International journal of imaging science and engineering

ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

CNN APPROACH TO CHANNEL ENCODER CLASSIFICATION

GR. Harshith[1], B. Abhilash,[2], N. Pavan Kumar [3], V. Chandra Prakash [4]
[1,2,3] UG Scholar, Dept of IT, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
[4]Assistant Professor, Dept of IT, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
durgaprasadgatla@gmail.com

Abstract:

In digital communication systems, channel encoders play a crucial role in rectifying random errors introduced by the channel. Typically, information about the type and parameters of channel encoders used at the transmitting end is available at the receiver. However, in non-cooperative scenarios like military communication systems, encoder types and parameters may be only partially known or entirely unknown. This paper explores the feasibility of employing a deep learning approach to classify four different types of encoders: block, convolutional, Bose-Chaudhuri-Hocquenghem (BCH), and polar encoders. Utilizing a convolutional neural network (CNN) model for classification, our proposed approach achieves classification accuracy exceeding 95% upto bit-error- rate (BER) value of 0.03. The results also indicate that the accuracy improves with the input sample length.

Keywords: Convolutional neural network (CNN), channel encoder classification, deep learning, non-cooperative scenarios

1. INTRODUCTION

In digital communication, forward error-correcting (FEC) codes play a pivotal role in mitigating random errors at the transmitter [1]. Understanding FEC encoders at the receiving end is crucial for decoding. While some receiver systems possess prior knowledge of the encoder used at the trans- mitter, enabling successful decoding, situations arise where blind estimation of the channel encoder becomes imperative, particularly when the receiver lacks prior knowledge [2]. Con- sequently, various innovative techniques and algorithms for the blind reconstruction of channel encoders have been introduced. However, these advancements pose new challenges. Address- ing these challenges have significant implications, especially in non-cooperative communication scenarios, where accurate reconstruction of the channel encoder is vital for successfully decoding the signals from unknown sources. Blind recognition of channel encoder parameters can enhance spectral efficiency by conserving channel resources [1], [2]. The blind recovery of convolutional encoders has been explored in prior research, as seen in works such as [2] and [3], leveraging algebraic and dual reconstruction of a parallel concatenation of two recursive systematic convolutional (RSC) encoders using it- erative expectation-maximization (EM) and the least-square method. Methods in [6] were based on the rank deficiency of the data matrix for recognizing encoders parameters, while [7] employed hamming weight distribution for the same purpose. The authors introduced parameter estimation algorithms for Reed-Solomon (RS) codes, leveraging the count of non-zero columns and non-zero elements in the column echelon form of the data matrix. Recent literature explored blind identification of convolutional codes based on convolutional neural network (CNN) with accuracy above 90 %. Existing models, such as rank-based and mathematical algorithmic models, are sensitive to low signal-to-noise ratios and computationally complex. In contrast, our CNN model faces challenges with sequential dependencies in channel-encoded data, lacks memory for long- range dependencies, and may not inherently understand the physics of channel encoding.

A. Motivations and Contributions

Notably, while existing research has focused on employing deep learning techniques for recognizing individual FEC codes, there is a gap in addressing the classification of channel encoders using CNN. The principal objective of the proposed work is to leverage deep learning techniques for the classify- cation of four different channel encoders from the incoming noisy signal and assess the classification accuracy, specifically the probability of correct identification, under varying bit error rate (BER) conditions. We consider Hamming, convolutional, Bose-Chaudhuri-Hocquenghem (BCH), and polar encoders for the classification process.

