A study on Image Statistics and Image Features on Coding Performance of Medical Images

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Abstract – The aim of this paper is to investigate which medical image characteristics affect the coding performance. To explore to this problem and to understand how the various image features affects the coding performance, statistical analysis of grey scale images are studied on a set of medical images of different modalities. For medical application, we show the effectiveness of these image statistics and analyze their image gradient, sensitivity and robustness. Image statistics are investigated and studied based on first and higher order statistics that capture certain statistical regularities of medical images. Quantitative and qualitative comparisons are made in order to provide useful information about the characteristics of the image and the coding performance of the medical compression system. The simulation results indicate that coding performance is dependent on certain image statistics like edges, image gradient, skewness and kurtosis. Potentially, these image statistics can be applied a wide variety of problems such as image compression, image retrieval, general image classification and scene categorization.

Keywords – Medical image analysis, image statistics, image features, wavelet transform, coding performance

I. INTRODUCTION

IMAGE compression is concerned with minimizing the number of bits required to represent a digital image for a given quality [1]. Image compression is one of the successful and predominant research areas in the field of image processing [1],[2],[4]. Given a fidelity criterion, rate-distortion theory provides theoretical limits for compressing stationary sources [2],[11]. However, there is not a well known bound for images which are apparently non-stationary. This absence of a theoretical lower bound makes the problem of image compression more challenging. It is not clear how further we can compress an image. There is no perceptually acceptable distortion measure which can be used as a standard to compare the quality of different images [5],[8],[11].

An efficient and optimal image coder not only depends on compression algorithm but also counts on the statistics of the input image [3]. Much of the research work was mainly focused on the objective analysis of the compressed image based on the peak signal to noise ratio (PSNR), Mean square error (MSE), compression ratio (CR) and bit per pixel (BPP) of the coder [3]-[4]. Peak signal-to-noise ratio (PSNR) has been used for the purpose of comparison because it is easy to calculate and is mathematically tractable [5]. Motivation of this study is to investigate the correlation between the image characteristics and coding performance based on certain image statistics like entropy, energy, edges, image gradient, skewness and kurtosis [3],[4],[9].

The paper is organized as follows. In Section II, we discuss the related works of image compression with respect to image statistics and image features of medical images. In Section III, we derive a generalized measure of similarity to the medical images using mathematical line models and analyze image characteristics. In Section IV, we refer to several aspects of the implementation of the method. In Section V, we give experimental results for head MRI, chest X-ray, brain CT and ultrasound liver vessel segmentation. In Section VI, we discuss the conclusion work and indicate the directions of future research.

II. RELATED WORK

Image compression techniques are mainly used to reduce their storage size and transmission time. During the last few years, a wide variety of image compression system has been proposed for both lossy and lossless for diverse applications by the computer scientists, mathematician and academic researchers. Different types of image compression standards such as JPEG, JPEG-2000, JPIP, and JPEG-LS have been used for the DICOM system. JPIP (JPEG 2000 Interactive Protocol) is a contemporary standard which is used for growing need to access medical images fast while enabling interoperability in clinical and radiological system [1]-[3]. Bostanci et al. [1] used a spatial statistics of image features for performance comparison and they conducted an experiment based on colour and edge properties of the images. Saha et al. [4] comprehended on how image statistics can impact lossy coding performance. Sheikh et al. [5] studied in depth on image information and visual quality and argued that image quality depends on the coder and the background of the images. Field [8] suggested that a knowledge of the statistical features can lead to a better understanding of why the visual system codes does and also stressed that one must understand the nature of the environment before one can understand the nature of visual processing. The main thrust of this paper is that images from the medical modalities should not be presumed to be random patterns. Such images show a number of consistent statistical properties [6].

III. IMAGE ANALYSIS

Medical images, on the whole, appear to be rather complex. They are filled with objects and shadows and various surfaces containing various patterns at a wide range of orientations. Amid this complexity, it may seem surprising that such images share any consistent statistical features. Consider the six images shown in Fig. 1, such images may seem widely different, but as a group they can be easily distinguished from a variety of other classes of image. A fundamental task in many statistical analyses is to characterize the location and variability of a data set.

Fig. 1 Bench mark test medical images

(A) First and Higher Order Statistics

Image statistics are investigated and studied based on first and higher order statistics that capture certain statistical regularities of medical images.

