## PAPER • OPEN ACCESS

# Classification of Channel Coding Structure Based on 1-D Inception Architecture

To cite this article: Feng Tian et al 2021 J. Phys.: Conf. Ser. 2026 012008

View the article online for updates and enhancements.

# You may also like

- Prediction of breast cancer molecular subtypes using DCE-MRI based on CNNs combined with ensemble learning Rong Sun, Zijun Meng, Xuewen Hou et al.
- White matter structural connectivity as a biomarker for detecting juvenile myoclonic epilepsy by transferred deep convolutional neural networks with varying transfer rates Xiaopeng Si, Xingjian Zhang, Yu Zhou et al.
- An inception network for positron emission tomography based dose estimation in carbon ion therapy
  Harley Rutherford, Rohan Saha Turai, Andrew Chacon et al.





DISCOVER how sustainability intersects with electrochemistry & solid state science research



This content was downloaded from IP address 3.138.110.119 on 14/05/2024 at 00:11

# **Classification of Channel Coding Structure Based on 1-D Inception Architecture**

Feng Tian<sup>1</sup>, Jin Zhang<sup>2</sup>, Jiao Wang<sup>2</sup> and Jianqing Li<sup>2\*</sup>

<sup>1</sup>Chengdu Aircraft Industry (Group) Co., Ltd, Chengdu, China
<sup>2</sup>School of Electronic Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China
Email: 13837354232@163.com

**Abstract.** The channel coding structure classification based on the traditional method usually requires the coding type and prior knowledge to be known, which is completely invalid for the unknown signals that are usually intercepted in the current communication environment. In order to solve this problem, this paper proposes a method of blind classification of channel coding structure based on one-dimensional Inception. First, we use MATLAB to generate signal datasets with different channel coding structures under different signal-to-noise ratios (SNR), and then construct a Convolutional Neural Network (CNN) model based on the one-dimensional Inception, and use the datasets to train the network model. The final classification accuracy rate is 96%. This experimental result demonstrates the effectiveness of the proposed method.

Keywords. 1-D inception; channel coding; CNN; deep learning.

#### 1. Introduction

To ensure the reliability of information in the transmission process, channel coding technology is usually used in the signals. The widespread application of channel coding makes the technology of channel coding classification and recognition attracted a large number of researchers. In the field of non-cooperative communication, the problem of blind classification and recognition of channel coding has become an important research direction. In the civilian field, channel coding classification technology can quickly identify the coding parameters and codes of signals, and managers can efficiently manage the signal spectrum based on the recognition results. In the military field, contemporary warfare is mainly information warfare between rival parties. After demodulating the information intercepted from the enemy, it is necessary to use channel coding classification and recognition technology to obtain important information.

Common channel coding techniques in signals include Bose Chaudhuri Hocquenghem code (BCH), Reed-Solomon code (RS), Low-Density Parity-Check (LDPC) codes [1], TPC codes, Turbo codes [2] and convolutional codes. In the traditional method of channel coding classification and recognition, such as the blind recognition of binary primitive BCH codes parameters based on Euclidean division [3], it uses the Euclidean division method in the binary domain to obtain the exponentiation of common factors of the code word. After that, the frequency threshold and code length are determined according to the regularity of its distribution, and the generator polynomial is obtained according to the threshold. The algorithm needs to traverse the code length and analyse the law of the exponentiation of common factors. There are cumbersome steps, and the fuzzy threshold selection will lead to recognition errors. In [4], Valembois assumes that the observed binary data

stream has passed through the [n, k] encoder and binary symmetrical channel, and continuous codewords can be extracted from it. The problem studied in this paper is to find the [n, k] code (on the Hamming distance) that is the closest to the extracted code word. The paper proposes an algorithm based on double code word recognition, which can be effectively applied to codes up to 512 bits in length when the average code word error does not exceed 1.5 code words. Reference [5] proposed a method of constructing a specific matrix rank for the bit stream intercepted by observation. Compared with reference [4], this method has the advantage of low complexity. In reference [6], a soft decision method based on root distribution entropy for BCH coding is proposed. For the identification of convolutional interleaver, reference [7] proposed a method for identifying block-coded convolutional interleaving streams, but the assumptions in this article are not always the case in practice, so reference [8] considers and solves this problem. Regarding the identification of the scrambler, Gautier, as the earliest scholar to study this problem, projected the observation data to the encoder orthogonal subspace in [9] to estimate the scrambling sequence offset.