The process of classifying the FEC encoders is illustrated in Fig. 1. Initially, a series of randomly generated information bits represented as $b = [b_1, b_2, ..., b_k]$ is introduced into the FEC encoder. This encoder manages the continuous information bits with a block size of k and produces an encoded data bit sequence with a block size of n, denoted as $c = [c_1, c_2, ..., c_n]$, where each c_i is an element of the Galois Field GF(2). The code rate is given by $r = k/n$, where k and n denote code dimension and codeword length, respectively. After encoding, the resultant digital sequence undergoes modulation before transmission through the communication channel. The selected modulation schemes include binary phase-shift keying (BPSK) at the transmitter. Upon arrival at the receiving terminal, the received signal undergoes demodulation to extract the data bits, represented as $y = [y_1, y_2, ..., y_n]$. After that the data bits are then transmitted to the FEC decoder for the retrieval of the original information bits. This research predominantly focuses on the autonomous identification or classification of encoders using a CNN model. The channel encoders under considera- tion find extensive applications in digital communication and storage systems, including satellite communications, wireless fidelity (Wi-Fi), and mobile communication standards like global system for mobile communications (GSM), code di-vision multiple access (CDMA), and 5G new-radio (NR).

A. Dataset Generation

In our experimental setup, MATLAB is employed to gen- erate datasets for four different coding schemes. We

International journal of imaging science and engineering
ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

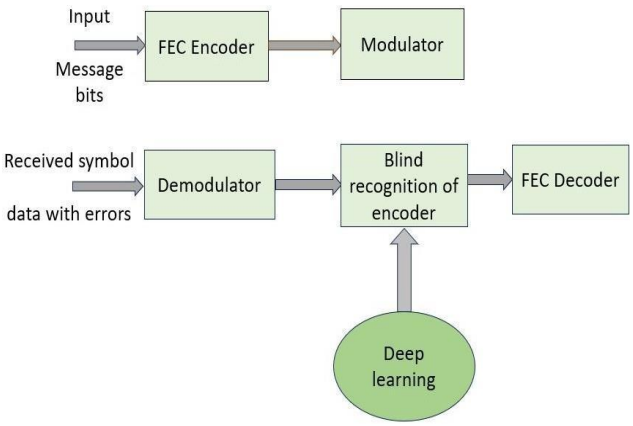


Fig. 1. Encoder classification process CNN-based blind encoder classification

assume successful demodulation of information signal at the receiving end, along with perfect frame synchronization. Consequently, we assume additive white Gaussian noise (AWGN) channel. The paper features four FEC codes, including polar code. Polar codes, being the first codes with explicit proof of achiev- ing channel capacity for symmetric binary-input, discrete, memoryless channels (B-DMC), are based on the concept of channel polarization. The reliability sequence is crucial for both encoding and decoding, defined using a generator matrix established recursively through the Kronecker product [9].

In contrast, block codes operate by segmenting data into fixed- size blocks, treating each independently. For our exper- iment, the choice is a Hamming block code, often applied for single- error correction. In addition, BCH codes, also falling under the category of block codes, are renowned for their robust error correction capabilities, proficient in addressing both randomand burst errors across diverse applications. On the other hand, convolutional encoder deviates from block codes as it operates on a continuous data stream. It utilizes a shift register to process input data bit by bit, combining shift register contents through modulo-2 additions to generate the encoded output.

Block codes are typically denoted as (n, k), where $r = n-k$ denotes the length of the parity or redundancy bits. The convo- lutional code described in this paper is denoted by (n, k, N_0), where N_0 represents the length of the coding constraint. The polar codes described in this paper are denoted by (N, K), where N represents the codeword length, always taking the form of an exponent of 2, i.e. 2^n ($n \geq 2$), and K represents

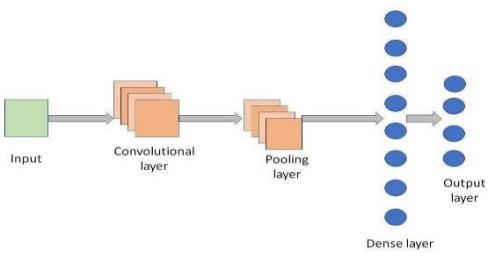
Fig. 2. Basic structure of CNN

the number of message bits. The difference $N-K$ corresponds to the number of frozen bits with reliability sequence Q [9].

