Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Distributed arithmetic coding with interval swapping

Junwei Zhou^{a,b,*}, Kwok-Wo Wong^a, Yanchao Yang^a

^a School of Computer Science and Technology, Wuhan University of Technology, Wuhan, PR China
^b Department of Electronic Engineering, City University of Hong Kong, Hong Kong, PR China

ARTICLE INFO

Article history: Received 24 July 2014 Received in revised form 8 April 2015 Accepted 19 April 2015 Available online 24 April 2015

Keywords: Data compression Correlated data Distributed source coding Slepian-Wolf coding

ABSTRACT

In distributed source coding, ambiguity is usually introduced in the encoding process as it allows multiple plaintext sequences encoded to the same codeword. All these plaintext sequences are decodable and are considered as candidates at the decoder. With the help of side information, the decoder is able to determine which sequence in the candidate set is the best choice. Both the cardinality and the minimum *Hamming distance* of the candidate set are significant to the decoding performance. In this paper, a Slepian–Wolf code based on arithmetic coding is studied. By employing the interval swapping technique, a linear code is incorporated into binary arithmetic coding. The incorporated linear code improves the minimum *Hamming distance* within the candidate set which leads to a lower bit error probability. Moreover, binary arithmetic coding exploits the *a priori* knowledge of the source to reduce the cardinality of the candidate set. Simulation results show that this approach leads to superior performance for moderately skewed sources with linear encoding complexity, which meets the low power consumption requirement of applications such as wireless sensor networks and low-complexity multimedia compression.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Distributed source coding (DSC) is a source coding approach based on information and communication theories. It refers to the compression of two or more correlated information sources not communicating with each other. Slepian and Wolf proved that these sources can be losslessly compressed at a rate close to their joint entropy [1]. There are various applications adopting DSC as the source coding method. Examples are wireless sensor networks [2–4], image authentication [5], biometric system [6] and low-complexity multimedia compression [7,8]. Ambiguity is usually introduced in the encoding process of DSC as it allows multiple sequences to share the same

* Corresponding author. Tel.: +86 27 87298267.

E-mail addresses: junweizhou@whut.edu.cn (J. Zhou),

itkwwong@cityu.edu.hk (K.-W. Wong), yangyc@whut.edu.cn (Y. Yang).

http://dx.doi.org/10.1016/j.sigpro.2015.04.013 0165-1684/© 2015 Elsevier B.V. All rights reserved. codeword. All these plaintext sequences are decodable and are considered as candidates at the decoder. With the help of side information, the decoder is able to determine which sequence in the candidate set is the best output. Both the cardinality and the minimum *Hamming distance* of the candidate set play an important role in the decoding performance. DSC based on channel codes usually meets the maximum *Hamming distance* constraint. Therefore, powerful channel codes such as linear block codes [9], turbo codes [10,11] and LDPC codes [12,13] are usually employed in DSC. Moreover, DSC based on channel codes is particularly efficient for long sequence lengths and uniform sources.

Since traditional source coding schemes exhibit remarkable properties in compression capability, coding efficiency and easy extension to context-based statistical models, source coding methods such as Huffman coding and arithmetic coding (AC) are also extended to DSC. A punctured conditional arithmetic code was used for DSC [14]. The problem of







decoder de-synchronization, caused by the causal decoding of punctured arithmetic codes, was solved by coupled arithmetic coders [15]. By considering guasi-arithmetic codes as finitestate machines for memory and memoryless sources [16], an optimal BCIR algorithm [17] was employed in the decoding process. It was reported that this scheme results in an efficient decoding performance for short sequences compared to wellknown DSC schemes based on channel codes. An optimal lossless and near-lossless source coding approach for multiple access networks was studied in [18]. It was proved that the zero-error instantaneous coding of correlated sources with length constraints is NP-complete [19] which is unaffordable in applications requiring a low encoding complexity. Based on a modified interval partitioning strategy, in which the interval length is proportionally enlarged, a Slepian-Wolf (S-W) code named distributed arithmetic coding (DAC) was suggested in [20.21]. The enlarged subintervals lead to a larger final interval, and hence a shorter codeword. The encoder is almost the same as the conventional AC encoder with linear coding complexity which leads to great potential in low power consumption applications. Moreover, it was reported that DAC possesses some advantages over the existing DSC schemes, which leads to good performance for short sequences generated from skew sources, especially highly correlated sources with heavily skewed distributions. It was found that DAC could provide a better performance than the scheme based on turbo codes, even exploiting the *a priori* knowledge of the source. However, there is still room for improvement when the correlation between the sources is weak and the coding rate is high [22].

