Deep-Learning Based Blind Recognition of Channel Code Parameters over Candidate Sets under AWGN and Multi-Path Fading Conditions

Sepehr Dehdashtian, Matin Hashemi, Member, IEEE, and Saber Salehkaleybar, Member, IEEE

Abstract—We consider the problem of recovering channel code parameters over a candidate set by merely analyzing the received encoded signals. We propose a deep learning-based solution that I) is capable of identifying the channel code parameters for any coding scheme (such as LDPC, Convolutional, Turbo, and Polar codes), II) is robust against channel impairments like multi-path fading, III) does not require any previous knowledge or estimation of channel state or signal-to-noise ratio (SNR), and IV) outperforms related works in terms of probability of detecting the correct code parameters.

Index Terms—Blind Recognition, Channel Coding, Deep Learning, Channel Impairments

I. INTRODUCTION

Forward error correcting (FEC) codes have been utilized to improve the performance of communication systems by detecting or correcting the errors occurred during transmission through noisy channels. As more users join wireless networks, allocating communication resources like channel bandwidth become more challenging. Several approaches have been proposed to address the challenges in utilizing communication resources. One of the main approaches is to replace fixed transmission parameters with adaptive modulation and coding (AMC) in which the transmitter changes the modulation scheme and coding rate frequently to adapt to changing channel status. To achieve this goal, the receiver needs to be informed about transmission parameters with a signaling protocol whenever the transmitter adjusts these parameters. However, the main drawback of this approach is that the signaling messages from the transmitter to the receiver occupy part of the channel bandwidth.

To resolve this issue, blind recognition algorithms have been proposed to recover the transmission parameters without any signaling from the transmitter. In this scenario, the receiver tries to identify the parameters merely from the received encoded signal (Fig. 1).

The blind recognition algorithms have several applications in cognitive radio and wireless sensor networks. In cognitive radio networks, the intelligent receiver needs to adjust itself to specific configurations by blindly analyzing the received data. In wireless sensor networks, transmitters can adopt AMC techniques to choose different encoders of different rates and code-word lengths in order to reduce energy consumption or maximize bandwidth utilization [1], [2].

Previous approaches in blind recognition of channel codes fall in two main categories. In the first category, blind recognition algorithms aim at estimating unknown numerical parameters. For instance, code-word length \( n \) and information length \( k \) are estimated for convolutional codes in [3], [4], and for LDPC codes in [5], [6]. The elements of parity-check matrix for blocking codes are estimated in [7], [8]. As another example, interleaver parameters are estimated in [9]–[12] for convolutional codes [9] and Reed-Solomon codes [12].

The blind recognition algorithms in the second category, however, recover the parameter(s) only among a candidate set of parameters. This is because many standard AMC schemes do not freely adjust all possible parameters, and instead, only select among a set of pre-defined parameters [13]–[30]. Our solution falls in this category, i.e., recovers the code parameters among a candidate set.

In [13]–[16], the candidate set consists of different coding schemes. For instance, the blind recognition algorithm proposed in [16] recovers the selected coding scheme among QC-LDPC, SC-LDPC, and convolutional codes. In [17]–[30], however, the coding scheme is fixed and known, and the candidate set consists of different parameters for that coding scheme. This type is the focus of our work and we try to recover the code parameters for a specific coding scheme such as the code rate. For instance, IEEE 802.11n WiFi standard with code-word length \( n = 648 \), employs only four different LDPC codes with code rates \{1/2, 2/3, 3/4, 5/6\} [17].

Most previous methods are limited to additive white Gaussian noise (AWGN) channels [17]–[27], because they mostly rely on considering AWGN channel characteristics in the signal processing algorithms that recover the coding parameters. In most real applications, however, channel impairments such as fading and multi-paths effects need to be considered in devising a resilient solution. Recently, deep-learning based methods have been employed in blind recognition of coding parameters [13], [15], [16], [24]. Deep-learning based methods are more resilient to signal conditions compared to classical approaches.