The above-mentioned traditional methods all propose a channel coding identification method based on a specific channel coding mood, which leads to their poor application versatility and cumbersome steps. In order to solve the cumbersome steps and manual extraction of signal features of traditional methods, the application of deep learning methods was born.

In 2006, deep learning master, Geoffrey Hinton, formally put forward the concept of deep learning, and proposed a layer-by-layer training method in [10] to efficiently train the network, effectively solving the problem that the multi-layer neural network has always been difficult to train. The proposal opened the curtain on the development of deep learning. Since then, deep learning has been widely used in image processing, natural language processing, speech recognition and other fields, a large number of new networks in these fields have been proposed. In the paper, Christian Szegedy et al. proposed a two-dimensional Inception [11] structure for extracting image features. This structure mainly approximates or replaces the optimal local sparse structure by using a dense component. This model uses the parallel method of multi-kernel convolutional layers with kernels size of  $1 \times 1$ ,  $3 \times 3$  and  $5 \times 5$  to increase the width of the network. Due to the use of convolution kernels of various sizes, the image information extracted by the network is richer. The network achieved excellent results in the ILSVRC14 competition. In reference [12], the author uses the Inception module to construct a CNN network for feature learning and classification recognition of the pre-processed true and false signature images. In several public datasets, CEDAR and BH-Sig260 signature corpus, the classification accuracy can reach more than 95%. It is confirmed that the Inception structure is effective in image recognition. Reference [13] proposed a convolutional neural network using Inception module and LSTM module. The network was tested on UCR time series classification archives, and its error rate was lower than the baseline model. It can be concluded that the Inception module also has good results for feature extraction of one-dimensional sequences. What's more, reference [14] proposed a recognition of error correction coding method based on deep learning. This method uses the DCNN network to train the pre-processed signal to obtain a network model that recognizes the three encoding methods of LDPC, convolutional code and Hamming code. When the SNR is greater than 8dB, the achieved accuracy is greater than 80%. Reference [15] proposes a digital modulation recognition method based on a deep convolutional neural network. This method uses the VGG-19 network [16] to train signals with three different modulation modes of 4QAM, 16QAM and 64QAM. When the SNR is greater than 4dB, the recognition accuracy obtained is above 95%.

From the above works, deep learning has significant effects in the field of image processing, channel coding classification and recognition, and modulation recognition in the field of communication signals. In deep learning, we usually increase the network depth to improve the accuracy of network recognition, and the Inception module mentioned above increases the width of the network by paralleling convolutional layers of different sizes. Different convolution kernels enable the network to extract information features in more detail, and at the same time, the use of  $1 \times 1$  convolution kernel reduces the amount of network parameters. Thinking of the excellent results of the Inception module in image processing and the advantages, we apply the module in our research. In this

paper, we use the Inception structure to build a channel coding structure classification network. We use MATLAB to generate datasets with different coding structures, including signals that use channel coding, channel coding and interleaving, and signals that are scrambled after channel coding and interleaving. Then input the datasets into the network for training and testing, and finally obtain the classification results of the channel coding structure.

## 2. Method

This part will introduce the details of the method proposed in this paper.

## 2.1. One-dimensional Inception Structure

This paper is mainly about one-dimensional signal, so we need to modify the two-dimensional Inception structure to one-dimensional, that is, the convolution kernel becomes  $1\times1$ ,  $3\times1$ , and  $5\times1$ , while keeping Max Pooling operation. In order to reduce the amount of network parameters, the input can be reduced in dimension, that is, a convolutional layer with a kernel of  $1\times1$  is added before the convolutional layers with kernels of  $3\times1$  and  $5\times1$  and after the Max Pooling layer. The structure is shown in figure 1b.

## 2.2. Convolutional Layer and Batch Normalization Layer Modules

In order to construct the network more clearly and conveniently, this paper defines a convolution normalization module, which includes two network layers, a one-dimensional convolution layer and a batch normalization processing layer. The two are connected by taking the output of the convolutional layer as the input of the batch normalization processing layer.

## 2.3. ReLU Activation Function and Adam Optimizer

As a non-linear function, the activation function can approximate almost any function, greatly improving the ability of deep neural networks [17]. The activation function used in this method is ReLU [18], and its formula can be expressed as:

$$f(x) = \max(0, x) \tag{1}$$

The formula shows that the value of the derivative of input value greater than zero is 1 after ReLU, which avoids the problem of the disappearance of the gradient caused by the smaller derivative value. Since there is no exponential calculation in the function formula, the calculation amount will be greatly reduced.

