Survey on Image Compression Techniques: Using CVIP Tools

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Abstract. Due to the heavy increase of network traffic caused by multimedia data, compression and transmission of medical image for telemedicine applications have made the stringent demand on the quality of the reconstructed signal.In this paper, we are comparing different types of image compression techniques using CVIP tools by considering the values of Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR) and Root Mean Square (RMS) error.

Keywords: Image Compression, CR, PSNR, RMS error and CVIP tools.

1 Introduction

The growth in demand for image and video information has made the compression technology at a major task. In telemedicine, medical images generated from hospitals and medical centers with efficient image acquisition devices need to be transmitted conveniently and retrieved efficiently. Thus, efficient data compression is a powerful, technology that plays a vital role in the information age. Image compression is nothing but reducing redundancy of the image to store or transmit data in an efficient form. There are two types of image compression - Lossy and Lossless.

Lossy compression methods used at low bit rates which introduce high compression rates. These methods are especially suitable for natural images where minor amount of loss is acceptable. Lossless compression is mainly used in medical image processing for getting each and every bit of data without loss. These techniques may get the low compression ratio but gives high Signal to Noise Ratio’s. This paper compares the different types of image compression techniques using CVIP tools.

CVIP (Computer Vision and Image Processing) tools [46] is a collection of computer imaging tools providing services to the users at four layers: the C function layer, the COM interface layer, the CVIP Image layer and the Graphical User Interface (GUI). The C function layer consists of all image and data processing procedures and functions. The Common Object Module (COM) interface layer implements the COM interface for each higher level CVIP tools function, primarily

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the Toolbox functions with a few Toolkit functions. The CVIP Image layer encapsulates the COM interface functions and provides an Object Oriented Programming (OOP) approach. The GUI implements the image queue and manages user input and resultant output.

2 Issues Related to Image and Video Compression

The major issues or factors related to image or video compression are shown in Figure 1 which include compression ratio, transmission rate, PSNR, RMS, Compression rate and entropy

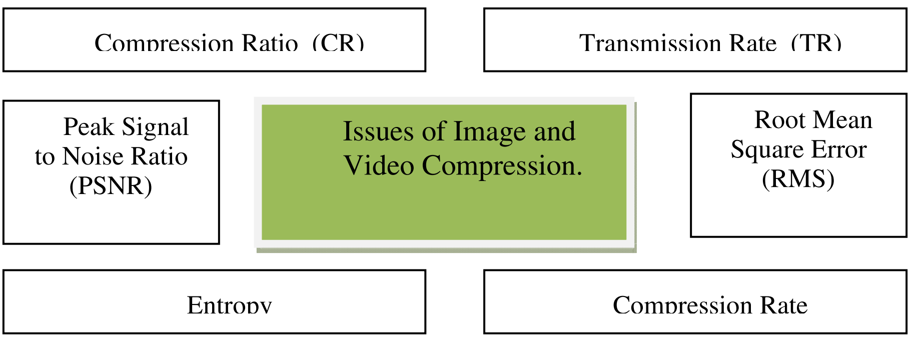

Fig. 1. Issues of image and video compression

2.1 Compression Ratio (CR)

Compression Ratio is the most significant part of the image processing. Getting the maximum CR as well decompressing the data without any loss is the criteria to be focussed. Many researchers have discussed about CR in their research papers.In papers [3], [6], [10], [11], [13], [15], [16], [38], [43] and [45] the authors have used stripe-based SPIHT, 3-D & 4-D integer wavelet transforms, residual approach, Haar wavelet transform, wavelet transforms, evolved wavelets, CREW context model, Advanced video coding (H.264/AVC) and context-based adaptive binary arithmetic coder (CABAC) respectively for the calculation of CR.

In [1], Geetha et al., proposed Embedded Set Partitioning Significant and Zero Block Coding (ESPSZBC) for medical images and gave a conclusion that the proposed method produces a good quality image with excellent compression ratio. In [26], the author used selective image compression scheme in which the ROI is compressed with fuzzy c-means clustering algorithm and wavelets for remaining parts of the image and in [31] different methods have been proposed for analysis of CR and the quality of images. Gloria Menegaz [33] has surveyed different papers and compared the lossless rates of all the traditional compression techniques like JPEG2K, JPEG-LS and EZW (Embedded Zero tree Wavelet Based Coding) and concluded that the compression performance can be improved by combining the real and synthetic data. In [5], the author compared both the state of art and traditional approaches used for Image compression by calculating byte CR.