This paper proposes a deep-learning based algorithm for recognition of channel code parameters over candidate set by blindly analyzing the received encoded signal. The main contributions of the proposed solution are as the following. I) The proposed method works for different coding schemes, and is not tied to any specific coding. II) It also works under any channel impairment settings, including AWGN, fading, or multi-path conditions. III) No previous knowledge of channel state or signal-to-noise ratio (SNR), or their estimation is
required in our method. IV) Experiment results show that the achieved accuracy is much higher compared to previous methods, across different coding schemes and signal conditions.

The rest of this article is organized as the following. Section II describes a basic digital transceiver model and reviews blind channel code recognition. Section III presents our blind recognition algorithm based on a deep neural network model. Section IV presents the results of applying our approach to different coding schemes and channel models. The proposed approach is also compared with previous works. Finally, we conclude the paper in Section V.

II. PRELIMINARIES

A. Basic Transceiver Model

The green blocks in Fig. 1 show a basic digital wireless transceiver model. At the transmitter side, message \( M \) with \( K \) bits is first encoded into codeword \( \hat{c} \) with \( n \) bits (\( K < n \)). Code rate \( R \) is defined as the ratio \( \frac{K}{n} \). Both \( M \) and \( \hat{c} \) are in Galois field of two, i.e., GF(2). Codeword \( c \) is formed based on generator matrix \( G \) as the following:

\[
c_{1 \times n} = M_{1 \times K} \cdot G_{K \times n}.
\]

Next, vector \( c \) is modulated, the result is converted to the analog domain, and frequency up-conversion is performed. Finally, the generated signal is transmitted through the wireless channel.

At the receiver side, after frequency down-conversion and demodulation, codeword \( \hat{c} \) is obtained. Due to non-idealities that exist in channel, transmitter, and receiver, \( \hat{c} \) is not necessarily equal to \( c \). Note that the demodulator provides every bit \( \hat{c}[i] \) in vector \( \hat{c} \) as a log-likelihood ratio (LLR) defined as

\[
\log \frac{P\{\hat{c}[i] = 0\}}{P\{\hat{c}[i] = 1\}}
\]

where \( P\{\hat{c}[i] = 0\} \) and \( P\{\hat{c}[i] = 1\} \) denote the probability of bit \( \hat{c}[i] \) taking value 0 and 1, respectively. The provided LLR values are processed by the decoder block in order to obtain message \( \hat{M} \).

B. Problem Definition: Blind Channel Code Recognition

There exist different parameters for a coding scheme. For instance, IEEE 802.11n WiFi standard employs four different LDPC codes with different code rates for code-word length

![Diagram](image.png)

Fig. 1: Green color: block diagram of a basic digital wireless transceiver model. Blue color: An additional block which automatically recognizes the channel code parameter.

Fig. 2: Proposed blind channel code recognition method.

\( n = 648 \). Normally, the parameters are adapted according to the channel conditions and desired data rates. Without blind recognition (i.e., without the blue box in Fig. 1), the selected code parameters (shown as vector \( \theta \) in Fig. 1) need to be sent to the receiver side as well. Code parameter vector \( \theta \) is required by the decoding block in order to correctly decode the message.

However, to save part of the bandwidth and to provide the possibility of continuous modifications, the overhead of this negotiation can be removed by having the receiver obtains the selected parameters (shown as \( \hat{\theta} \) in Fig. 1). This can be achieved by employing a blind channel code recognition algorithm. The algorithm analyzes the received data and automatically selects \( \hat{\theta} \) from a set of known candidates. For instance, in IEEE 802.11n WiFi standard with \( n = 648 \), the candidate set for \( \theta \) is the code rates \{1/2, 2/3, 3/4, 4/5, 5/6\}.

Similar to [17]–[30], we consider that the code parameters inside the candidate set are known, i.e., the set of corresponding generating matrices is known. It is noteworthy to mention that the problem addressed here is different from recognition of the coding scheme itself (e.g., recognition between LDPC and convolutional) as in [13]–[16].

III. PROPOSED RECOGNITION ALGORITHM

A. Deep-Learning Based Method

Fig. 2 illustrates a schematic of the proposed solution. First, in order to extract features, \( \hat{c} \) is processed by decoding blocks with parameters \( \theta_1, \theta_2, \cdots, \theta_m \). In other words, we decode \( \hat{c} \) for a known coding scheme with parameter \( \theta_j \) for \( j = 1, \cdots, m \). Every block represents one of the candidate parameters in the candidate set. The generated output vector from every block \( \theta_j \) is of size \( n \).

