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Joint Channel Coding based on LDPC Codes with Gaussian Kernel Reflecton and CS Redundancy

Fei Zhong, Shuxu Guo* and Xu Xu

College of Electronic Science and Engineering, Jilin University, Changchun, Jilin, P. R. 130012, China

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Abstract: This paper proposes a new joint decoding algorithm frame based on compressed sensing CS and LDPC (Low-Density Parity-Check) codes. Redundant information can be effectively extracted and amplified by CS reconstruction as a compensation to correct decoding of LDPC codes. We adopt Gaussian kernel function of image segmentation as a reflection. Simulation results indicate, compared with LDPC algorithm, the algorithm presented in this paper can obviously make BER (bit error ratio) lower and improve system decoding performance, and different variance of Gaussian kernel function can obtain different results.

Keywords: Compressed sensing (CS), joint channel coding, low-density parity-check (LDPC) codes, Gaussian kernel function, joint decoding.

1 Introduction

Compressed sensing (CS) was developed from signal sparse decomposition and approximate theory by Donoho [1] and Cands [2], etc. CS is a new signal processing theory that processes signal data by collecting, encoding and decoding. It can be shown that we can obtain a precise reconstruction of a signal using only limited linear measurement. Therefore, CS is extensively using for different kinds of areas. The main areas of research are rapid decoding algorithm and application for image compression, etc.

LDPC (Low-Density Parity-Check) codes are a kind of linear error correcting code that was originally invented by Gallager in 1962. Due to a lack of analysis tools, LDPC was not paid extensive attention to until the mid 20th century. Mackay and Neal rediscovered LDPC codes. LDPC codes [3] can achieve a remarkable performance of iterative decoding that is very close to the Shannon limit. Consequently, LDPC codes have become one of high-attention points in channel coding area. Many efforts have been made in decoding algorithms [4–6].

Unfortunately, LDPC codes can not transmit without error. To alleviate this problem, we propose joint channel coding to overcome the problem in communication systems. Making use of redundant information in the receiver to perform joint decoding and checking for errors is the key point for this paper. In this paper, based on CS and LDPC codes, we propose a joint channel coding algorithm, which aims to reduce system BER and improve coding performance. This paper is organized as follows: LDPC and CS codes are shown in Section II. In Section III, we introduce the system model for joint channel coding algorithm. In Section IV, we apply Gaussian kernel function of image segmentation as reflection and specify the proposed joint channel coding algorithm. Section V presents the simulation result and information parameter analysis which have influence on joint decoding system.

2 The delayed Dalgaard and Strulik model

2.1 LDPC Codes

LDPC codes are usually described by (N, d_v, d_c) , where N is the length of the codeword, d_v and d_c respectively denoted the degrees of check nodes and variable nodes. Given M=N-k, M is checking bit and k is information bit. Let $x = (x_1, x_2, \dots, x_N)$ be a codeword that is encoded with a LDPC parity check matrix*H*. The codeword *x* is transmitted over an additive white Gaussian noise (AWGN) channel. At the output of the channel, $x = (y_1, y_2, \dots, y_N)$ is obtained. [10]

^{*} Corresponding author e-mail: guosx@jlu.edu.cn



2.2 Compressed sensing

A signal *u* can be described as a linear combination of a group of sparse basis as below: $\Psi^T = (\Psi_1, \Psi_2, \dots, \Psi_M)$ Then we can get *u*:

$$u = \sum_{k=1}^{N} \Psi_k \alpha_k = \Psi \alpha \tag{1}$$

Here exchange coefficient vector α is $N \times 1$ matrix. *u* is $N \times N$ matrix which is also the sparse basis of signal. We define

$$w = \Phi u \tag{2}$$

 Φ is measurement matrix as below: $\Phi := [\Phi_1^T, \Phi_2^T, \dots, \Phi_M^T]$ Observation vector can be described as:

