Expert Systems With Applications 56 (2016) 360–367

Contents lists available at ScienceDirect

Expert Systems With Applications

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

Toward practical guideline for design of image compression algorithms for biomedical applications

Nader Karimi[a], Shadrokh Samavi[a], S.M.Reza Soroushmehr[b,*], Shahram Shirani[c], Kayvan Najarian[b,d]

[a] Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran
[b] Emergency Medicine Department, University of Michigan, Ann Arbor, MI, USA
[c] Electrical and Computer Engineering Department, McMaster University, Hamilton, ON, Canada
[d] Department of Computational Medicine and Bioinformatics, University of Michigan, Ann Arbor, MI, USA

ARTICLE INFO

Article history:
Received 4 February 2015
Revised 25 February 2016
Accepted 26 February 2016
Available online 16 March 2016

Keywords:
Medical data compression
Compression performance analysis
Lossless compression
Big data compression

ABSTRACT

Improvements in medicine and healthcare are accelerating. Information generation, sharing, and expert analysis, play a great role in improving medical sciences. Big data produced by medical procedures in hospitals, laboratories, and research centers needs storage and transmission. Data compression is a critical tool that reduces the burden of storage and transmission. Medical images, in particular, require special consideration in terms of storage and transmissions. Unlike many other types of big data, medical images require lossless storage. Special purpose compression algorithms and codecs could compress variety of such images with superior performance compared to the general purpose lossless algorithms. For the medical images, many lossless algorithms have been proposed so far. A compression algorithm comprises of different stages. Before designing a special purpose compression method we need to know how much each stage contributes to the overall compression performance so we could accordingly invest time and effort in designing different stages. In order to compare and evaluate these multi-stage compression techniques and to design more efficient compression methods for big data applications, in this paper the effectiveness of each of these compression stages on the total performance of the algorithm is analyzed.

1. Introduction

The role of new technology and expert systems in the field of healthcare is on the rise. Hospitals, laboratories, and research centers are producing large volumes of medical data. The role of expert systems, such as data mining, has been essential in the achieved improvements of healthcare systems (Purwar & Singh, 2015; Thong et al., 2015). These medical data should be locally stored, and at need, should be transmitted and shared. Hence, compression algorithms play essential role in efficient storage and transmission of medical data. In the following we mention three examples of medical data for which expert systems have been utilized to extract medical and diagnostic knowledge. We will show the importance of special-purpose data compression methods for these examples. One of the goals of healthcare systems has been the utilization of big data by combining patients' genomic data with clinical, behavioral, and environmental data to improve the quality and efficiency of care (Phillips et al., 2014). While data analytics can improve the quality of patient care and also shrink the health care costs (Nambiar, Bhardwaj, Sethi, & Vargheese, 2013), the major challenge ahead is the exponential growth of the data volume. One of the major types of big data in life-science is the data generated by the high throughput molecular assay (Dai, Gao, Guo, Xiao, & Zhang, 2012). Microarray, a subset of such technologies, for the first time introduced life sciences to such large volume of data (Nekrutenko & Taylor, 2012). Microarray experiments measure the expression of messenger RNA (mRNA) of many genes and are used in variety of studies such as exploring the impact of medications or genetic mutations on gene expression or monitoring cell growth under different conditions (Nguyen, Bulak Arpat, Wang, & Carroll, 2002). Beside the enormous volume of genomic and proteomic data, other characteristics such as velocity and variety of these data position them among the most challenging types of big data (Phillips et al., 2014). For instance, a popular type of such data is generated by RNA inference (RNAi) experiment which involves marking of cells with various fluorescent dyes to capture three components of interest, namely, DNA, Actin, and PH3 channels (Falschlehner, Steinbrink, Erdmann, & Boutros, 2010). The aggregation of bio-informatic data with other kinds of health

* Corresponding author. Tel.: +1 7346477259.
E-mail addresses: nader.karimi@cc.iut.ac.ir (N. Karimi), samavi96@cc.iut.ac.ir (S. Samavi), ssoroush@umich.edu (S.M.R. Soroushmehr), shirani@mcmaster.ca (S. Shirani), kayvan@umich.edu (K. Najarian).

http://dx.doi.org/10.1016/j.eswa.2016.02.047
0957-4174/

oriented data is expected to improve the health provided to patients (Phillips et al., 2014) which results in the need for more storage and advanced analysis. Another type of important health oriented data commonly used in medical applications is clinical images. A family of clinical images significantly contributed to cancer decision support making is mammogram images (Oliver et al., 2010). Breast cancer, next to lung cancer, has the largest rate of mortality among women. Mammography is an imaging technique recommended to women above 40 as an early breast cancer detection and prevention method. The procedure is performed every one or two years and the images are saved resulting in large volumes of data. Lossless storage of images is required to preserve micro calcification and other details.