In [19], the average value for every output vector is computed, and the one with the maximum average is considered as the parameter \( \hat{\theta} \). This method is only accurate for high SNR ranges in AWGN channel. For lower SNR ranges and multipath fading channels, the output vectors need to be processed by more complex methods in order to accurately predict \( \hat{\theta} \).

In our proposed solution, however, every output vector is folded into a two-dimensional matrix of size \( \sqrt{n} \). All such reshaped 2D matrices are stacked to form a 3D feature matrix as shown in Fig. 2. Next, the extracted 3D feature matrix is processed by the following convolutional neural network model.

The neural network consists of four convolutional layers. Convolutional kernel sizes are \( 1 \times 1 \) in the first layer and \( 2 \times 2 \)
in the next layers. The employed activation function is ReLU. Batch normalization [31] is added after every convolution layer in order to reduce internal covariate shift and improve the performance.

Next, the output of the convolutional layers are fed into dense neural network layers in order to classify the code parameter $\theta$. In specific, this network consists of three dense layers along with ReLU activation functions and softmax. Dropout [32] is added after the non-linearity in order to apply regularization and avoid overfitting.

The output size of the last dense layer is $m$, i.e., the number of candidates. We employ cross-entropy (CE) as the loss function. The proposed neural network model is trained using back propagation. The employed optimization algorithm is Nadam.

B. Channel Models

Many previous works rely on analytical techniques which are often limited to the AWGN channel model [17]–[27]. The proposed deep-learning based solution, however, is capable of learning different hidden patterns in the signals and hence can support different channel conditions. We consider three channel models:

Model 1: AWGN channel adds zero mean Gaussian noise with $\sigma^2$ variance to the signal. The signal to noise ratio (SNR) is given by $\frac{a^2}{\sigma^2}$, where $a$ is the signal’s amplitude.

Model 2: Single-path Rayleigh channel models fading effects. Similar to [28], we consider Doppler frequency to gain ratio $f_D/f_s = 0.001$, where $f_D$ is the Doppler frequency and $f_s$ is the sample rate.

Model 3: The last channel model is dual-path Rayleigh channel that models the effects of both fading and multiple paths. We consider two paths and the same Doppler frequency as the previous channel model.

Note that one of the main advantages of our approach is that it does not require channel parameters such as signal-to-noise ratio (SNR) or channel state. This is in contrast to some other approaches that assume such parameters [19], [20], [22], [29] or estimate them with another algorithm [17], [18], [21], [28].

C. Training Method and Hyper-Parameter Selection

Our dataset consists of 100,000 codewords for every code parameter and every SNR value. The dataset is split in three portions, namely, train (60%), validation (20%), and test (20%). Training is performed for multiple epochs. In every epoch, train dataset is randomly shuffled and provided to the model. Training phase terminates when the loss function on validation dataset stops changing for 10 consecutive epochs.

There are a number of guidelines and recommendations for selecting the hyper-parameters in neural network based algorithms [33]. Here, for a certain set of hyper-parameters, the model is trained, and then, classification accuracy over the validation dataset is recorded. The procedure is repeated for different sets of hyper-parameters, and finally, the set of hyper-parameters that yields the highest recorded accuracy is selected.

We perform a grid search on the range of 3 – 5 for the number of convolution layers, 64 – 256 for the number of kernels in every convolution layer, 1 – 3 for the size of convolution kernels, and relu and tanh for the activation functions. We also perform a grid search on the range of 1 – 3 for the number of dense layers, 512 – 2048 for the number of their output neurons, and relu and tanh for the activation functions.

We found that the following hyper-parameter selections achieve the best results over the validation dataset. The number of convolution layers is selected to be equal to 4, and the number of kernels 128. In the first layer, the kernel size is 1, and in the other layers 2. The selected activation function is relu. The number of dense layers is selected to be equal to 3. In the first two dense layers, 1024 hidden neurons are used. The output dimension of the third dense layer is set equal to the number of the code parameters, i.e. $m$, in the candidate set. The selected activation function is relu. Dropout rate is set to 0.65.