After studying the characteristics of the candidate set, we find that the cardinality of the candidate set is reduced by employing DSC based on source codes such as DAC [21] by exploiting the a priori knowledge of the source. Therefore, for skew sources, it possesses a better performance than the schemes based on channel codes. However, since the length of the interval assigned to each sequence is unequal for skew sources, it is hard to maintain a large minimum Hamming distance within the candidate set. It was shown in [23] that the minimum Hamming distance could be equal to 1 when termination is not considered. In this paper, a novel scheme named distributed arithmetic coding with interval swapping (DACIS) is proposed to improve the distance characteristic of the candidate set by sacrificing the *a priori* knowledge. The source sequence is divided into two parts: one encoded by a linear code producing the parity bits; the other by an arithmetic code with the interval swapping technique. The minimum Hamming distance within the candidate set is enlarged by the linear code. The a priori knowledge of the part encoded using AC is totally retained, and thus the cardinality of the candidate set is reduced. Simulation results justify that the performance of our scheme is better than that of DAC for moderately skewed sources in terms of decoding error rate.

The rest of this paper is organized as follows. In the next section, some notations and preliminaries are introduced. Section 3 is devoted to the description of the proposed scheme. The cardinality and the minimum *Hamming distance* within the candidate set are also discussed in this section. The performance evaluation results are presented in Section 4. In the last section, some concluding remarks are given.

2. Notations and preliminaries

2.1. Problem description

Let the pair of memoryless correlated binary sources *X* and *Y* generates, at each instant, a pair of symbols (x,y) from the product set $\mathcal{A} \times \mathcal{A}$ according to the joint probability $P_{X,Y}(x,y)$, where the symbol set is $\mathcal{A} = \{0, 1\}$. The joint probability is equal to $P_{X,Y}(x,y) = P_{X|Y}(x|y) \times P_Y(y) = P_{Y|X}(y|x) \times P_X(x)$ where $P_X(x)$ and $P_Y(y)$ denote the marginal distributions of sources *X* and *Y* over the symbol set \mathcal{A} , respectively. Moreover, $P_{Y|X}(y|x)$ and $P_{X|Y}(x|y)$ refer to the conditional distributions of *Y* given X=x and of *X* given Y=y, respectively. Here, the correlation between *X* and *Y* is modeled as a binary symmetric channel with crossover probability ϵ , where *X* is the channel input and *Y* is its output. The likelihood function $P_{Y|X}(y|x)$ is given by:

$$P_{Y|X}(y|x) = \begin{cases} 1 - \epsilon & \text{if } x = y \\ \epsilon & \text{if } x \neq y \end{cases}$$

Suppose that the sources *X* and *Y* are separately encoded by $\mathcal{E}_X(\mathbf{x})$ and $\mathcal{E}_Y(\mathbf{y})$ with code rates R_X and R_Y , respectively, where \mathbf{x} and \mathbf{y} have length *N*. Both $\mathcal{E}_X(\mathbf{x})$ and $\mathcal{E}_Y(\mathbf{y})$ know the distribution $P_{XY}(x, y)$, but no communication is allowed between them.

$$\mathcal{E}_{X}(\mathbf{x}): \mathbf{x} \to \{0, 1\}^{R_{X}N}$$
$$\mathcal{E}_{Y}(\mathbf{y}): \mathbf{y} \to \{0, 1\}^{R_{Y}N}$$
(1)

At the decoding side, a joint decoder (2) is employed to recover the codewords.

$$\mathcal{D}: (\mathcal{E}_X(\mathbf{x}), \mathcal{E}_Y(\mathbf{y})) \to (\hat{\mathbf{x}}, \hat{\mathbf{y}})$$
(2)

Slepian and Wolf [1] proved that the total code rate is $R_X + R_Y \ge H(X, Y)$, where $R_X \ge H(X|Y)$ and $R_Y \ge H(Y|X)$. Here, H(X, Y) is the joint entropy of X and Y; H(X|Y) and H(Y|X) are conditional entropies. In this paper, the asymmetric version of S–W codes is considered. We only focus on the design of the encoder $\mathcal{E}_X(\mathbf{x})$ which compresses X at a rate approaching the conditional entropy H(X|Y). The source Y is considered as the side information which is encoded by a traditional entropy coder at a rate $R_Y = H(Y)$ and is decoded without error. At the decoding side, a joint decoder $(\hat{\mathbf{x}}, \mathbf{y}) = \mathcal{D}(\mathcal{E}_X(\mathbf{x}), \mathcal{E}_Y(\mathbf{y}))$ is employed to recover the information.

Definition 1 (*Candidate Set*). The encoder $\mathcal{E}_X(\mathbf{x})$ allows multiple sequences to have the same codeword **c**. All these plaintext sequences are decodable and are considered as candidates at the decoder. They form the *candidate set*:

$$\mathcal{S}_{\mathbf{c}} = \{\mathbf{x} | \mathcal{E}(\mathbf{x}) = \mathbf{c}, \mathbf{x} \in \mathcal{A}^N \}.$$

The cardinality of the set S_c is denoted as $|S_c|$. With the help of side information *Y*, the decoder is able to determine which sequence in S_c is the best output by the

Download English Version:

https://daneshyari.com/en/article/562401

Download Persian Version:

https://daneshyari.com/article/562401

Daneshyari.com