

Estimation of Convolutional Interleaver in a Non-cooperative Context

Yoonji Kim*, Geunbae Kim*, Dongweon Yoon*

*Department of Electronics and Computer Engineering, Hanyang University, Seoul, Korea

dwyoona@hanyang.ac.kr

Abstract— In this paper, we propose the method for blind estimation of convolutional interleaver parameters in a non-cooperative context by analysing repetitive patterns in interleaved sequences. Simulation results verify that proposed method could effectively estimate convolutional interleaver parameters in a noisy environment.

Keywords— blind estimation, convolutional interleaver, gaussian elimination, rank, block code

I. INTRODUCTION

There have been various researches focused on the blind estimation of interleaver parameters exploiting the linear dependence in codewords in a non-cooperative context. If the data sequence is block channel encoded and then block or convolutionally interleaved before transmission, the parameters of interleaver can be estimated since there is a linear dependence between redundant bits and message bits of codeword remains after interleaving [1]-[7]. Especially, in the case of convolutional interleaver, there are repetitive patterns that can offer a clue to the interleaver parameters. In this paper, we propose a blind estimation method for convolutional interleaver parameters when the transmitted sequence is block channel encoded and convolutionally interleaved.

This paper is organized as follows: Section 2 briefly explains the analytical matrix method which used in the estimation process. Section 3 focuses on a blind estimation of interleaver parameters for block channel encoded and convolutionally interleaved data stream and shows simulation results. Section 4 gives conclusions.

II. DIVIDING CONVOLUTIONALLY INTERLEAVED SEQUENCE

To find out the repetitive interleaved patterns, we divide convolutionally interleaved data sequence into data blocks of an arbitrary length N_e and load the data blocks to an analytical matrix $H(N_e, L)$ column by column, on condition that $L \geq N_e$, where L is the number of columns in the matrix $H(N_e, L)$. If redundant bits are aligned in the same rows, the rank of $U(N_e, L)$ is smaller than N_e where $U(N_e, L)$ is the result of applying Gaussian elimination to $H(N_e, L)$ [8].

To identify the rank of $H(N_e, L)$, we define ρ_i as

$$\rho_i = \frac{\text{The number of '1' bits in the } i\text{-th row of } U(N_e, L)}{\text{The number of '0' bits in the } i\text{-th row of } U(N_e, L)}, \quad (1)$$

where $i = 1, 2, 3, \dots, N_e$.

In error-free conditions, if redundant bits are aligned in the same rows for specific N_e , the minimum value of the ρ_i converges to zero. Meanwhile, in a noisy channel, it converges near to zero, since there are some remaining bits in the rows of redundant bits.

As a simple example, for (7, 4) Hamming coded and convolutionally interleaved ($B=8, M=1$) sequences, we depict the minimum values of ρ_i of $U(N_e, L)$ in a noiseless channel and a noisy channel in Figure 1 and Figure 2, respectively.

As shown in Figure 1, the minimum values of the ρ_i converge to zero when $N_e = 56$ and $N_e = 112$. In other words, the ranks of are smaller than $H(N_e, L)$ when N_e is 56 and 112. This means that, in case of a convolutionally interleaved sequence, the redundant bits can be aligned in same rows in $H(N_e, L)$ for specific N_e , and the rank of $H(N_e, L)$ can be smaller than N_e .

However, as we previously mentioned, the minimum values of ρ_i are not zero but less than 0.1 at the BER of 10^{-2} in Figure 2. Therefore, in this example, for a noisy channel, if the minimum value of ρ_i converges under 0.1, we consider that rows of redundant bits are eliminated and rank of $H(N_e, L)$ is smaller than N_e .

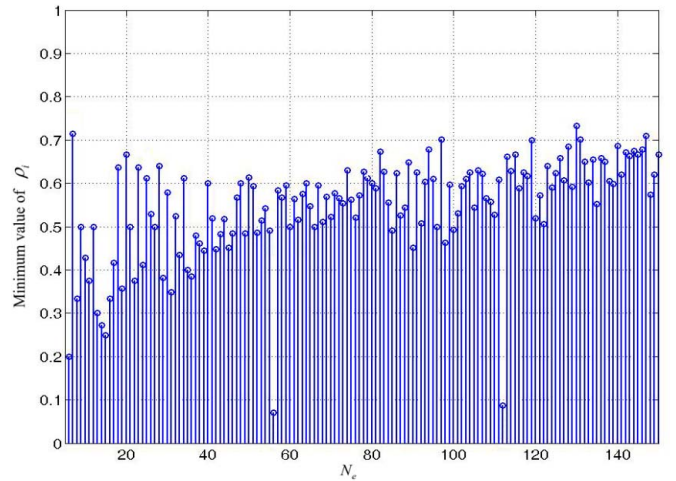


Figure 1. Minimum values of ρ_i of $U(N_e, L)$ for (7, 4) Hamming coded and convolutionally interleaved ($B=8, M=1$) sequence