Using seismic data compression[37] ,Compression ratio of 165:1 can be obtained and also with irreversible compression technique given in [2], highest CR can be obtained. In [42], V. Sanchez et al., proposed a lossless compression technique for 4D medical images and shown the performance evaluations that H.264/AVC significantly outperforms 3D-JPEG2000, with the highest CR of 12.38:1

2.2 Peak Signal to Noise Ratio (PSNR)

PSNR gives how much signal is resistant to the noise. If the PSNR value is high, we can bet the compressed image with less amount of loss of information. So, all the compression techniques try to get the better PSNR values. In the papers [4], [7], [9], [14], [20], [23], [24] and [44] the authors have used Joint Statistical Characteristics in Wavelet Domains, SPIHT, Wavelet techniques, Discrete Wavelet (DW), Adaptive 3D Discrete Cosine Transform (DCT), DFT (Discrete Fourier Transform) & DHT (Discrete Hartley Transform), DCT and 3D SPIHT & 3D QTL (Quad Tree Limited) respectively for the calculation of PSNR. In [29], [22] and [21] , the results are shown with flexible values of PSNR and the authors have used EBCOT spatial, modified SPIHT, DCT with spectral similarity and obtained 40.49, 50.6, 44.98 respectively. Wen Sun et al., in [32] proposed a lossless compression method which utilizes the VOI (value of interest) settings of the medical images, so that only a small part of the coded bit-stream is needed at the decoder to lossless display the original image and obtained the PSNR value as 81.7

2.3 Transmission Rate (TR)

After the compression of image, there is a significant need for efficient transmission of data with greater rate especially in medical image processing. Hence, TR plays a vital role in image processing. In [41], the author has shown TR up to 388 kbps which is very high for remote areas.

2.4 Compression Rate

The rate at which original data is compressed is known as Compression Rate. Along with TR, Compression Rate also plays a major role for fast transmission of the image.

In [17], [18] and [19] they are using Haar transform, wavelet transform and wavelet transform with adaptive prediction for image compression respectively.In [28], [37], [39], [40] and [41] also the authors have mentioned about Compression Rates and suggested few techniques like integer to integer wavelet transforms and high-dimensional wavelet transforms to get high values and especially in [39], J.D.Villasenor used Feed Forward Neural Networks and got the compression rate up to 2.22 and in [27] & [36] the authors have used Region of Interest (ROI) based compression and obtained the compression rate of 2.5

2.5 Entropy

For better processing of an image, the entropy value is expected to be as low as possible. Entropy is the lower bound of bitrate that can represent the source without distortion.So, every compression technique will try to reduce the entropy as low as possible. Here, in [30], the author used Adaptive Lifting Algorithm which can reduce the entropy up to 2.63 whereas [34]and [8] could reduce up to 2.858 and 4.04 which uses Adaptive Predictive Multiplicative Autoregressive Model and Multi-resolution representation for lossy and lossless compression respectively.

2.6 Root Mean Square Error (RMS)

Root Mean Square Error (RMS) gives the difference between the predicted and the observed values of a system. So, it must be as low as possible for getting the lossless image after compression.In [25] and [35], the authors have used perceptual quality metrics and vector quantization method and obtained RMS value as 3.16

3 Our Approach

This section explains the way of our approach about image compression. Table 1 clearly gives the explanation about different image transforms like DCT, FFT, Haar, Hadamard, Walsh and Wavelet.

Table 1. Different Transforms Taken into Consideration

Transform Name	Description
Discrete Cosine Transform (DCT)	It is a technique for converting a signal into elementary frequency components.
Fast Fourier Transform (FFT)	It is a discrete Fourier transform algorithm which reduces the number of computations needed for N points from $2N^2$ to$2N \ln N$, where ln is the base-2 logarithm.
Haar Transform	It is a simplest wavelet transform which cross multiplies a function against the Haar wavelet with various shifts and stretches.
Hadamard Transform	It is a Real, Fast and Simple Transform Based on pulse waveforms: +1 and -1.
Walsh Transform	Walsh and Hadamard use the same transform kernels, or basis images, but with different ordering. The Walsh is sequential-ordered and Hadamard uses natural ordering.
Wavelet Transform	It is a transform based on the tree structure with D levels that can be implemented by using an appropriate bank of filters.

3.1 Lossless and Lossy Compression

Lossless compression is mainly used in medical image processing for getting each and every bit of data without loss. These techniques may gives low compression ratio but produces high Signal to Noise Ratio's. Huffman Coding is variable length entropy encoding algorithm used for lossless data compression. Ziv-Lempel Coding is a variable to fixed length code with limited (practical) and unlimited (theoretical) dictionary sizes. Differential Predictive Coding (DPC) is a common coding scheme for natural images where the predicted pixel value is simply the value of the preceding pixel. Bit plane Run Length Coding (BRLC) is a simple and popular data compression algorithm, which is based on the idea of replacing a long sequence of the same symbol by a shorter sequence.