Efficient data compression has a major role in storage and transportation of biomedical data. In particular, medical images contain information that requires complete data fidelity after the reconstruction. This type of compression has been intensively studied and many multi-stage methods/standards have been developed for lossless compression that attempt to achieve better compression performance by modifying one or more stages/steps of compression. Medical images, due to exponential growth in their contents, require special tools to efficiently store and transmit them (Santos, Guarda, Rodrigues, & Faria, 2015). They contain spatial characteristics that allow custom-made compression schemes to compress them more efficiently when compared to the standard compression tools. To exploit this potential, designers of lossless compression schemes need to be aware of the contribution that each stage of a compression algorithm would have on the overall performance of the codec. This is particularly more important when the real-time implementation of the codec is required or when the complexity of the algorithm is of importance. These considerations become much more significant in big data setting. In such cases the designer need to decide whether addition of a stage is worthwhile.

Produced medical images have big data characteristics and general purpose compression methods are not suitable for them. Special-purpose multi-stage image compression methods are designed for sub-groups of medical images. The goal of this research is to provide new insight into the importance of different stages that are generally used in compression algorithms. To the best of our knowledge there is no study on investigating the contribution of each compression stage on the overall performance of the biomedical data compression. In this paper a comprehensive classification and comparison of compression methods are presented. Based on the presented categorization we will analyze a group of compression schemes that are most suitable contributors to big data compression. Specifically, general-purpose lossless image compression methods are thoroughly analyzed and characteristics of major components and common stages in the design of these methods are extracted. After investigating which stages are mostly used in standard and general purpose lossless compression methods we explore how extensively each stage contributes to the overall performance of the method. For big data applications where velocity of generation and volume of biomedical data are very large, the design of lossless compression methods could greatly benefit from our findings. As examples for our analysis, we utilize three types of bio-medical images: microarrays, RNAi, and mammograms. The variety of these images, their high velocity of production, and their large volume, make these images suitable representative examples for big data applications.

The rest of this paper is organized as follows. In Section 2, common stages of a typical lossless compression scheme are reviewed. Section 3 represents the experimental results on the above mentioned types of biomedical images where the contribution of each compression stage is measured in terms of reduction in bit-per-pixel (bpp) values. In this section, the information of neighboring pixels for prediction purposes is also analyzed. Finally, Section 4 concludes the paper.

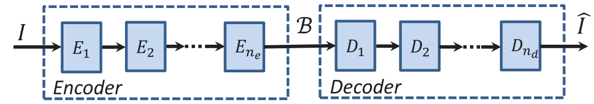

Fig. 1. Encoder and decoder using multiple stages.

2. Influential stages of lossless image compression methods

We can define the lossless compression as an optimization problem shown as:

$$\min_{S.T. \|I-\hat{I}\|_2=0} |\mathscr{B}| \tag{1}$$

where $\mathscr{B}$ is the bit stream output of the encoder and $|.|$ shows the cardinality of a set. Also, I and $\hat{I}$ are respectively the original and reconstructed images. A compression method that minimizes the encoder bit rate and preserves the information can be an NP-complete problem (Wu, 1996). Different compression scenarios have been devised to solve this problem. In each scenario multiple stages might be involved and the goal of many compression techniques is to reduce the bit rate by designing new stages or modifying some existing stages. Fig. 1 shows $\{E_1, \ldots, E_{n_e}\}$ and $\{D_1, \ldots, D_{n_d}\}$ respectively as encoder and decoder stages where n_e and n_d are respectively the number of corresponding stages. In symmetric compression methods such as JPEG (ISO/IEC 10918–1, 1994) and JPEG-LS (Weinberger, Seroussi, & Sapiro, 2000), where the decoder performs the reverse steps of the encoder, n_e and n_d are identical. However, in asymmetric methods either the encoder or decoder performs more/complicated tasks.

By in-depth analysis of many standards and a number of highly efficient non-standard methods including Chen, Braeckman, Munteanu, and Schelkens (2013), Christopoulos, Skodras, and Ebrahimi (2000), Dai, Xiong, Wang, and Zheng (2014), Moghaddamzadeh and Bourbakis (1997); Verma and Sinha (2013), Naik and Holambe (2013), Oliver et al. (2010), Penedo, Pearlman, Tahoces, Souto, and Vidal (2003), Prattipati, Swamy, and Meher (2013) and Zhao and He (2010a) we found 10 fundamental stages commonly used in lossless compression methods. Table 1 shows some of the most cited/recent methods that we analyzed and also the common stages used in the analyzed methods. In this table the column named *Standardization* shows whether the method is used as a standard method.

In the followings we discuss these stages and in the next section we analyze the impact of each stage on the total performance of the compression.

2.1. RLE

Run length encoding (RLE) is a compression technique in which runs of n symbols are replaced with number n followed by the symbol (Prattipati et al., 2013; Salomon, 2004).

2.2. Transform

Image compression can be performed in spatial domain where pixels are directly worked on. Also, compression could be performed in the transform domain where the output of a transform function such as discrete cosine transform (DCT) (Chen et al., 2013; Langdon, Gulati, & Seiler, 1992; Sadhvi Potluri et al., 2014; Wallace, 1992), discrete wavelet transform (DWT) (Christopoulos et al., 2000; Naik & Holambe, 2013; Venugopal, Mohan, & Raja, 2016; Yea & Pearlman, 2006), contourlet transform