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Tail-biting LDPC convolutional codes over power line communication system

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Abstract

A study of low-complexity tail-biting LDPC convolutional code to power line communications has not been reported. The performance of this code is investigated under various channel and code conditions. Results show that the application of tail-biting LDPC convolutional code to power line channel is excellent. Moreover, tail-biting LDPC convolutional code can provide the identical performance comparing to LDPC block code over power line channel.

Keywords: LDPC convolutional codes, Tail-biting, Power line communications

1. Introduction

Power lines used in household serve as the medium in supplying power to electrical appliances. Besides, there is enough bandwidth to be used for data transfer. The communication using power lines as a medium or a channel is called "Power Line Communications (PLC)". However, many electrical appliances cause the impulsive noise on power line channels which is the most problematic for PLC channels. Middleton's class A noise model [1] is usually used as the model of impulsive noise environment of PLC channels.

Low-density parity-check (LDPC) codes, first proposed by Gallager [2], can achieve the performance equivalent to Shannon limit [3]. However, the disadvantage of LDPC codes is that they require highly complex encoder. Later, the LDPC convolutional codes were proposed by Felstrom and Zigangirov [4]. These codes can transmit data in bit stream of arbitrary length and low complexity encoding. Nonetheless, the LDPC convolutional codes need a *zero-tail* for the termination of codes which causes unavoidable *code rate loss*. Then, the tail-biting LDPC convolutional codes are introduced [5] to avoid this loss while the same decoding performance and complexity are maintained.

The rest of this paper is organized as follows. The overview of Middleton's class A noise model, LDPC convolutional codes and tail-biting LDPC convolutional codes are described in section 2. Section 3 shows the simulation results. Finally, conclusions are given in section 4.

2. Background

2.1 Middleton's class A noise model

Middleton's class A noise model composes of sum of Gaussian noise and impulsive noise. Class A noise model is known to represent the noise on power line. [6] The probability density function of the noise amplitude is as follows

$$p(z)=\sum_{m=0}^{\infty}\frac{e^{-A}A^m}{m!}.\frac{1}{\sigma_m\sqrt{2\pi}}\exp\left(-\frac{z^2}{2\sigma_m^2}\right),$$

$$\sigma_m^2=\sigma^2\frac{(m/A)+\Gamma}{1+\Gamma}.$$

where, A is the impulsive index which is the density of the impulsive noise in unit time. If the value of A is high, so it causes the error in the transmitted signal. $\Gamma=\frac{\sigma_G^2}{\sigma_I^2}$ is the GIR (Gaussian-to-impulsive noise power ratio). If the value of GIR is lower than 1 that means the impulsive noise power is more than Gaussian noise power, it also causes the transmitted signal error. σ_G^2 is Gaussian noise power. σ_I^2 is impulsive noise power. σ_m^2 is class A noise power. $\sigma^2=\sigma_G^2+\sigma_I^2$ is the total noise power and z is noise amplitude.

2.2 LDPC convolutional codes

In this section, the basic concept of LDPC convolutional codes of code rate $\frac{b}{c}$ is briefly described. The information sequence is defined to be

$$\mathbf{u}_{[0,t]}=(u_0,u_1,\ldots,u_t),$$

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where $u_i = \left(u_i^{(0)}, u_i^{(1)}, \ldots, u_i^{(b-1)}\right), u_i^{(\cdot)} \in \{0,1\}$,
the codeword sequence is given by

$$\mathbf{v}_{[0,t]} = (v_0, v_1, \ldots, v_t),$$

where $v_i = \left(v_i^{(0)}, v_i^{(1)}, \ldots, v_i^{(c-1)}\right), v_i^{(\cdot)} \in \{0,1\}$.

A time-varying LDPC convolutional codes is defined as the set of all sequences $v_{[0,\infty]}$ satisfying the equation

$$\mathbf{v}_{[0,\infty]}\mathbf{H}_{[0,\infty]}^T = 0,$$

where

$$\mathbf{H}_{[0,\infty]}^T = \begin{pmatrix} H_0^T(0) & \cdots & H_{m_s}^T(m_s) & & 0 & \\ & \ddots & & \ddots & & \ddots \\ 0 & & H_0^T(t) & \cdots & H_{m_s}^T(t+m_s) & \\ & & \ddots & & \ddots & \end{pmatrix} \quad (1)$$

$H_{[0,\infty]}^T$ is a semi-infinite transposed parity-check matrix, called *syndrome former*. For a rate $\frac{b}{c}$, the elements of $H_{[0,\infty]}^T$ are sub-matrices of dimension $c \times (c-b)$ given by

$$H_i^T(t) = \begin{pmatrix} h_i^{1,1}(t) & \cdots & h_i^{1,c-b}(t) \\ \vdots & \ddots & \vdots \\ h_i^{c,1}(t) & \cdots & h_i^{c,(c-b)}(t) \end{pmatrix}, \quad i = 0,1,\ldots,m_s,$$

where, t is time-instant and $H_{m_s}^T(t) \neq 0$. The value m_s is the *syndrome former memory*. With this structure, the LDPC convolutional codes are called *periodical LDPC convolutional codes*. One of the most popular methods for constructing periodical LDPC convolutional codes is unwrapping technique, see [4] for details.