IV. EXPERIMENTAL RESULTS

We experiment with four different channel codes, namely, LDPC codes, convolutional codes, turbo convolutional codes, and polar codes. Note that the proposed solution is not limited to any specific coding scheme. In each of the above four coding schemes, we consider the three channel models discussed earlier in Section III-B. The employed modulation is BPSK. To evaluate the effectiveness of the proposed solution, and also to quantitatively compare with previous works, probability of detection is defined as

$$\text{Probability of detection} = \frac{N_{\text{true}}}{N_{\text{total}}}$$

for every code parameter in a candidate set, where $N_{\text{true}}$ is the number of truly-classified samples, and $N_{\text{total}}$ is the total number of samples in that specific class. This is the same metric used in [17], [19], [29].

A. LDPC Codes

IEEE 802.11n (WiFi) standard with $n = 648$ is used to experiment with LDPC codes. The candidate set consists of four different LDPC codes with code rates $R = K/n = 1/2$, $2/3$, $3/4$, and $5/6$. This is the exact same candidate set as the blind channel code recognition method in [19]. Belief Propagation (BP) algorithm is employed to decode LDPC codes.

Fig. 3(a) presents the probability of detection among the LDPC codes, versus different SNR ranges, for the three channel models discussed in Section III-B, namely, AWGN, single-path Rayleigh fading, and dual-path Rayleigh fading channels with delay spread 10$\mu$s.

In addition, Fig. 3(a1) compares our results with the probability of detection in the blind channel code recognition method in [17] under AWGN channel. As the figure shows, the proposed solution achieves more accurate results compared to previous works. For example, at 0 dB SNR, the probability of detection is between 50% to 75% higher compared to [17]. The proposed method reaches about 100% accuracy at about 2 dB SNR while the method in [17] reaches this point at about 7 dB SNR. In addition, the probability of detection in all cases reaches above 60% after 0 dB SNR, and after 6 dB SNR, in the proposed solution and in [17], respectively.
Fig. 3: Probability of detection among different (a) LDPC codes, (b) convolutional codes, (c) turbo codes, and (d) polar codes, versus different SNR ranges, for AWGN channel (1st column), Rayleigh fading channel (2nd column), and multi-path Rayleigh fading channel (3rd column). The black curves show the results for previous works, i.e., [17], [19], and [24].

B. Convolutional Codes

The candidate set for the convolutional codes in our experiments consists of code rate $1/2$ with seven different generator polynomials (in octal representation) as the following: $C_1 = (5, 7)$, $C_2 = (15, 17)$, $C_3 = (23, 35)$, $C_4 = (53, 75)$, $C_5 = (133, 171)$, $C_6 = (247, 371)$, and $C_7 = (561, 753)$, and constraint length 3, 4, 5, 6, 7, 8, and 9, respectively. The information length $K$ is set to 50. This is the same candidate set employed in the blind channel code recognition methods in [18], [19], and [24]. Viterbi algorithm is employed to decode convolutional codes.

Fig. 3(b) presents the probability of detection versus different SNR ranges, for AWGN, single-path Rayleigh fading, and dual-path Rayleigh fading channels with delay spread 10µs. In addition, Fig. 3(b1) compares our results with the methods in [19] and [24]. As the figure shows, the proposed solution achieves more accurate results compared to previous works. For example, at 0 dB SNR, the probability of detection is between 70% to 85% which is higher than [19] and [24]. The proposed method reaches about 100% accuracy at about 4 dB SNR while the other methods reach this point at about 2 dB SNR.
C. Turbo Codes

The candidate set for the turbo codes in our experiments consists of two different length sequences as the following: \( T_1 = (33, 25, 17), T_2 = (15, 13, 24), T_3 = (27, 37, 15), T_4 = (25, 27, 37) \), and feedback sequence 33, 37, 35, and 31, respectively. Constraint length is 5 and information length is 400. Iterative turbo decoder algorithm is employed to decode the codes. Fig. 3(c) presents the probability of detection versus different SNR ranges, for AWGN, single-path Rayleigh fading, and dual-path Rayleigh fading channels with delay spread 120\( \mu \)s. The proposed method reaches more than 60% accuracy after about -5 dB SNR, -3 dB SNR, and 5 dB SNR under AWGN, fading and multi-path fading conditions, respectively.