Lossy compression methods used at low bit rates which introduce high compression rates. These methods are especially suitable for natural images where minor amount of loss is acceptable. Block Truncation Coding (BTC), which works by replacing a sub-image (block) with two gray values (two-level block truncation) and a bit string to identify which pixel in each block gets which gray level. BRLC lossy, is same as that of BRLC (lossless) but it will perform compression for a selected blocks and exclude the remaining blocks. DPC lossy takes advantage of the fact that adjacent pixels in an image are highly correlated. Thus, it helps to predict the next value based on the previous value(s), and then need to compress the error signal. The error signal is the difference between the predicted value and the actual value. The prediction equation used is based on a weighted sum of the previous value and the global mean for the image. DWRLC (Dynamic Window-Based Run Length Coding) finds the gray-level values that lie within a dynamic range and the dynamic window range, and then encode them in the form (C, L). C represents approximations of the pixel gray levels and L the run length. Fractal uses the quadtree scheme to partition the image into sub images and each of the sub images is compared to the domains (which also are sub images) and the mapping equations are stored in the compressed file. Joint Photographic Experts Group (JPEG), which compresses the data in multiple passes of higher detail.

Multilevel Block Truncation Coding (MBTC) is an extension of BTC method which uses a four-level block coding method instead of two level block coding. Predictive Multilevel Block Truncation Coding (PMBTC), which is an extension of MBTC method which uses a predictive algorithm to increase the complexity as well as CR. Transform (PCT), which is designed for experimentation with spectral transform based compression. The color space is Principal Component Transform (PCT) and coding method is Huffman. Transform (RGB), which is designed for experimentation with spectral transform based compression. The color space is RGB and coding method is Huffman. Transform (YCbCr) is designed for experimentation with spectral transform based compression. The color space is YCBCR (Y is the luma component and CB and CR are the blue-difference and red-difference chroma components) and coding method is Huffman. Vector Quantization works by dividing the image into blocks (vectors) and generating a codebook for those vectors. The codebook contains the vectors, which can be as sub-images, which are used to represent the image. The index into the codebook is stored in place of the pixel values. XVQ is designed for compression using vector quantization in the discrete wavelet or discrete cosine transform domains. Zonal is transform domain based compression. After the transform is performed, only selected "zones" in the transform domain are selected for compression, and the other transform coefficients are eliminated. The retained coefficients are linearly quantized to byte-sized data (0-255), and the linear mapping values for each block are retained for the decompression process.

4 Comparison of Experimental Results

Using CVIP tools, an image (Lena Image) which has a size of 256, has been converted to a different image transform techniques, lossless and lossy compression techniques which is shown in Figure 2-4.

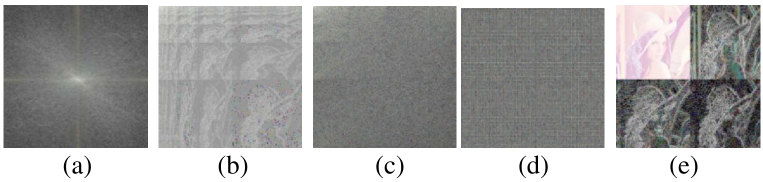

Fig. 2. Image Transform Techniques (a) DCT (b) FFT (c) Haar (d) Hadamard (e) Walsh and (f) Wavelet transforms

Fig. 3. Lossless Compression Techinques (a) Huffman (b) Ziv-Lempel (c) DPC and (d) BRLC codings