1. Mean

This is a average which indicates the general brightness of the image and is given by

$$\text{Mean}(\mu) = \frac{1}{\text{M*N}} \sum_{x=1}^{M} \sum_{y=1}^{N} p(x,y)$$

where $\sum\sum$ p(x,y) represents the summation of all pixel values of the image and M*N is the size of the image. An image with a high mean indicates that the image is bright image and the dark image will have a low mean.

2. Standard deviation (σ)

The measure of the frequency distribution of a pixel value of an image is known as standard deviation of that image. The standard deviation can be calculated by given formula.

$$\text{std dev}(\sigma) = \sqrt{\frac{1}{M*N} \sum_{x=1}^{M} \sum_{y=1}^{N} (p(x,y) - \mu)^2}$$

where $\sum\sum$ p(x,y) represents the summation of all pixel values of the image and M*N is the size of the image.

3. Variance

The variance is the square of the standard deviation and is calculated by the given formula.

$$\text{variance} = (\text{std dev})^2$$

An image with a high variance means that the image has a high contrast and an image with low variance indicates that the image has low contrast.

4. Energy

Energy is defined based on a normalized histogram of the image. Energy shows how the gray levels are distributed. When the number of gray levels is low then energy is high. Sometimes the energy can be a negative measure to be minimised and sometimes it is a positive measure to be maximized. The energy can be calculated in the given formula.

$$\text{Energy (E)} = \frac{1}{M*N} \sum_{x=1}^{M} \sum_{y=1}^{N} p(x,y)^2$$

where MxN is the size of the image and p(x,y) is the value of the pixel of the image.

5. Entropy

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is calculated for gray scale image and a scalar value representing the entropy of gray scale image. If an image is thought of as a source of symbols or gray levels, then entropy is the measure of information content. The entropy of an image in this research is measured by

(i) Normal entropy

$$\text{Normal Entropy } (E_n) = \sum_{x=1}^{M} \sum_{y=1}^{N} p(x,y)\log_2(p(x,y))$$

(ii) Shannon entropy

$$\text{Shannon Entropy } (E_s) = -\frac{1}{M*N} \sum_{x=1}^{M} \sum_{y=1}^{N} p(x,y)^2 \log_2(p(x,y)^2)$$

(iii) log energy

$$\text{Log Energy } (E_l) = -\frac{1}{M*N} \sum_{x=1}^{M} \sum_{y=1}^{N} \log_2(p(x,y)^2)$$

(B) Measures of Skewness and Kurtosis

A further characterization of the data includes skewness and kurtosis. The histogram is an effective graphical technique for showing both the skewness and kurtosis of data set.

(1) Skewness

Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. The skewness for a normal distribution is zero, and any symmetric data should have a skewness near zero. Negative values for the skewness indicate data that are skewed left and positive values for the skewness indicate data that are skewed right. By skewed left, we mean that the left tail is long relative to the right tail. The skewness is calculated by using the following formula.

$$\text{Skewness}(s) = -\frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}\left[\frac{p(x,y)-\mu}{\sigma}\right]^3$$

where

$$\text{Mean }(\mu) = \frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}p(x,y)$$

$$\text{std dev}(\sigma) = \sqrt{\frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}(p(x,y)-\mu)^2}$$

(2) Kurtosis

Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. Data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. Kurtosis (k) is calculated by using the given formula

$$k = -\frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}\left[\frac{p(x,y)-\mu}{\sigma}\right]^4 - 3$$

(C) Image Acitvity Measure (IAM)

In addition to the above mentioned statistics features, image activity measure (IAM) is also used. IAM is establishes how busy the image in terms of edges and contours. The following IAM were used in this research that is edge information and image gradient.

(1) Edge information

$$EI = \left[\frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}B(x,y)\right]*100$$

where B(i) is the binary image derived from the Sobel edge extraction operator.

(2) Image gradient

This method calculates activity values by applying functions like the logarithm or square root to horizontal and vertical gradient.

$$IG = \left[\frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}|p(x,y)-p(x+1,y)| - \sum_{x=1}^{M}\sum_{y=1}^{N}|p(x,y)-p(x,y+1)|\right]$$

(D) Image Quality Metrics

Many objective measures of quality require the existence of a distortion-free copy of an image, called the reference image, that can be used for comparison with the image whose quality is to be measured. The dimensions of the reference image matrix and the dimensions of the degraded image matrix must be identical. The peak signal-to-noise ratio measure of quality works by first calculating the mean squared error (MSE) and then dividing the maximum range of the data type by the MSE. This measure is simple to calculate but sometimes does not align well with perceived quality by humans. Peak Signal to Noise Ratio (PSNR) is calculated by the given formula.

$$PSNR = 20.\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

where MAX of density levels is 255 for gray scale image and Mean Square Error (MSE) is given below.

$$MSE = \frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}[p(x,y)-\delta(x,y)]^2$$

where MxN is the size of the image, p(x,y) is the value of the pixel of the original image and $\delta(x,y)$ is the value of the pixel of the reconstructed image.