D. Polar Codes

The candidate set for the polar codes in our experiments consists of four different rate-matched output length as the following: \( P_1 = 150, P_2 = 160, P_3 = 170, \) and \( P_4 = 180, \) with input length of 144. Successive-cancellation list decoder of length 8 is used as decoders in the parallel decoders stage. Fig. 3(d) presents the probability of detection versus different SNR ranges, for AWGN, single-path Rayleigh fading, and dual-path Rayleigh fading channels with delay spread 120\( \mu \)s. The proposed method reaches more than 60% accuracy after about 3 dB SNR, 10 dB SNR, and 13 dB SNR under AWGN, fading and multi-path fading conditions, respectively.

V. CONCLUSION

In this paper, we considered the problem of recovering channel code parameters over a candidate set from the received encoded data. We proposed to decode the data with different parameters in the candidate set by a common decoding algorithm and feed the stack of them to a convolutional neural network in order to recover the true code parameters. The proposed method works for any coding scheme and any channel impairment settings. Experiments showed the proposed method outperforms previous works in different coding schemes.

REFERENCES

[1] S. Hakimi and G. A. Hodaani, “Optimized distributed automatic modulation classification in wireless sensor networks using information theoretic measures,” IEEE Sensors Journal, vol. 17, no. 10, pp. 3079–3091, 2017.

[2] J. L. Xu, W. Su, and M. Zhou, “8 distributed modulation classification in the context of wireless sensor networks,” Building Sensor Networks: From Design to Applications, p. 141, 2017.

[3] M. Marzlin, R. Gautier, and G. Burel, “Blind recovery of k/n rate convolutional encoders in a noisy environment,” EURASIP Journal on Wireless Communications and Networking, vol. 2011, no. 1, p. 168, 2011.

[4] L. Huang, W. Chen, E. Chen, and H. Chen, “Blind recognition of k/n rate convolutional encoders from noisy observation,” Journal of Systems Engineering and Electronics, vol. 28, no. 2, pp. 235–243, 2017.

[5] A. Bonnard, S. Houcke, R. Gautier, and M. Marzlin, “Classification based on euclidean distance distribution for blind identification of error correcting codes in noncooperative contexts,” IEEE Transactions on Signal Processing, vol. 66, no. 6, pp. 2572–2583, 2018.

[6] S. Ramabadran, A. M. Kumar, W. Guohua, and T. S. Kee, “Blind recognition of ldpc code parameters over erroneous channel conditions,” IET Signal Processing, vol. 13, no. 1, pp. 86–95, 2018.

[7] G. Li, J. Liu, J. Long, C. Li, and G. Wu, “Blind recognition of binary linear block code,” in International Conference on Computer Systems, Electronics and Control, 2017, pp. 909–913.

[8] W. Wang, H. Peng, and L. Ji, “Blind identification of ldpc codes based on decoding,” in 2017 International Conference on Computer Technology, Electronics and Communication (ICCTEC). IEEE, 2017, pp. 998–1001.

[9] Y. Xu, Y. Zhong, and Z. Huang, “An improved blind recognition method of the convolutional interleaver parameters in a noisy channel,” IEEE Access, vol. 7, pp. 10175–101784, 2019.

[10] J. B. Tamakouwa, “Blind identification of block interleaved convolution code parameters,” Defence Science Journal, vol. 69, no. 3, pp. 274–279, 2019.

[11] C. Choi and D. Yoon, “Novel blind interleaver parameter estimation in a noncooperative context,” IEEE Transactions on Aerospace and Electronic Systems, vol. 55, no. 4, pp. 2079–2085, 2018.

[12] R. Swaminathan, A. Madhakumar, G. Wang, and T. S. Lee, “Blind reconstruction of reed-solomon encoder and interleavers over noisy environment,” IEEE Transactions on Broadcasting, vol. 64, no. 4, pp. 830–845, 2018.