$$w = \Phi u = \Phi \Psi \alpha \tag{3}$$

Theoretical proof, under the conditions of known observation vector *w* and measurement matrix ϕ , we can accurately reconstruct unknown signal *u* from observation vector*w* by means of solving optimal norm l_0 [7,8]:

$$\hat{u} = \min \|u\|_0 \tag{4}$$

CS reconstructed algorithm mainly include Basis Pursuit (BP), Matching Pursuit (MP) and Orthogonal Matching Pursuit (OMP) [9]. Unlike BP and MP need a large number of iterations for a large block size giving rise to a large number of computations, OMP makes selected atomic set orthogonal by recursion to ensure the iterative optimization. Therefore, we adopt OMP as reconstructive algorithm.

3 Joint Channel Codes System Model

Shannon has proposed: any redundant information which is not eliminated by source coding could weaken the influence of noise in receiver. Joint channel coding is making use of probability structure form of source redundant information by statistics to lower decoding error in receiver. In this paper, we propose the joint channel coding based on CS and LDPC codes. On image segmentation, due to a kernel function in the data fitting term, intensity information in local regions is extracted [12]. We lead this idea into the channel coding. In the sender, signal is encoded by LDPC codes; and sent into channel. In the receiver, the received signal is respectively sent into LDPC decoder and CS codec. Contrasting with original signal and reconstructive signal of CS algorithm, we can obtain information residual difference. We adopt Gaussian kernel function of image segmentation as a reflection to process information residual difference. This redundant information can be extracted and amplified as a-priori information, which is sent into LDPC decoder as compensation. Fig. 1 is principle diagram for joint channel coding based on both CS and LDPC.



Fig. 1 Principle diagram for joint channel coding based on both CS and LDPC.

4 Joint Channel Coding algorithm

Joint channel decoding presented in this paper is integrating min-sum decoding algorithm with CS coding. Min-sum algorithm (MSA) is simplified from belief propagation (BP) algorithm [11]. Joint channel decoding can be represented by the following steps:

Step 1, Initialization All variable nodes are initialized using original information from channel transmitting.

$$Q_{ij} = LLR(y_i) = \log \frac{P(x_i = 1/y_i)}{P(x_i = -1/y_i)} = y_i$$
(5)

Step 2, Information update from check nodes to variable nodes

$$R_{ij} = \left(\prod_{i \in R_{j/i}} sign(Q_{ij})\right) \min_{i \in R_N} |Q_{ij}|$$
(6)

Step 3, Information update from variable nodes to check nodes

$$Q_{ij} = LLR(y_i) + \sum_{j \in C_{i/j}} R_{ij} \tag{7}$$

Step 4, Calculating posterior probability

$$Q_{ij} = LLR(y_i) + \sum_{j \in C_i} R_{ij}$$
(8)

Step 5, Results of judgment

if
$$Q_{ij} < 0 \ \hat{x}_i = 1 \ else \ \hat{x}_i = 0$$
 (9)

In other words, we reconstruct signal by CS algorithm. Contrasting with signal and reconstructive



signal, we can obtain information residual difference. On image segmentation, because of a kernel function in the data fitting term, intensity information in local regions is extracted, we lead this idea into the channel coding. What we defined Gaussian kernel is counterbalancing the signal distance. As a reflection, Gaussian kernel function of image segmentation is amplifying redundant difference weight of reconstructive signal [12]. This CS redundant information can be extracted and amplified as the a-priori information. We use such information as compensation to correct decoding of LDPC codes. By formula (12) transformation, information redundancy can be extracted effectively. As the a-priori information, information redundancy rectifies LDPC decoding. Here Gaussian kernel function is formulated as:

$$P_1(n) = \frac{1}{\sqrt{2\pi N_0}} exp(-\frac{(v-u)^2}{2\sigma^2})$$
(10)