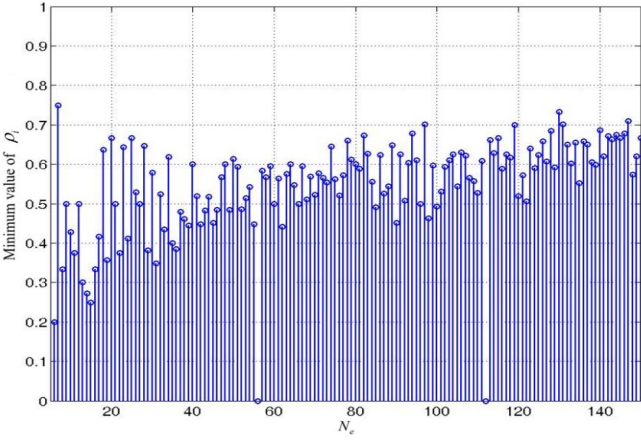


Figure 2. Minimum values of ρ_i in a noisy channel at BER of 10^{-2}

III. PROPOSED ALGORITHM

We discuss blind estimation of convolutional interleaving parameters with two cases: when codeword length is shorter than convolutional interleaving depth, and when they are equal. If codeword length is longer than convolutional interleaving depth, it is vulnerable to burst error compare to other cases. Therefore, we consider the above two cases.

We construct matrix $H(N_e, L)$ with received sequence while increasing N_e , and detect N_e when the minimum value of ρ_i is less than threshold obtained from simulations. We assume that $C^{(i)}$ is a block channel coded sequence and a codeword can be represented as $C^{(i)} = [C_1^{(i)}, C_2^{(i)}, \dots, C_k^{(i)}, C_{k+1}^{(i)}, \dots, C_n^{(i)}]$, where n is codeword length, k is the number of message bits and $i=1,2,3,\dots$.

A. Case 1: When Codeword Length Is Shorter Than Convolutional Interleaving Depth

Figure 3 depicts an analytical matrix consisting of convolutionally interleaved sequence when codeword length n is shorter than convolutional interleaving depth B .

As shown in Figure 3, when message bits and redundant bits are aligned in the same rows, the analytical matrix consists of data blocks of $n \times B \times M$ bits, i.e., $N_e = n \times B \times M$, where M is the size of shift register. Similarly, we can observe the next alignment when $N_e = n \times B \times M + n \times B$. Using these characteristics, we can derive the following relations which can estimate convolutional interleaver parameters,

$$M = \frac{n_a^{1st}}{n_a^{2nd} - n_a^{1st}}, \quad (2)$$

and

$$B = \frac{n_a^{2nd} - n_a^{1st}}{n}, \quad (3)$$

where n_a^{1st} and n_a^{2nd} are the values of N_e when the first alignment and the second alignment of redundant bits appear in

the same rows, respectively. Now, we can reduce the number of candidates of B and n .

B. Case 2: When Codeword Length Is Equal to Convolutional Interleaving Depth

When n is equal to B , repetitive interleaved patterns show different tendencies from the case 1. Figure 4 depicts an analytical matrix consist of convolutionally interleaved sequence when the first alignment of message bits and redundant bits appears.

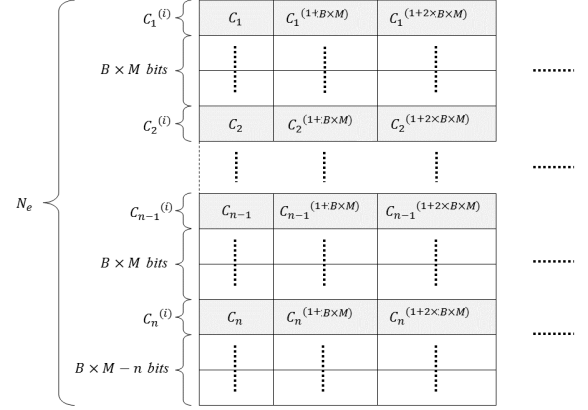


Figure 3. Analytical matrix with convolutionally interleaved sequence for $n < B$

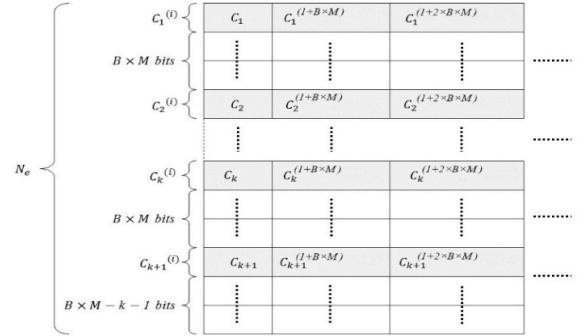


Figure 4. Analytical matrix with convolutionally interleaved sequence for $n = B$