[13] B. Shen, H. Wu, and C. Huang, “Blind recognition of channel codes via deep learning,” in 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP). IEEE, 2019, pp. 1–5.

[14] Y. Liu and F. Wang, “Blind channel estimation and data detection with unknown modulation and coding scheme,” arXiv preprint arXiv:1909.11306, 2019.

[15] J. Wang, J. Li, H. Huang, and H. Wang, “Fine-grained recognition of error correcting codes based on 1-d convolutional neural network,” Digital Signal Processing, vol. 99, p. 106655, 2020.

[16] Y. Ni, S. Peng, L. Zhou, and X. Yang, “Blind identification of ldpc code based on deep learning,” in International Conference on Dependable Systems and Their Applications. IEEE, 2020, pp. 460–464.

[17] T. Xia and H. C. Wu, “Novel blind identification of ldpc codes using average lrr of syndrome a posteriori probability,” IEEE Transactions on Signal Processing, vol. 62, no. 3, pp. 632–640, 2013.

[18] R. Moosavi and E. G. Larsson, “Fast blind recognition of channel codes,” IEEE transactions on communications, vol. 62, no. 5, pp. 1393–1405, 2014.

[19] P. Yu, H. Peng, and J. Li, “On blind recognition of channel codes within a candidate set,” IEEE Communications Letters, vol. 20, no. 4, pp. 736–739, 2016.

[20] C. Condo, S. A. Hashemi, and W. J. Gross, “Blind detection with polar codes,” IEEE Communications Letters, vol. 21, no. 12, pp. 2550–2553, 2017.

[21] Z. Wu, L. Zhang, and Z. Zhong, “A maximum cosinoidal cost function method for parameter estimation of rsc turbo codes,” IEEE Communications Letters, vol. 23, no. 3, pp. 390–393, 2018.

[22] Z. Wu, L. Zhang, Z. Zhong, and R. Liu, “Blind recognition of ldpc codes over candidate set,” IEEE Communications Letters, 2019.

[23] H. Sun, R. Liu, K. Tian, B. Dai, and B. Feng, “A novel blind detection scheme of polar codes,” IEEE Communications Letters, vol. 23, no. 8, pp. 1289–1292, 2019.

[24] X. Qin, S. Peng, X. Yang, and Y.-D. Yao, “Deep learning based channel code recognition using textcm,” in International Symposium on Dynamic Spectrum Access Networks, 2019, pp. 1–5.

[25] A. Jalali and Z. Ding, “Joint detection and decoding of polar coded 5g control channels,” IEEE Transactions on Wireless Communications, 2020.

[26] C. Condo, S. A. Hashemi, A. Ardakani, F. Ercan, and W. J. Gross, “Design and implementation of a polar codes blind detection scheme,” IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 66, no. 6, pp. 943–947, 2018.

[27] R. Swaminathan and A. Madhakumar, “Classification of error correcting codes and estimation of interleave parameters in a noisy transmission environment,” IEEE Transactions on Broadcasting, vol. 63, no. 3, pp. 463–478, 2017.

[28] T. Xia, H.-C. Wu, and S. Mukhopadhyay, “Ldpc encoder identification in time-varying flat-fading channels,” in 2014 IEEE Global Communications Conference. IEEE, 2014, pp. 3537–3542.

[29] Y. Liu, F. Wang, J. Zhang, B. Ai, and Z. Zhong, “Blind identification of ldpc codes in multipath fading channel via expectation maximization,” in IEEE Global Communications Conference (GLOBECOM), 2018, pp. 1–6.

[30] Y. Liu and F. Wang, “Blind data detection with unknown channel coding,” IEEE Communications Letters, 2020.

[31] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” arXiv preprint arXiv:1502.03167, 2015.

[32] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: a simple way to prevent neural networks from over-fitting,” The journal of machine learning research, vol. 15, no. 1, pp. 1929–1958, 2014.

[33] Y. Bengio, “Practical recommendations for gradient-based training of deep architectures,” CoRR, vol. abs/1206.5533, 2012.