2. LITERATURE SURVEY

Channel encoder, which includes a forward error correcting (FEC) code followed by an interleaver, plays a vital role in improving the error performance of digital storage and communication systems. In most of the applications, the FEC code and interleaver parameters are known at the receiver to decode and de-interleave the information bits, respectively. But the blind/semi-blind estimation of code and interleaver parameters at the receiver will provide additional advantages in applications such as adaptive modulation and coding, cognitive radio, non-cooperative systems, etc. The algorithms for the blind estimation of code parameters at the receiver had previously been proposed and investigated for known FEC codes. In this paper, we propose algorithms for the joint recognition of the type of FEC codes and interleaver parameters without knowing any information about the channel encoder. The proposed algorithm classify the incoming data symbols among block coded, convolutional coded, and uncoded symbols. Further, we suggest analytical and histogram approaches for setting the threshold value to perform code classification and parameter estimation. It is observed from the simulation results that the code classification and interleaver parameter estimation are performed successfully over erroneous channel conditions. The proposed histogram approach is more robust against the analytical approach for noisy transmission environment and system latency is one of the important challenges for the histogram approach to achieve better performance.

This paper gives a solution to the blind parameter identification of a convolutional encoder. The problem can be addressed in the context of the noncooperative communications or adaptive coding and modulations (ACM) for cognitive radio networks. We consider an intelligent communication receiver which can blindly recognize the coding parameters of the received data stream. The only knowledge is that the stream is encoded



International journal of imaging science and engineering
ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

using binary convolutional codes, while the coding parameters are unknown. Some previous literatures have significant contributions for the recognition of convolutional encoder parameters in hard-decision situations. However, soft-decision systems are applied more and more as the improvement of signal processing techniques. In this paper we propose a method to utilize the soft information to improve the recognition performances in soft-decision communication systems. Besides, we propose a new recognition method based on correlation attack to meet low signal-to-noise ratio situations. Finally we give the simulation results to show the efficiency of the proposed methods.

This paper investigates blind identification methods for linear scramblers under non-cooperative conditions, which are essential for the inverse analysis of communication protocols using scramblers. In this paper, a blind identification scheme for feedback polynomials of synchronous scramblers is proposed. A variable Y¯$\overline{\Upsilon }$ is first proposed that measures the correctness of the test polynomial by using the soft information of the received sequence, then the mean and variance of the variable Y¯$\overline{\Upsilon }$ in different cases are obtained, and finally the optimal threshold value to determine whether the test primitive polynomial is correct or not is obtained. That is, the blind identification problem is transformed into a hypothesis testing problem. The simulations verify that the proposed scheme requires a much smaller scrambled sequence length than existing blind identification schemes. Furthermore, the proposed scheme is more fault tolerant than existing schemes and has a signal-to- noise ratio (SNR) gain of at least 3 dB when the intercepted scrambled sequences are of the same length and high identification accuracy is achieved.

Blind estimation of forward error correction code parameters at the receiver plays a significant role in non-cooperative communication, adaptive modulation and coding systems, and reconfigurable receiver systems. Turbo convolutional codes, a parallel concatenation of multiple convolutional codes, are used in digital communication and storage systems to achieve low bit error rate. The present paper proposes innovative algorithms for the blind estimation of code parameters and reconstruction of turbo convolutional encoder over noisy scenario. The turbo convolutional code is designed using two component codes along with an interleaver. Recursive systematic convolutional codes are used as component codes. Any imperfection in synchronization of received data for the proposed code parameter estimation algorithm is compensated through a bit position adjustment parameter. The performance of the proposed algorithms in terms of parameter estimation accuracy is investigated for different modulation order, code rate, and constraint length values. It is observed that the performance improves with decrease in modulation order and constraint length values. Blind estimation of forward error correction code parameters at the receiver plays a significant role in non-cooperative communication, adaptive modulation and coding systems, and reconfigurable receiver systems. Turbo convolutional codes, a parallel concatenation of multiple convolutional codes, are used in digital communication and storage systems to achieve low bit error rate. The present paper proposes innovative algorithms for the blind estimation of code parameters and reconstruction of turbo convolutional encoder over noisy scenario. The turbo convolutional code is designed using two component codes along with an interleaver. Recursive systematic convolutional codes are used as component codes. Any imperfection in synchronization of received data for the proposed code parameter estimation algorithm is compensated through a bit position adjustment parameter. The performance of the proposed algorithms in terms of parameter estimation accuracy is investigated for different modulation order, code rate, and constraint length values. It is observed that the performance improves with decrease in modulation order and constraint length values.