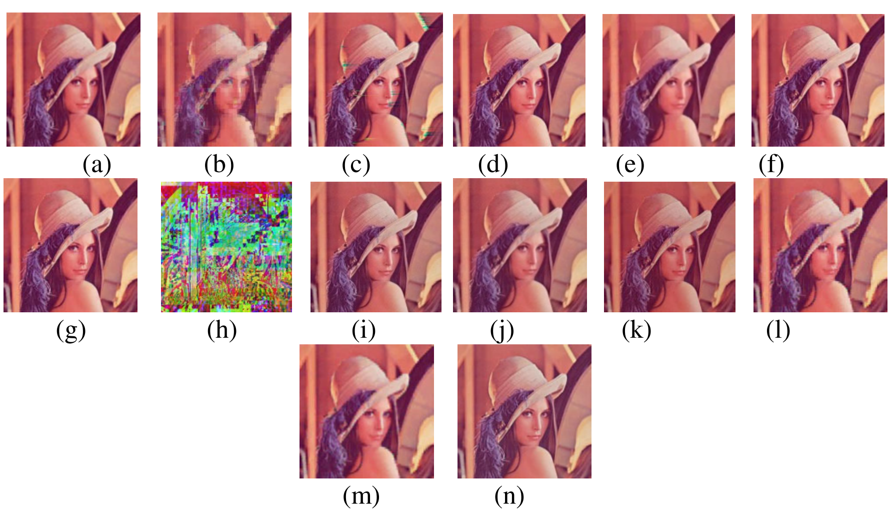

Fig. 4. Lossless Compression Techniques (a) BRLC, (b) BTC, (c) DPC lossy, (d) DWRLC, (e) Fractal, (f) JPEG, (g) MBTC, (h) PMBTC, (i) Transform(PCT), (j) Transform(RGB), (k) Transform(YCbCr), (l) Vector Quantization, (m) XVQ and (n)zonal codings

The comparison of different lossy, lossless compression and image transforms using CVIP tools is listed in Table 2.

Table 2. Comparison using CVIP Tools

Type	Method used	CR (In %)	PSNR			RMS		
			Band 1	Band 2	Band 3	Band 1	Band 2	Band 3
Lossy Codings	BRLC lossy	37	32.491	33.305	31.800	6.053	5.512	6.554
	BTC	**51.15**	24.245	23.483	25.271	15.641	17.075	13.900
	DPC lossy	38	25.296	28.892	29.407	13.859	9.161	8.633
	DWRLC	40	**33.814**	**35.151**	**33.204**	**5.198**	**4.457**	**5.576**
	Fractal	49.5	29.443	29.484	29.312	8.598	8.557	8.729
	JPEG	43	33.635	34.864	32.397	5.307	4.606	6.119
	MBTC	38.5	32.453	32.774	32.123	6.080	5.859	6.316
	PMBTC	-58	9.210	8.202	11.143	88.312	99.183	70.694
	Transform comp- PCT	38	26.380	31.015	31.602	12.233	7.175	6.706
	Transform comp-RGB	40	25.365	30.258	30.716	13.750	7.828	7.425
	Transform comp- YCbCr	44	22.881	22.291	22.840	18.301	19.588	18.389
	Vector Quant.	47.5	26.890	26.779	27.266	11.536	11.685	11.047
	XVQ	40.5	28.779	31.160	31.556	9.281	7.056	6.741
	Zonal	46	27.487	27.385	29.266	10.769	10.896	8.755
Lossless Codings	BRLC	40	34.577	35.934	33.443	4.761	4.072	5.425
	DPC	40	34.588	35.938	33.443	4.755	4.070	5.425
	Huffman	40	34.588	35.938	33.443	4.755	4.070	5.425
	Ziv-Lempel	**40**	**34.588**	**35.938**	**33.443**	**4.755**	**4.070**	**5.425**
Transforms	DCT	91.80	34.588	35.938	33.433	4.755	4.070	5.425
	Haar	91.80	34.588	35.938	33.443	4.755	4.070	5.425
	Walsh	91.80	34.588	35.938	33.443	4.755	4.070	5.425
	FFT	91.80	34.588	35.938	33.443	4.755	4.070	5.425
	Wavelet	65.45	34.588	35.938	33.443	4.755	4.070	5.425
	Hadamard	**91.85**	**34.588**	**35.938**	**33.443**	**4.755**	**4.070**	**5.425**

* Bold values represent the best results of each type.

By considering the image of resolution 256x256, we calculated the above values using CVIP tools. For the transformation techniques, block size is 256. And for wavelet transform, we have used Haar transform as the base and decomposition size as '1'. In DPC lossless compression technique, we used the correlation factor as 0.9 and the scan direction as horizontal. The table 2 shows that all the compression technique gives the same results of CR, PSNR and RMS errors. For the lossy compression techniques, block size used as ‘8’, except for the zonal compression and for DWRLC, block size as ‘16’ and ‘10’ respectively. Transform compression technique using DCT as transform and Huffman as the coding technique. BTC gives the highest compression ratio but DWRLC gives the maximum PSNR and minimum RMS error.

5 Conclusions

In this paper, we have compared different lossy, lossless and transformation techniques for image compression using CVIP tools. Every technique is having its own pros and corns. Here, we have compared six transforms, four lossless codings and fourteen lossy coding techniques using CVIP tools. In that “Hadamard Transform” is providing the better results for CR, PSNR and RMS error values when compared to all other techniques. In near future, we can work on development of Hadamard Transform by applying some “Truncation” algorithms to get even better results.

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