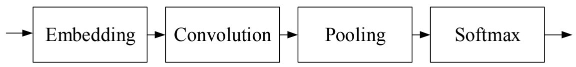

Fig. 3. TextCNN structure.

The first layer is the embedding layer. It conducts the process of word2vec and generates a 2-dimensional sentence matrix X. In the convolution layer, X is processed and an output matrix is obtained,

$$a_i = f(W \cdot X_{i:i-p+1} + b) \tag{3}$$

where f is the activation function selected by the network, W is the weight matrix of convolution kernel, $X_{i:i-p+1}$ is the ith submatrix of X, p is the height of the convolution kernel and b is the bias term. Max-pooling is selected in the pooling layer to reduce the number of model parameters and guarantee the fixed length output. The last layer is the fully connected layer that utilizes Softmax classifier to produce the classification result.

C. Network Training

In order to train a TextCNN model to achieve LDPC code identification, the training and validation data sets are firstly generated. For each channel code, the former contains 160,000 received sequences, and the later contains 20,000 received sequences. All received sequences in both data sets are labeled according to the channel code adopted in the sequences.

Both data sets are fed into TextCNN for training. Our training platform is equipped with TensorFlow, CUDA and Nvidia GTX 1080Ti under the Ubuntu 16.04 system. The hyper-parameters of training are adjusted by observing the loss value and the precision value obtained. Part of our hyper-parameter settings are listed in TABLE II.

TABLE II.
HYPER-PARAMETER SETTINGS OF TRAINING

Parameter	Value
Active Function	ReLu
Learning Rate	10e-3
Number of Iterations	25000
Batch Size	128

After tens of minutes of training, a trained TextCNN model can be obtained for the identification of LDPC code.

IV. EXPERIMENT RESULTS

This section gives some experimental results to test the performance of DL based LDPC code identification algorithm proposed in this paper. For each code, the test data set contains 20,000 received sequences.

In order to show the capability of proposed algorithm to identify different types of LDPC codes, we firstly consider that the candidate set comprises one QC-LDPC and one SC-LDPC. The QC-LDPC is constructed with code length of 256, code rate of 1/2, spreading factor of 22. The code length and code rate of SC-LDPC are also 256 and 1/2, respectively. Other parameters of SC-LDPC are $l=3$, $r=6$, and $L=128$.

Fig. 4 plots the curves of identification accuracy versus sequence length N ranging from 40 to 320 at the SNR of 2dB. As shown in this figure, the identification accuracy of both LDPC codes increases with the sequence length. On the whole, the identification accuracy is very high. For example, both curves are constantly above 93% even with a small sequence length of 40, and almost equal to 100% when the sequence length exceeds 150. These phenomena indicate that our algorithm is fairly powerful to identify different types of LDPC codes.

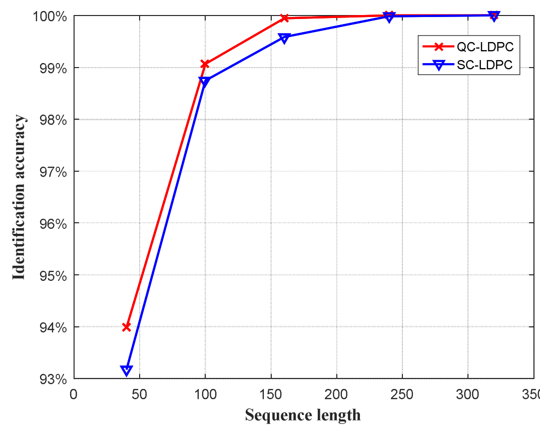

Fig. 4. Identification accuracy of DC-LDPC and SC-LDPC versus sequence length with SNR = 2dB.

Fig. 5 shows the curves of identification accuracy versus SNR ranging from -5dB to 7dB with the sample length of 100. Obviously, the identification accuracy rises as SNR increases. When SNR is -1dB, the identification accuracy is above 90%. This result demonstrates that our algorithm works well at low SNR regions.

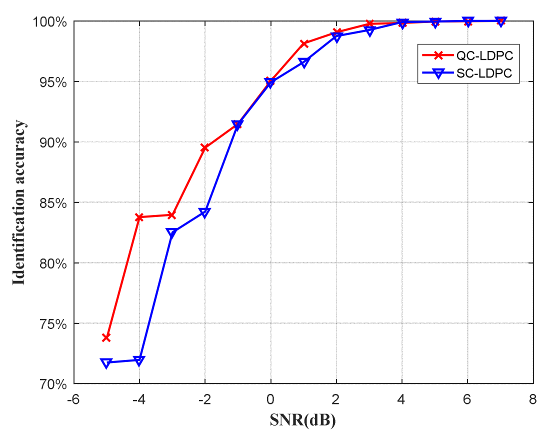

Fig. 5. Identification accuracy of DC-LDPC and SC-LDPC versus SNR with N = 100.