As shown in Figure 4, the first alignment of message bits and redundant bits appears when $N_e = (M \times k + 1) \times B$ (after $M \times k + 1$ times rotating), since the first redundant bit is included in the output sequence of convolutional interleaver for the first time after $M \times k + 1$ times rotating. In the same way, we can observe the second alignment when $N_e = (M \times k + 1) \times B + B$. Using these characteristics, we can also derive the following relations which can estimate convolutional interleaver parameters,

$$M = \left(\frac{n_a^{1st}}{B} - 1 \right) / k, \quad (4)$$

and

$$B = n_a^{2nd} - n_a^{1st}. \quad (5)$$

Therefore, we can reduce the number of candidates of M and k . With these reduced candidates, we perform convolutional deinterleaving, and then verify which value is correct parameter.

C. Simulation Results

We validate the proposed algorithm by computer simulations. We assume a binary symmetric channel and perform 1,000 Monte Carlo simulations for each BER, where for simplicity we set $\rho_i=0.1$ as the threshold for detection, and $M=1$.

As shown in Figure 5, the detection probabilities increase as the code rate decreases, since the detection of N_e becomes obvious as the portion of redundant bits in a codeword increases. Note that, for the same value of B , (15, 11) Hamming and BCH codes show almost the same detection probabilities, since they have the same code rate. We can expect that the proposed algorithm can effectively estimate convolutional interleaver parameters.

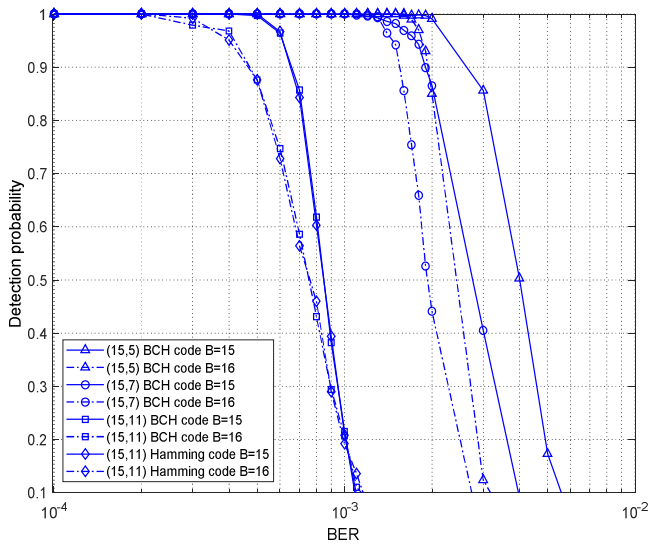


Figure 5. Detection probabilities of convolutional interleaver parameters

IV. CONCLUSIONS

In this paper, we proposed the method which can blindly estimate convolutional interleaver parameters, e.g., interleaving depth and the size of shift register especially when the transmitted data are block channel encoded and convolutionally interleaved. We first found the repetitive patterns in interleaved sequences for two cases: when codeword length is shorter than convolutional interleaving depth, and when they are equal. By exploiting the linear dependence between redundant bits and message bits that remains in a codeword after convolutional interleaving, we derived equations that can estimate the interleaving depth and the size of shift register. Through computer simulations in noisy channels, we presented detection probabilities of convolutional interleaver parameters, and showed that proposed method could effectively estimate convolutional interleaving parameters.

ACKNOWLEDGMENT

This work was supported by the research fund of Signal Intelligence Research Center supervised by Defense Acquisition Program Administration and Agency for Defense Development of Korea.

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Yoonji Kim received the B.S. degree in electronic engineering from Hanyang University, Seoul, Korea, in 2019, where she is currently pursuing the M.S. degree with the Department of Electronics and Computer Engineering. Her research interests are in digital communication theory and wireless communications.



Geunbae Kim received the B.S., M.S. and Ph.D. degrees in electronic communications engineering from Hanyang University, Seoul, Korea, in 1991, 1993 and 2012, respectively. He is currently a Research Professor of the Signal Intelligence Research Center, Hanyang University. His research interests include channel coding, signal intelligence and wireless communications.



Dongwon Yoon received the B.S. (summa cum laude), M.S. and Ph.D. degrees in electronic communications engineering from Hanyang University, Seoul, Korea, in 1989, 1992 and 1995, respectively. From March 1995 to August 1997, he was an Assistant Professor in the Department of Electronic and Information Engineering of Dongseo University, Busan, Korea. From September 1997 to February 2004, he was an Associate Professor in the Department of Information and Communications Engineering of Daejeon University, Daejeon, Korea. Since March 2004, he has been on the faculty of Hanyang University, Seoul, Korea, where he is now a Professor in the Department of Electronic Engineering and the Director of Signal Intelligence Research Center. His research interests include digital communications theory and system, detection and estimation, satellite and space communications, and wireless communications.