2.3 Tail-biting LDPC convolutional codes

The tail-biting technique can avoid code rate loss of the LDPC convolutional codes by wrapping the last $(c-b) \cdot m_s$ columns of the syndrome former in (1) after N time instants. The code sequences $\tilde{\mathbf{v}}_{[0,N-1]}$ of the tail-biting LDPC convolutional codes satisfy the equality.

$$\tilde{\mathbf{v}}_{[0,N-1]}\tilde{\mathbf{H}}_{[0,N-1]}^T = 0.$$

Thus $\tilde{\mathbf{H}}_{[0,N-1]}^T$ can be written as

$$\tilde{\mathbf{H}}_{[0,N-1]}^T = \begin{pmatrix} H_0^T(0) & H_1^T(1) & \cdots & H_{m_s}^T(m_s) & 0 & & \cdots & & 0 \\ 0 & H_0^T(1) & \cdots & H_{m_s-1}^T(m_s) & H_{m_s}^T(m_s+1) & 0 & \cdots & & 0 \\ & \ddots & & & \ddots & & & \ddots & \\ H_{m_s}^T(N) & 0 & & \cdots & & 0 & H_0^T(N-m_s) & \cdots & H_{m_s-1}^T(N-1) \\ H_{m_s-1}^T(N) & H_{m_s}^T(N+1) & 0 & & & & & & \vdots \\ \vdots & & & & & & 0 & H_0^T(N-2) & H_1^T(N-1) \\ H_1^T(N) & H_2^T(N+1) & \cdots & H_{m_s}^T(N+m_s-1) & 0 & & \cdots & 0 & H_0^T(N-1) \end{pmatrix}$$

Tail-biting LDPC convolutional codes can be considered as both block or convolutional codes and can design the parity-check matrix by using the small size base matrix. Therefore, tail-biting LDPC convolutional codes can be encoded like the convolutional codes and the encoding algorithm for LDPC block codes can also be used.

2.4 Log-likelihood ratio of LDPC decoding for PLC channel

In this research, the log-likelihood ratio (LLRs) of LDPC decoder, proposed by Nakagawa [7], which is suitable for PLC channel is used. It is commonly known that PLC channel differs from additive white Gaussian noise (AWGN) channel. The appropriate LLRs for AWGN channel is

$$LLR_G(y_n) = \frac{2y_n}{\sigma^2}.$$

If LLR_G is used to decode LDPC codes on PLC channel, BER performance will be decreased. Therefore, the appropriate LLRs for PLC channel can be defined as

$$LLR_A(y_n) = \ln \sum_{m=0}^{\infty} \frac{A^m}{m!}\frac{1}{\sigma_m}\exp\left(-\frac{(y_n-1)^2}{2\sigma_m^2}\right) - \ln \sum_{m=0}^{\infty} \frac{A^m}{m!}\frac{1}{\sigma_m}\exp\left(-\frac{(y_n+1)^2}{2\sigma_m^2}\right). \quad (2)$$

Where, y_n is amplitude of received signal.

3. Simulation results

In this section, the performances of tail-biting LDPC convolutional codes are investigated. All simulation results are performed by BPSK system over PLC channels.

Figure 1 presents performance comparison between tail-biting LDPC convolutional codes over PLC channels for LLR_A and LLR_G at similar block length N=1200. At BER equal to 10^{-4}, the LLR_A codes provide significant coding gain over the LLR_G codes by approximately 7-8 dB for both iterations of decoding.

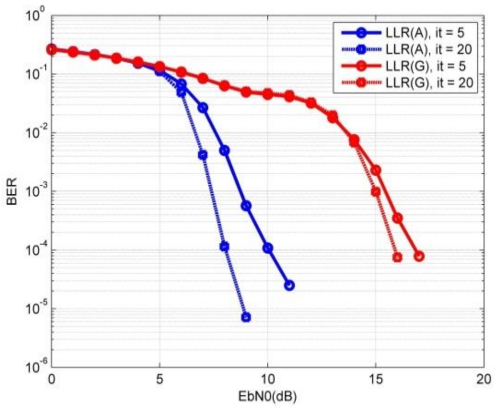

Figure 1 BER performance comparison between tail-biting LDPC convolutional codes using LLR_A and LLR_G.

