COMPARING IMAGE COMPRESSION METHODS IN BIOMEDICAL APPLICATIONS

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Summary Compression methods suitable for image processing are described in this article in biomedical applications. The compression is often realized by reduction of irrelevance or redundancy. There are described lossless and lossy compression methods which can be use for compress of images in biomedical applications and comparison of these methods based on fidelity criteria.

Abstrakt Príspevok sa zaoberá kompresnými metódami vhodnými pre spracovanie obrazu v biomedicínskych aplikáciách. Kompresia je prevažne realizovaná prostredníctvom redukcie irelevancie alebo redundancie. V článku sú uvedené bezstratové a stratové kompresné metódy, ktoré možno použiť v biomedicíne. Porovnanie týchto metód je uskutočnené na základe kritérií vierohodnosti.

1. INTRODUCTION

Image compression has been pushed to the forefront of the image processing field. This is largely a result of the rapid growth in computer power, the corresponding growth in the multimedia market, and the advent of the World Wide Web, which makes the Internet easily accessible for everyone. Compression algorithm development starts with applications to two-dimensional (2D) still images.

2. COMPRESSION

Image compression involves reducing the size of image data files, while retaining necessary information. The ratio of the original, uncompressed image file and the compressed file is referred to as the compression ratio. The compression ratio is denoted by [1], [2]:

$$Compression\ ratio = \frac{size_U}{size_C},$$

where $size_U$ – uncompressed file size,
$size_C$ – compressed file size.

Compression algorithms are developed by taking advantage of the redundancy that is inherent in image data. Three primary types of redundancy can be found in images: coding, interpixel, psycho visual redundancy.

If we want to create a successful compression scheme, we must differentiate between data and information. For digital images, data refers to the pixel gray-level values that correspond to the brightness of a pixel at a point in space. Information is an interpretation of the data in a meaningful way. For example, in a binary image that contains text only, the necessary information may only involve the text being readable, whereas for a medical image the necessary information may be every minute detail in the original image.

2.1 Compression System Model

The compression system model consists of two parts: the compressor and the decompressor.

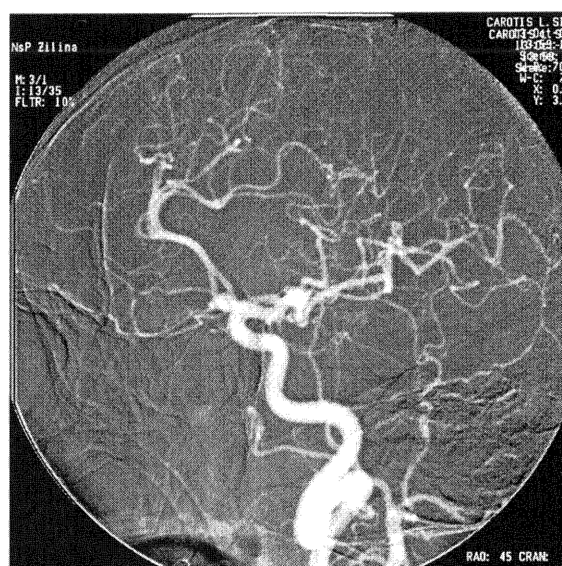


Fig. 1 Original image.

The compressor consists of a preprocessing stage and encoding stage, whereas the decompressor consists of a decoding stage followed by a postprocessing stage. Before encoding, preprocessing is performed to prepare the image for the encoding process, and consists of any number of operations that are application specific. After the compressed file has been decoded, postprocessing can be performed to eliminate some of the potentially undesirable artifacts brought about by the compression process.

3. BASIC COMPRESSION TECHNIQUE

3.1 Lossless compression methods

Lossless compression methods are necessary in some imaging applications. The most known algorithms are Huffman coding, Run-Length coding, LZW coding (Lempel-Ziv-Welch), arithmetic coding [3]. Many of the lossless techniques were developed for non-image data and, consequently, are not optimal for image compression. In general, the lossless techniques alone provide marginal compression of complex image data, often in the range of only a 10% reduction in file size. Compression methods comparing is presented by original image Fig. 1 (image is used from Hospital of Žilina).

Run – Length coding (RLC)

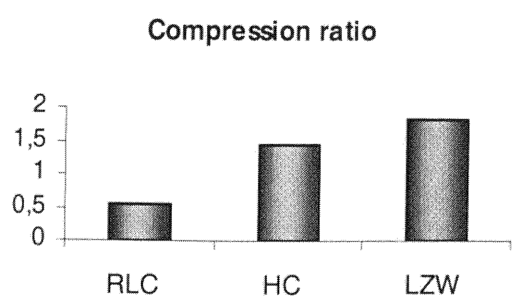
Run-length coding is an image compression method that works by counting the number of adjacent pixels with the same gray-level value. This count, called the run length, is then coded and stored. Basic RLC is used primarily for binary images but can work with complex images that have been preprocessed by thresholding to reduce the number of gray levels to two. We can either use horizontal RLC, or vertical RLC.