Table III presents the confusion matrix of identifying two LDPC codes with the sequence length of 100 at the SNR of 2dB. It can be seen from this matrix that both LDPC codes suffer from few identification errors, and the SC-LDPC is a bit harder to be identified.

TABLE III.
CONFUSION MATRIX OF IDENTIFYING QC-LDPC AND SC-LDPC WITH N=100 AND SNR = 2dB

Type	QC-LDPC	SC-LDPC	Accuracy
QC-LDPC	19813	187	99.07%
SC-LDPC	251	19749	98.75%

Moreover, in order to test the performance of proposed algorithm to distinguish LDPC code from other channel codes, a convolutional code (2,1,4) is added into the candidate set. Fig. 6 shows the impacts of sequence length on identification accuracy at the SNR of 0dB. Similarly, better identification accuracy can be achieved with larger sequence length. When the sequence length exceeds 240, the accuracy is above 95%, which verifies the effectiveness of our algorithm to identify LDPC code in presence of an extra channel code.

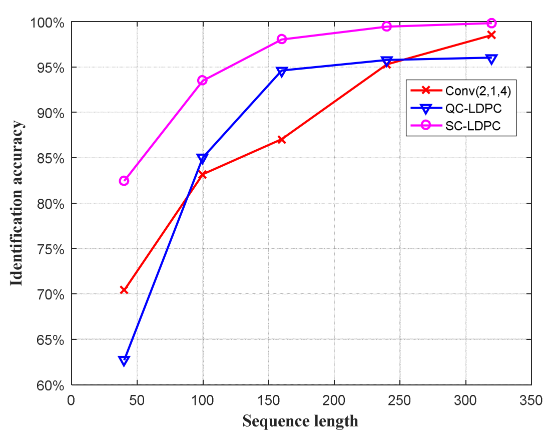

Fig. 6. Identification accuracy of three channel codes versus sequence length with SNR = 0dB.

Fig. 7 shows the identification accuracy of three types of channel codes at different SNRs with the sequence length of 100. According to this figure, better identification accuracy is obtained if SNR is higher. When SNR= 3dB, the identification accuracy of the three codes is close to 100%. As a result, although there exits another code, LPDC code can be correctly identified at a large SNR region.

TABLE IV shows the confusion matrix of identifying three codes with sequence length of 100 at SNR of 0dB. As shown in this confusion matrix, SC-LDPC achieves high identification accuracy although it is possibly mistaken for QC-LDPC. But the convolutional code (2,1,4) and QC-LDPC are probably confused with each other.

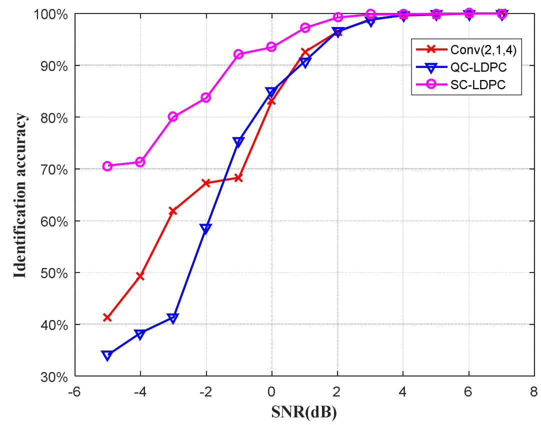

Fig. 7. Identification accuracy of three channel codes versus SNR with N=100.

TABLE IV.
CONFUSION MATRIX OF IDENTIFYING THREE CHANNEL CODES WITH N=100 AND SNR = 0dB

Type	Conv(2,1,4)	QC-LDPC	SC-LDPC	Accuracy
Conv(2,1,4)	16633	3093	274	83.17%
QC-LDPC	2248	17000	752	85.00%
SC-LDPC	218	1087	18695	93.48%

V. CONCLUSIONS

In this paper, a blind DL based LDPC code identification algorithm is proposed via regarding the received sequence as a text sentence that can be easily understood by TextCNN. The impacts of sequence length to the identification accuracy are analyzed. Different candidate sets of channel codes are tested. The proposed algorithm inherits the powerful classification capability from DL and is able to identify LDPC accurately as expected.

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