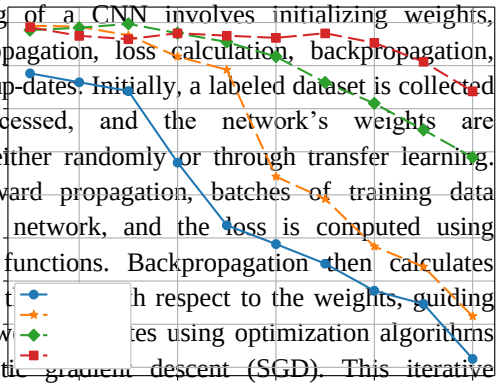
3. PROPOSED METHODOLOGY

A CNN architecture consists of key components [10], including an input layer, an output layer, and multiple layers for convolution, pooling, and fully-connected operations, as il- lustrated in Fig. 2. The input layer is designed to receive image or grid-like data. The core elements of a CNN are the convolu- tional layers, which employ multiple filters to extract features [11]. These filters conduct convolution operations across the input data, identifying patterns such as edges, textures, and basic shapes. Filters, also referred to as kernels, are small-sized matrices or tensors that convolve across the input data during the operation of convolutional layers. In the subsequent pool- ing layers, spatial dimensions of the feature maps are reduced while retaining crucial information. This reduction is achieved through commonly used pooling techniques like max-pooling and average-pooling. Finally, the features extracted from the previous layers are processed beyond the capabilities of fully- connected networks. This is accomplished through a softmax- based probability distribution.

A. CNN network learning

International journal of imaging science and engineering

ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025



The training of a CNN involves initializing weights, forward propagation, loss calculation, backpropagation, and weight up-dates. Initially, a labeled dataset is collected and preprocessed, and the network's weights are initialized, either randomly or through transfer learning. During forward propagation, batches of training data traverse the network, and the loss is computed using appropriate functions. Backpropagation then calculates gradients of t h respect to the weights, guiding subsequent w tes using optimization algorithms like stochastic gradient descent (SGD). This iterative process is repeated for multiple epochs and monitoring the validation loss is crucial for detecting potential overfitting.

B. Training and Testing

In this work, our Keras-based model uses cross-entropy loss and the Adam optimization algorithm with initial learning rate equal to 0.0001. Training and testing occur on a personal computer with 64 GB RAM and a core i9 processor in an