We substitute transforming signal and CS reconstructive signal into formula (10), and then amplify it properly. Given

$$P(n) = 0.5 - P_1(n) \tag{11}$$

P(n), as reflection, is a-priori information with redundancy. That means

$$P(n) = 0.5 - P_1(n) = \frac{1}{\sqrt{2\pi N}} exp(-\frac{(v-u)^2}{2\sigma^2})$$
(12)

Here, *u* denotes CS received signal. *v* denotes CS reconstructive signal. As a-priori information, P(n) is added to step3 formula (7) of LDPC decoding as correction and we can obtain formula (13).

$$Q_{ij} = LLR(y_i) + P(n_i) + \sum_{j \in C_{i/j}} R_{ij}$$
 (13)

Finally, we perform step4 calculation for LDPC decoding until decoding finished. It is proved that we can effectively correct error of received sequence using such additional information. BER will be lower. Further simulation indicates that we can adjust the value σ of Gaussian kernel function: the larger of σ , the larger of additional information, the lower of BER.

5 Simulation Results

We use AWGN channel model for joint decoding. Binary Phase Shift Keying (BPSK) modulation, noise obeys Gaussian distribution N (0, σ^2). N=256, M=128, iteration times are t=20. LDPC decoding is used in minimum summation algorithm. CS measurement matrix use Gaussian random matrix. Fig. 2 illustrates the performance comparison between LDPC codes and the joint codes presented in this paper. In this picture, the curves describe respectively LDPC codes and joint channel codes with CS redundant information. We conclude that decoding effect is better and system BER is much lower than single LDPC codes if using CS and LDPC codes because of the utilization of CS redundant information.



Fig. 2 performance comparison between LDPC codes and CS-LDPC joint codes



Fig. 3 Reconstructive signal and a-priori information

In the receiver, CS is encoded and reconstructed to signal. Information difference can be obtained compared with original signal and reconstructive signal. As a-priori information, redundant information can be effectively extracted by Gaussian kernel reflection. Gaussian kernel function of image segmentation as a reflection is amplifying redundant difference weight of reconstructive signal. Reconstructive signal and a-priori information as reflection are shown in Fig. 3.

Through further system performance simulation, we verified that, in Gaussian kernel function, different σ can also impact on system performance. If changed σ , different additional information can be obtained. Let σ be 0.5, 0.6, 0.7, 0.8, 0.9, 1, respectively. Through simulation, we conclude that, in system model, the larger the , the lower the BER. Corresponding to joint channel BER is as shown in Fig. 4.



Fig. 4 Different σ for joint channel joint BER

6 Conclusions

This paper has presented a new joint channel coding algorithm based on CS and LDPC codes. Using CS algorithm extracts redundant information. Then, we make use of Gaussian kernel function of image segmentation as reflection to process redundant information. This redundant information can be extracted and amplified as the a-priori information. Using the a-priori information, decoding algorithm of LDPC codes is rectified. Long-term simulation proved that the algorithm under study in this paper can effectively enhance decoding performance. In Gaussian kernel function, different can also impact on system performance, the larger the , the lower the BER. However, due to complexity and long-time calculation, the further work is to optimize CS algorithm.

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Fei Zhong is an Ph.D. student in College Science of Electronic Jilin Engineering at and University Jilin (China). University master. Her main research interests are in the areas of information coding , image processing and communication. She has

published research articles in international journals of information science. She is referee of several reputed international journals.



Shuxu Guo received the Ph.D. degree in Electronic Science and Technology at Jilin University (China). Since 2000, he has been a Professor with the State Key Laboratory on Integrated Optoelectronics, College of Electronic Science and Engineering, Jilin University, working on the information

and signal processing, reliability of semiconductor devices and wireless communication. He has published many research articles in reputed international journals of information science and signal processing.



Xu Xu received Ph.D. in College of Electronic Science and Engineering from Jilin University (China). He research interests are in the areas of image detection and image processing. He has published extensively in international journals.