Kingma and Lei Ba proposed the Adam optimizer [18], which combines the advantages of the previous AdaGrad and RMSProp optimization algorithms. It has simple implementation, efficient calculation, and parameter updates are not subject to gradient expansion advantages. Considering the principles and advantages of Adam above, we choose it as the optimizer of the network in this paper.

## 2.4. Network Architecture

In this paper, the main body of the network model includes Inception structures, convolution normalization modules, Max Pooling layers, Global Average Pooling layers, fully connected layers and Dropout layers. In the parameter setting of each convolutional layer, the ReLU function is set as the activation function, the step size is set to 1, and the padding is set to "same" to ensure that the size of the input layer and the output layer are equal. The pooling size of the Max Pooling layer is set to 2, and the dropout ratio of the Dropout layer is set to 0.3. Because the goal of this paper is to achieve the classification of the channel coding structure, the softmax activation function is used as the activation function of the last fully connected layer of the network, and the optimizer used is the Adam optimizer. The network model of channel coding structure classification constructed in this paper is shown in figure 1.

**IOP** Publishing

Journal of Physics: Conference Series

**2026** (2021) 012008 doi:10.1088/1742-6596/2026/1/012008



**Figure 1.** Illustration of network architecture based 1D Inception: (a) Network architecture; (b) Onedimensional Inception structure; (c) Detailed structure of Conv1d\_BN.

#### **3. Experiments**

#### 3.1. Datasets

This experiment uses MATLAB R2019a to generate data samples with different channel coding structures, that is, only channel-coded signals, channel-coded and interleaved signals, and channel-coded signals that are interleaved and pseudo-random sequence scrambled. In this paper, the channel coding is BCH code. The encoding method can be represented by [n, k], where *n* represents the length of the codeword, and *k* represents the length of the information. The interleaving uses convolutional interleaving, and the pseudo-random sequence scrambling uses the M sequence. After the input sequences are coded by channels of different structures, the coded signals are digitally modulated by BPSK, and then sent them to the additive white Gaussian noise channel to obtain outputs with error codes. Then, we demodulate the output signals and save the resulting signal sequences as data files.

In this paper, we have generated five kinds of parameter BCH codes, which are (7, 4), (15,11), (31,11), (31, 21), (31, 26). In the convolutional interleaver, we set the number of shift registers to 3 and the delay period to 2. And in scrambling, set the register feedback coefficient in the M sequence to "10001001". When passing through the additive white Gaussian noise channel, each type of signal will add a SNR in the range of 0dB-20dB. Under each SNR, the length of each type of signal is set to 1020 bits, 2000 data samples are generated, and datasets containing 630,000 signal samples is finally obtained. Divide the generated signal samples according to the ratio of training set: validation set: test set = 8:1:1 to generate training set, validation set and test set.

#### 3.2. Networking Training

Before network training, the data needs to be pre-processed. This paper uses the zero-mean normalization method to normalize the signal sequence value between [-1,1], which can be expressed as:

$$x = \frac{x - \mu}{\sigma} \tag{2}$$

where represents the mean of the series and is the standard deviation of the series.

The loss function is multi-class cross-entropy loss function, and the calculation formula is

$$C = -\frac{1}{n} \sum_{x} \left[ y \ln a + (1 - y) \ln (1 - a) \right]$$
(3)

where a is the actual output of the neuron and y is the expected output.

During training, we set batch size to 16, the maximum number of batch training for each iteration is set to 3000, the maximum number of training iterations epoch is 100, and the initial number of iterations is 1. Then input the training set into the network for training, and save the best classification result model as the final channel coding structure classification model of the experiment.



Figure 2. Classification accuracy curve.



Figure 3. Classification loss curve.

#### 3.3. Results

The experimental results of the network model on the training set and validation set are shown in figures 2 and 3. The former is the accuracy curve. The abscissa represents the number of iterations, and the ordinate represents the accuracy of the data set at each iteration. The dotted line represents the accuracy of the training set, and the solid line represents the accuracy of the validation set. The latter is the Loss value curve, the abscissa represents the number of iterations, and the ordinate represents the loss value of the data set at each iteration number. It can be seen from the figure that the accuracy rate increases to 0.96, and the loss function decreases to 0.09 when the curve converges and tends to stabilize, so the classification accuracy rate of this experiment is 96%. From this result, the network model has a good effect on the classification of the signal channel coding structure.