Figure 2 shows the performance of tail-biting LDPC convolutional codes with various A and GIR with block length N=1200. On the left figure, the BER performance improves with the decrease of A. Because the A value is proportional to the density of the impulsive noise. On the right figure, it is obviously seen that the BER performance improves with the increase of GIR because the GIR value is inversely proportional to impulsive noise power.

Figure 3 shows the performance of tail-biting LDPC convolutional codes with various block lengths and iterations of decoding. On the left figure, the BER performance improves when block length is increasing. On the right figure, it is seen that the BER performance improves when the number of iterations of decoding is increasing. However, the BER performance is saturated at the iteration number of 20.

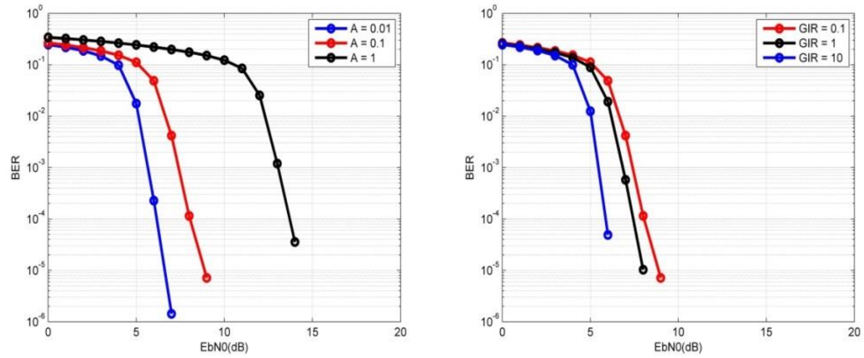

Figure 2 BER performances of tail-biting LDPC convolutional codes increasing A and GIR.

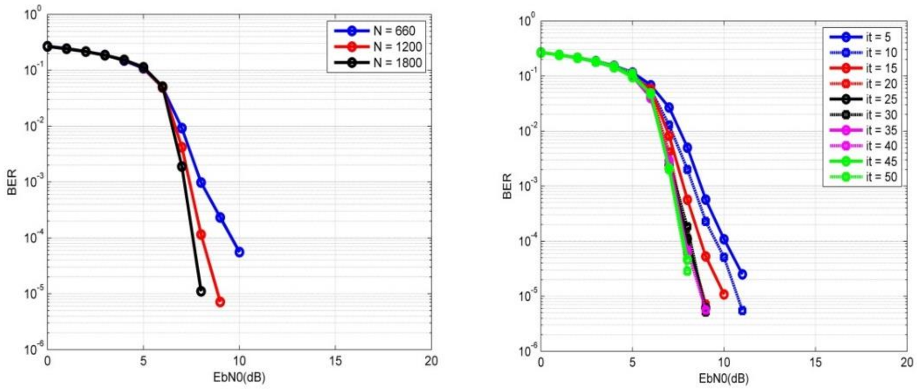

Figure 3 BER performances of tail-biting LDPC convolutional codes increasing block length and number of iterations of decoding.

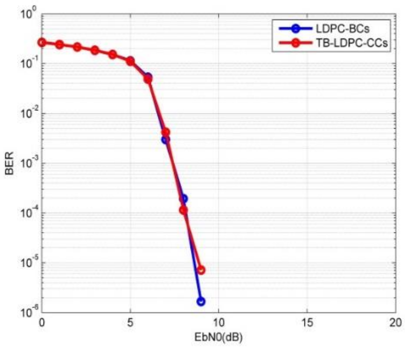

Figure 4 BER performance comparisons between tail-biting LDPC convolutional codes and LDPC block codes over PLC channels.

Figure 4 shows the performance comparison between tail-biting LDPC convolutional code and LDPC block code over PLC channels with block length $N = 1200$. From the figure, the performances of both codes are identical. However, the complexity of tail-biting LDPC convolutional codes is less than that of LDPC block code. This is because tail-biting LDPC convolutional codes can be designed from small size base matrix, as discussed in Section 2.3, and the tail-biting LDPC convolutional codes can be encoded like conventional LDPC convolutional codes [5].

4. Conclusions

In this paper, tail-biting LDPC convolutional codes over PLC channels are investigated. The BER performance of tail-biting LDPC convolutional codes depends on impulsive index and Gaussian- to- impulsive noise power ratio. Comparing with LDPC block codes, the tail-biting LDPC convolutional codes can provide the same BER performance with lower encoding and decoding complexities.

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