TABLE I

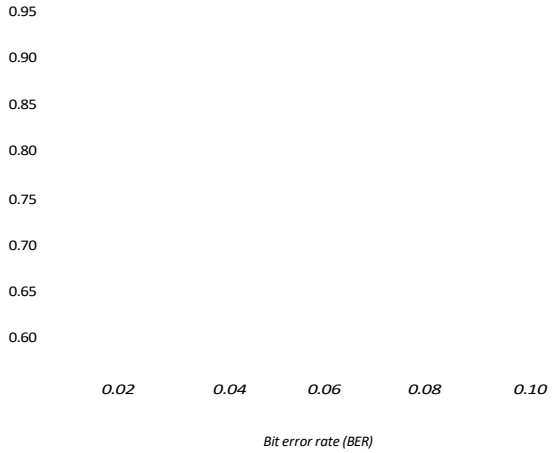
ARCHITECTURE SPECIFICATIONS OF THE CNN

Layer	Step size	Output size
Input	/	16384 × 1
Convolutional + ReLu	11 × 1/4	4094 × 96
Maxpooling	3 × 1/2	2046 × 96
Convolutional + ReLu	5 × 1/1	4094 × 128
Maxpooling	3 × 1/2	1022 × 128
Convolutional + ReLu	5 × 1/1	1022 × 192
Convolutional + ReLu	5 × 1/1	1022 × 192
Convolutional + ReLu	5 × 1/1	1022 × 128
Maxpooling	3 × 1/2	510 × 128
Global Average Pooling	/	128
Dense + ReLu	/	128
Dropout(0.5)	/	128
Dense + ReLu	/	64
Dropout(0.5)	/	64
Dense + Softmax	/	4

Anaconda Navigator environment. We generate a dataset of 10,000 samples, each 1000 in length (int32 format), allocating 80% for model training and 20% for evaluation. Further, we use one-dimensional (1-D) CNN model [10] and the specific details are outlined in Table I. Our goal is to assess the model's performance by calculating its classification accuracy using metrics like true positives (TP) and false positives (FP) for each encoder category as

$$\text{Accuracy(in \%)} = \frac{Tp}{TP + FP} \times 100$$

1.00



EXPERIMENTAL ANALYSIS

We adopt the Hamming code as the block en- coder, characterized by a codeword length of n = 7, code dimension k = 4, and generator matrix G = [1010011; 1001001; 0011011; 1000101]. Further, BCH code Is employed with n = 31 and k = 21. We consider a rate- 1/2 convolutional encoder with constraint length N_0 = 4 and generator polynomial g = [15, 17]. The fourth encoder utilized is a polar encoder with a reliability sequence of Q = 1024 for codeword length N = 16 and length of message bit K = 2.Following the training of the encoder dataset on the CNN model, we evaluated its performance using a dedicated test

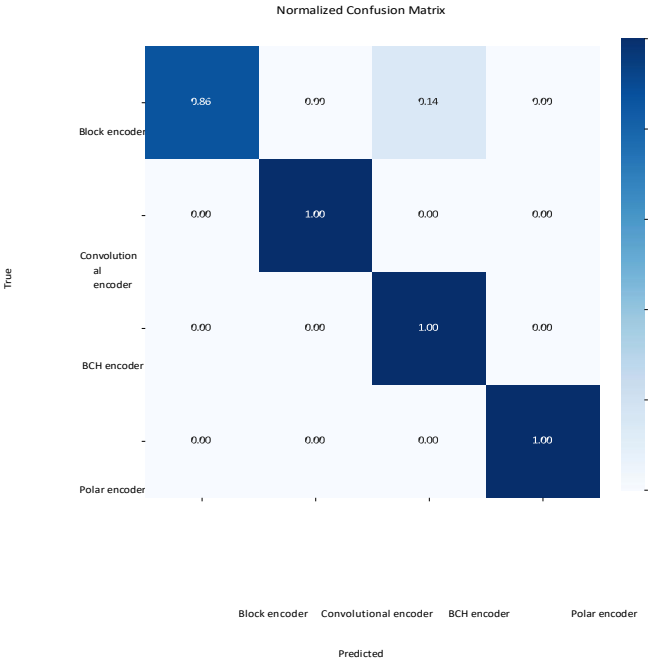


Fig. 4. Confusion matrix for the classification accuracy of encoders at 0.02 BER value

dataset. The classification accuracy of four distinct

ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

encoders (i.e. Hamming, BCH, convolutional, and polar) is illustrated in Fig. 3. The accuracy, as depicted in the figure, consistently surpasses 95% across varying input lengths for BER values below 0.03 and 100% for BER values less than 0.02, except for the input size 512. Notably, larger input sizes exhibit enhanced accuracy in the classification process. Fig. 4 presents the confusion matrix for encoder classification at an input size of 4096 and a BER of 0.02. Predicted values are rep- resented along the vertical axis, while test values are along the horizontal axis. In this matrix, dark blue squares signify the classification accuracy of encoders. The confusion matrix reveals that only the Hamming encoder exhibits an accuracy of 86%, whereas the remaining three encoders achieve a perfect 100% classification accuracy. This is because, Hamming codes introduce a relatively lower level of redundancy compared to other codes; hence, this lower redundancy results in fewer distinct patterns for the CNN to learn.