In order to verify the effectiveness of the network model, we input the test set into the trained network model, and the test results obtained are shown in table 1. The results show that the classification accuracy of the network for different coding structures can reach more than 95.00%. Besides, we test the correct classification probability of three types of signals with different coding structures under each SNR, and the result is shown in figure 4. Analyzing the three result curves of figure 4, we can conclude that the classification accuracy of signals with only BCH encoding under different SNR fluctuates at 0.95. And the other two types of signals with different coding structures reaches 1, when the SNR of the channel reaches 9dB. The above test results can show that the network classification method proposed in this paper can effectively classify the three types of signals with different coding structures.

Channel coding structure	Classification accuracy
ВСН	95.08%
BCH+ Convolutional interleaving	96.16%
BCH+ Convolutional interleaving +M sequence scrambling	95.67%





Figure 4. Accurate classification probability curves of three types of signals under different SNR.

## 4. Conclusion

This paper proposes a channel coding structure classification method based on one-dimensional Inception. This method is based on a multi-core parallel structure, which increases the network width while using different sizes of convolution kernels to extract richer features of the signal. The network model in this paper uses a cascade method to connect the multi-core parallel structure, convolutional normalization structure, max pooling layer, fully connected layer, etc., which increases the depth of the network. The generated signal data set is input into the network for training, and the training

accuracy is 96.50%. After that, the network model is tested on the data of the test set, and the classification accuracy is above 95.00%. It can be concluded that the network proposed in this paper is effective and feasible for channel coding structure classification. Compared with traditional methods, deep learning-based methods have the advantages of simple operation and low complexity, can effectively avoid the cumbersome steps of manually extracting signal features, can save a lot of labor costs, and are more universally applicable.

#### References

- [1] Gallager R 2008 Low-density parity-check codes *Journal of Circuits & Systems* 8 (1) 3-26.
- [2] Berrou C 1993 Near Shannon limit error-correcting coding and decoding: Turbo-codes *Proc. ICC93*.
- [3] Wang L X and Wang Y 2012 Blind recognition of binary primitive BCH codes parameters *Journal of Hebei University (Natural Science Edition).*
- [4] Valembois A 2001 Detection and recognition of a binary linear code *Discrete A ppl. Math.* **111** 199-218.
- [5] Barbierand J and Letessier J 2009 Forward error correcting codes characterization based on rank properties *Proc Wireless Communications & Signal Processing* pp 1-5.
- [6] Zhou J, et al. 2013 Information-dispersion-entropy-based blind recognition of binary BCH codes in soft decision situations *Entropy* **15** 1705-1725.
- [7] Lu L, Li K H and Yong L G 2009 Blind identification of convolutional interleaver parameters *IEEE International Conference on Information*.
- [8] Jia Y Q, Li L P and Li Y Z 2012 Blind estimation of convolutional interleaver parameters 8th International Conference on Wireless Communications, Networking and Mobile Computing pp 1-4.
- [9] Gautier R, Burel G, Letessier J and Berder O 2002 Blind estimation of scrambler offset using encoder redundancy *Conference Record of the Thirty-Sixth Asilomar Conference on Signals, Systems and Computers* pp 626-630.
- [10] Hinton G E, Osindero S and Teh Y 2006 A fast learning algorithm for deep belief nets *Neural Computation* **18** (7) 1527-1554.
- [11] Szegedy C, et al. 2015 Going deeper with convolutions *IEEE Conference on Computer Vision* and Pattern Recognition (CVPR) pp 1-9.
- [12] Mohapatra R K, Shaswat K and Kedia S 2019 Offline handwritten signature verification using CNN inspired by inception V1 architecture *Fifth International Conference on Image Information Processing (ICIIP)* pp 263-267.
- [13] Wang J, Wang W F and Wei S M 2019 Time series sequences classification with inception and LSTM module *IEEE International Conference on Integrated Circuits, Technologies and Applications (ICTA)* pp 51-55.
- [14] Liu J and Liu K 2019 Recognition of error correction coding based on deep learning *Electronic Measurement Technology*.
- [15] Peng C, Diao W and Du Z 2018 Digital modulation recognition based on deep convolutional neural network.
- [16] Simonyan K and Zisserman A 2015 Very deep convolutional networks for large-scale image recognition *3rd International Conference on Learning Representations*.
- [17] Lecun Y, Bengio Y and Hinton G 2015 Deep learning *Nature* **521** 436-444.
- [18] Glorot X, Bordes A and Bengio Y 2011 Deep sparse rectifier neural networks *Journal of Machine Learning Research* 15 315-323.
- [19] Kingma D P and Adam B J 2014 A method for stochastic optimization *arXiv:1412.6980*. http://arxiv.org/abs/1412.6980.