IV. RESEARCH METHODOLOGY AND WORKING ENVIORNMENT

The research methodology of the proposed work and algorithm steps (Fig. 2) are summarized as follows:

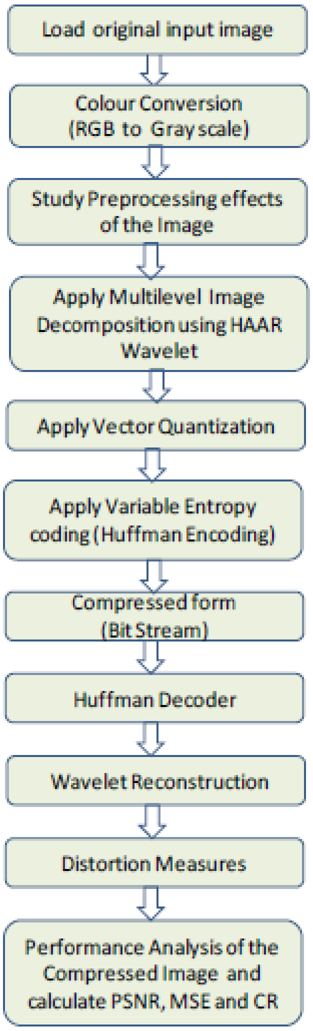

Fig. 2 Implementation of Compression Algorithm

Algorithm steps of the implementation of wavelet based compression technique are given below:

1. Load Image in MATLAB using Image Acquisition
2. Pre-processing of colour images
3. Study pre-processing effects of the given image (first order and second order statistics)
4. Apply Discrete Wavelet Transform (2D-DWT) based on HAAR mother wavelet.
5. Wavelet decomposition
6. Perform vector quantization
7. Apply codebook algorithm
8. Apply variable entropy coding Huffman or Arithmetic coding
9. Perform wavelet reconstruction
10. Study histogram probability reduction function on RGB components using Mean intensities (energy, entropy, and image gradients).
11. Study quality assessment of the compressed image based on CR, MSE and PSNR
12. Repeat the above all steps for rest of the images.

V. RESULTS AND DISCUSSIONS

The medical images which were used for investigation of this research work are downloaded from the online free medical data bases for the public utility services. The digitized images consist of 256 X 256 pixels with a depth of 8 bits/pixel (256 density levels). The images were analyzed on a MATLAB (2014-a) software tool [10].

The first and second order image statistics and image activity measures for a set of six different medical images of various modalities were calculated. The bench mark test medical images are given in Fig 1.The following tables (1-4) show the simulation results of the image statistics and image activity measures of our experiment.

Table 1 Performance of Statistical Analysis

Image	Mean	Variance	Std Dev	Energy
Brain_MRI	60.417	4405.27	66.3722	0.1242
Chest_Xray	149.378	4723.63	68.7286	0.7134
Hand_Xray	56.581	4238.96	65.1073	0.1763
Kidney_CT	101.857	7594.25	87.145	0.4848
Leg_MRI	91.858	5581.31	74.7081	0.328
Liver_US	83.534	2624.99	51.2347	0.1748

Table 2 – Performance of Image compression

Image	Bpp	cr	mse	psnr (db)
Brain_MRI	9.18	11.47	3.5498	42.629
Chest_Xray	5.28	6.599	3.6467	42.512
Hand_Xray	7.15	8.94	5.6769	40.59
Kidney_CT	8.01	10.01	1.4037	46.658
Leg_MRI	7.68	9.604	7.2638	39.519
Liver_US	6.51	8.137	7.4157	39.429

Table 3 – Analysis of Statistical Distribution of Pixels

Image	Entropy			Statistical Distribution of Pixels	
	Normal	Shannon	Log Energy	Skewness	Kurtosis
Brain_MRI	31055	0.124	0.12	1.6914	4.0103
Chest_Xray	55020	0.713	0.71	0.7714	0.7609
Hand_Xray	11320	0.176	0.18	1.2837	2.0547
Kidney_CT	24409	0.485	0.48	0.5647	0.2982
Leg_MRI	16532	0.328	0.33	1.0358	1.3237
Liver_US	15576	0.175	0.17	0.9575	1.443