Huffman coding (HC)

The Huffman code is a minimum length code. This means that given the statistical distribution of the gray levels, the Huffman algorithm will generate a code that is as close as possible to the minimum bound, the entropy. This method results in a variable length code, where the code words are of unequal length. For complex images, Huffman coding alone will typically reduce the file by 10 to 50%, but this ratio can be improved to 2:1 or 3:1 by preprocessing for irrelevant information removal.

Lempel-Ziv-Welch coding (LZW)

LZW coding algorithm works by coding strings of data. For images, these strings of data correspond to sequences of pixel values. It works by creating a string table that contains the strings and their corresponding codes. The string table is updated as the file is read, with new codes being inserted whenever a new string is encountered. If a string is encountered that is already in the table, the corresponding code for that string is put into the compressed file.



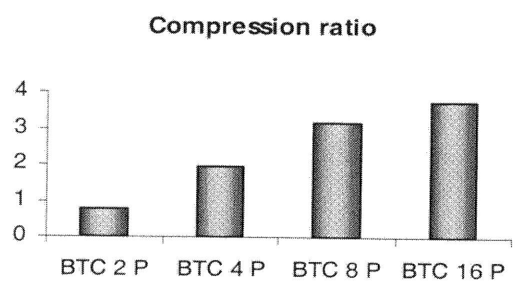
Graph 1 Compression ratio for lossless methods

3.2 Lossy compression methods

Lossy compression provides tradeoffs between image quality and degree of compression, which allows the compression algorithm to be customized to the application. With some of the more advanced methods, images can be compressed 10 to 20 times with virtually no visible information loss, and 30 to 50 times with minimal degradation. Many of the methods have adjustable parameters to allow the user to select the desired compression ratio and image fidelity [4].

Block truncation coding (BTC)

It works by dividing the image into small subimages and then reducing the number of gray levels within each block. This reduction is performed by a quantizer that adapts to the local image statistics. The levels for the quantizer are chosen to minimize a specified error criterion, and then all the pixel values within each block are mapped to the quantized levels. The basic form of BTC divides the



Graph 2 Compression ratio for predictive BTC

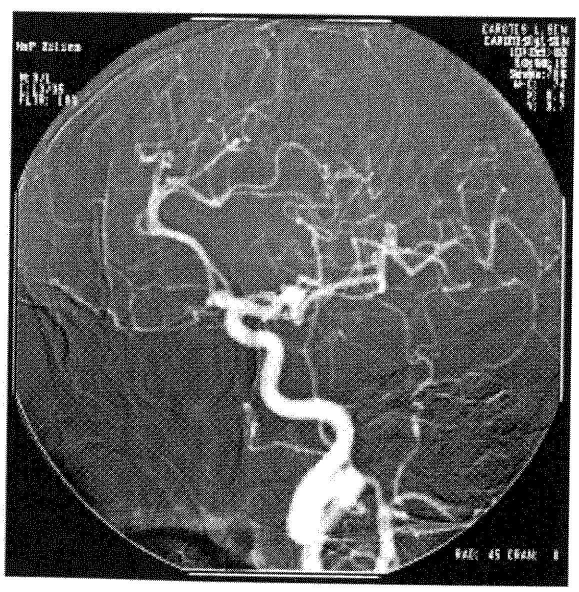


Fig. 2 Predictive BTC compression

image into 4x4 blocks and codes each block using a two-level quantizer.

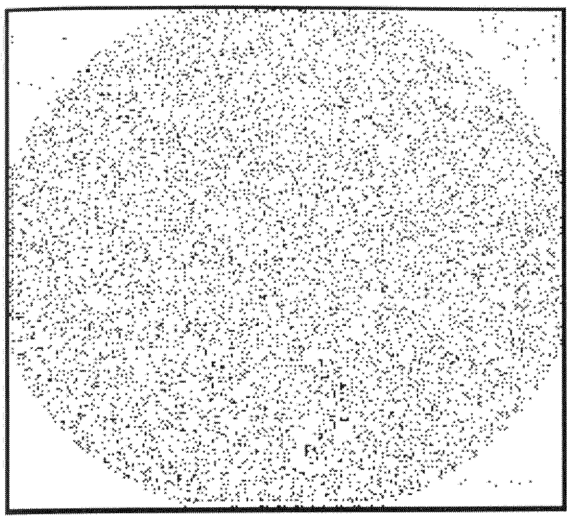
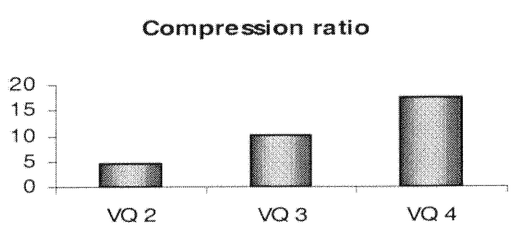