5. CONCLUSION

In this manuscript, we utilized a CNN model based on deep learning for the purpose of identifying the correct encoder among block, convolutional, BCH, and polar encoders over an AWGN channel. Our analysis of classification accuracy con- sidered varying input sample sizes, revealing that an increase in the input sample length correlates with higher accuracy. Notably, at lower BER, the accuracy consistently achieves 100% before reaching the BER value of 0.02.

REFERENCES

[1] R. Swaminathan and A. S. Madhukumar, "Classification of error correcting codes and estimation of interleaver parameters in a noisy transmission environment," IEEE Trans. on Broadcast., vol. 63, no. 3, pp. 463-478, Sept. 2017.

[2] M. Marazin, R. Gautier, and G. Burel, "Dual code method for blind identification of convolutional encoder for cognitive radio receiver design,"in Proc. IEEE GLOBECOM, Honolulu, USA, pp. 1–6, 2009.

[3] Y. Ding, Z. Huang, and J. Zhou, "An improved blind recognition method for synchronization position and coding Parameters of k/n rate convolutional codes in a noisy environment," IEEE Access, vol. 8, pp. 171305-171315, 2020.

[4] Y. G. Debessu, H.-C. Wu, and H. Jiang, "Novel blind encoder parameter estimation for turbo Codes," IEEE Commun. Lett., vol. 16, no. 12, pp. 1917–1920, Dec. 2012.

[5] ll Rev, vol. 53, no. 8, pp. 5455– 5516, Apr. 2020. convolutional and helical interleavers in a noisy environment," IEEE Access, vol. 5, pp. 6151-6167, 2017

[6] Swaminathan R, A. S. Madhukumar, N. W. Teck, and S. C. M. Samson, "Parameter estimation of.

[7] S. Wee, C. Choi, and J. Jeong, "Novel blind interleaver parameters estimation based on Hamming weight distribution of linear codes," Digital Signal Process., vol. 117, no. 103190, Oct. 2021.

[8] J. Wang, C. Tang, H. Huang, H. Wang, and J. Li, "Blind identification of convolutional codes based on deep learning," Digital Signal Process., vol. 115, no. 103086, Aug. 2021.

[9] P. Yu, J. Li, and H. Peng, "A least square method for parameter estimation of RSC sub-codes of turbo codes," IEEE Commun. Lett., vol. 18, no. 4, pp. 644–647, Apr. 2014.

[10] H. Song, Y. Chang and K. Fukawa, "Encoding and Decoding of Polar Codes for Frequency Selective Fading Channels," IEEE Vehicular Techno. Conf. (VTC), Helsinki, Finland, pp. 1-5, Aug. 2022.

[11] J. Wang, C. Tang, H. Huang, H. Wang, and J. Li, "Blind identification of convolutional codes based on deep learning," Digital Signal Process., vol. 115, no. 103086, Aug. 2021.

[12] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks," Artif Inte

[13] M. Marazin, R. Gautier, and G. Burel, "Dual code method for blind identification of convolutional encoder for cognitive radio receiver design,"in Proc. IEEE GLOBECOM, Honolulu, USA, pp. 1–6, 2009.

[14] P. Yu, J. Li, and H. Peng, "A least square method for parameter estimation of RSC sub-codes of turbo codes," IEEE Commun. Lett., vol. 18, no. 4, pp. 644–647, Apr. 2014.