Fig.3 Difference image between Fig.1 and Fig.2

Vector quantization (VQ)

Vector quantization is the process of mapping a vector that can have many values to a vector that has a smaller (quantized) number of values. For image compression, the vector corresponds to a small subimage, or block. Vector quantization treats the entire subimage (vector) as a single entity and quantizes it by reducing the total number of bits required to represent the subimage. This is done by utilizing a codebook, which stores a fixed set of vectors, and then coding the subimage by using the index (address) into the codebook.



Graph 3 Compression ratio for VQ

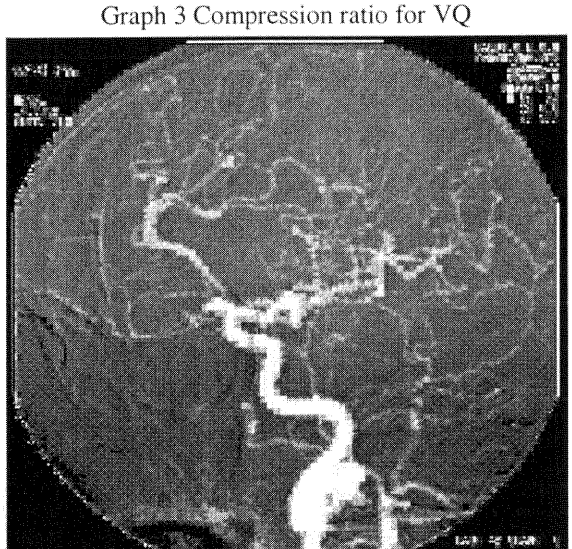


Fig. 4 VQ compression – 3x3 subimage

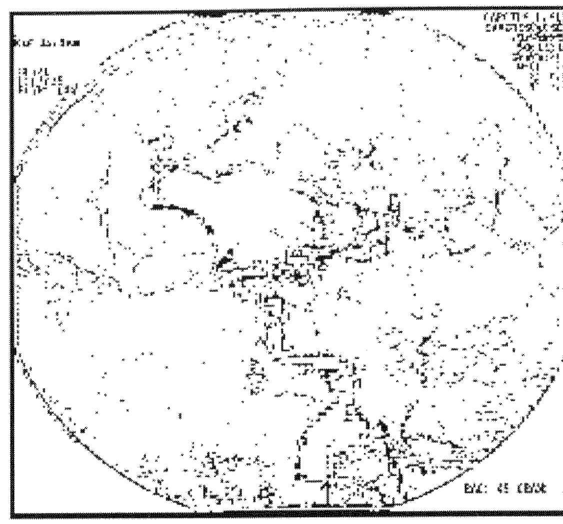


Fig.5 Difference image between Fig.1 and Fig.4

3. FIDELITY CRITERIA

Fidelity criteria can be divided into two classes: objective fidelity criteria, subjective fidelity criteria. The objective fidelity criteria are borrowed from digital signal processing and information theory and provide us with equations that can be used to measure the amount of error in the reconstructed image. Subjective fidelity criteria require the definition of a qualitative scale to assess image quality. This scale can then be used by human test subjects to determine image fidelity. The objective criteria, although widely used, are not necessarily correlated with our perception of image quality [1].

Commonly used objective measures are the root–mean-square error e_{RMS}, the root–mean-square signal-to-noise ratio SNR_{RMS}, the peak signal-to-noise ratio SNR_{PEAK}.

$$e_{RMS} = \sqrt{\frac{1}{N^2}\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}\left[\hat{I}(r,c) - I(r,c)\right]^2} \;;$$

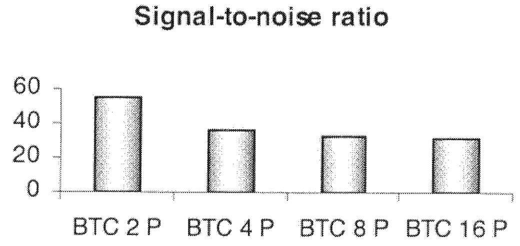
$$SNR_{RMS} = \sqrt{\frac{\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}\left[\hat{I}(r,c)\right]^2}{\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}\left[\hat{I}(r,c) - I(r,c)\right]^2}} ,$$

$$SNR_{PEAK} = 10\log_{10}\frac{(L-1)^2}{\frac{1}{N^2}\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}\left[\hat{I}(r,c) - I(r,c)\right]^2}$$

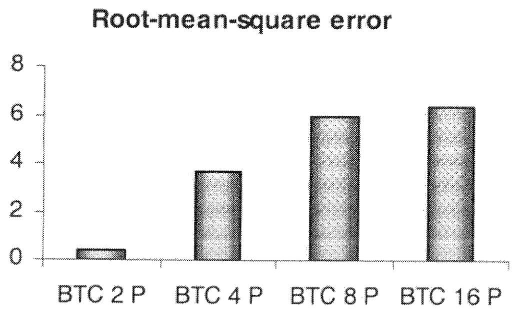
where $I(r,c)$ is the original image, $\hat{I}(r,c)$ is the decompressed image and NxN image size.

These objective measures are often used in research because they are easy to generate and seemingly unbiased, but remember that these metrics are not necessarily correlated to our perception of an image.

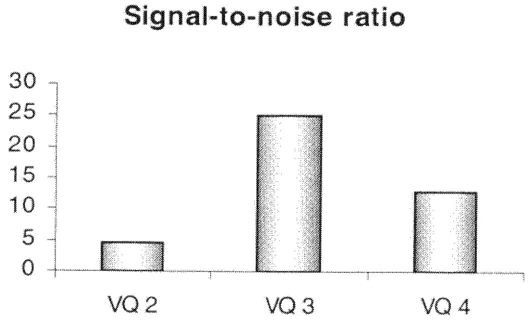
Subjective testing is performed by creating a database of images to be tested, gathering a group of people that are representative of the desired population. Subjective fidelity measures can be classified into three categories: impairment, quality and comparison tests.



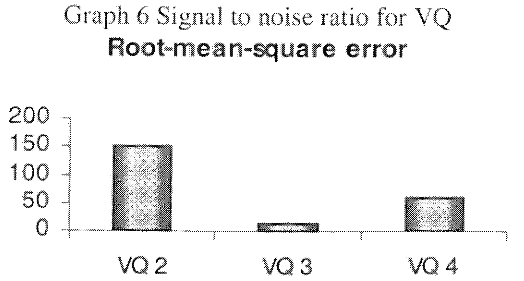
Graph 4 Signal to noise ratio for predictive BTC



Graph 5 Root mean square error for predictive BTC



Graph 6 Signal to noise ratio for VQ



Graph 7 Root mean square error for VQ

Subjective fidelity measures can be classified into three categories. The first type is referred to as impairment tests, where the test subjects score the images in terms of how bad they are. The second type is quality tests, where the test subjects rate the images in terms of how good they are. The third type is called comparison tests, where the images are evaluated on a side-by-side basis, are considered to provide the most useful results, as they provide relative measure, which is the easiest metric for most people to determine.

The comparison is done for block truncation coding (BTC) and vector quantization (VQ). Block size was 2, 4, 8, 16 for BTC and 2, 3, 4 for VQ. There is used predictive BTC (P). It marks in graphs follow: e.g. BTC 4 P – predictive BTC with block size 4.

4. CONCLUSION

Objective fidelity criteria comparing results are presented in followed from Graph 2 to Graph 7. The Graph 2 and 3 presents the Compression ratio between each of methods, the Graph 4 and Graph 6 are presented by the Ratio of signal to noise criterion and the Graph 5 and Graph 7 presents the root mean square criterion.

In Fig.3 and Fig.5 are illustrated lost of data, caused by compressions. These images was obtained by comparison of original image with compressed image, using function subtraction (contrast is increased for print matter).

With implementation of the objective fidelity, some important conclusions were reached: The compression method BTC 8P, BTC 16P, VQ3 and VQ4 presented here allows to obtain good results in the compression ratio. The compression method BTC 2P and BTC 4P provide a good result in the signal to noise ratio criteria. The method VQ 2, VQ 3 and VQ 4 have bad results in the root mean square error criteria.

In this paper are presented approaches to comparing some of image compression methods by the objective fidelity criteria. These criteria, although widely used, are not necessarily correlated with subjective perception of image quality. Subjective fidelity criteria require the definition of a qualitative scale to assess image quality. This scale can then be used by human test subjects to determine image fidelity.

Acknowledgement

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