Table 4 – Performance of Image Activity

Image	Edge	Img Gradient
Brain_MRI	2.35	64.841
Chest_Xray	2.143	76.864
Hand_Xray	4.033	45.606
Kidney_CT	3.552	93.822
Leg_MRI	4.167	94.707
Liver_US	2.605	51.357

HAAR mother wavelet is used to compress different types of medical images (Fig.1). Three levels of decomposition are used.

The results from analysis shows that negative correlation exist between edges and compression ratio. Correlation is statistical measure of how correlated a pixel is to its neighbour over the whole image. Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

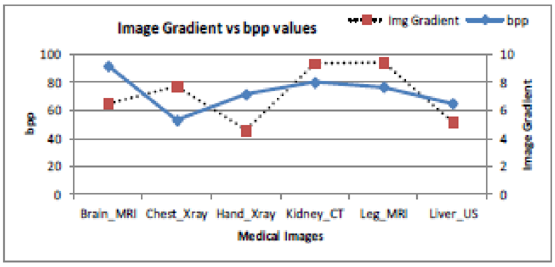

Fig 3 Image Gradient vs bpp values

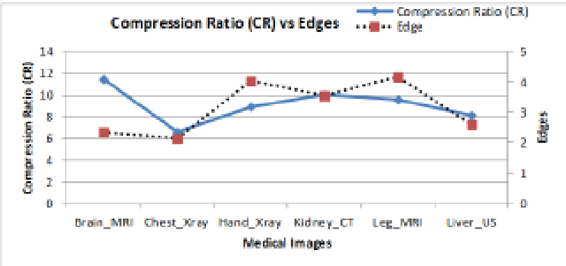

Fig. 4 Compression Ratio vs Edges

The analysis also reveals that the image gradient and bits per pixel (BPP) are positively correlated. The positive correlation exist between edges and bpp (Fig3 – Fig 4).

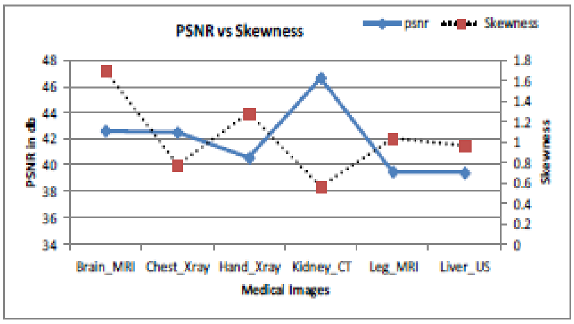

Fig. 5 Skewness vs PSNR

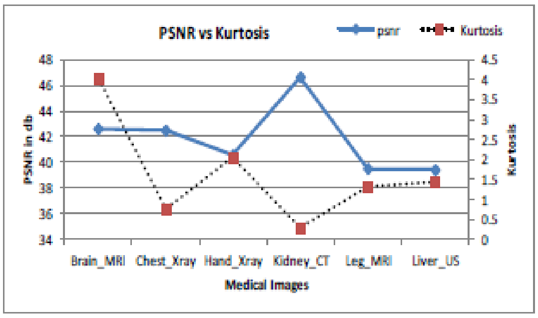

Fig. 6 Kurtosis vs PSNR

The skewness values show in the above figures (Fig.5-Fig.6) a strong positive correlation also exist between the kurtosis and PSNR values.

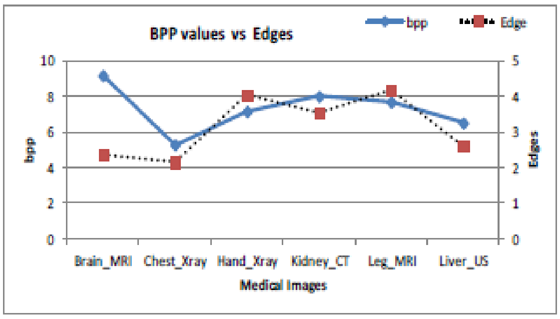

Fig.7 BPP vs Edges

The image activity measure is established how busy the image in terms of edges and contours and displayed in the Fig 7.

The following Fig. 8 shows that how the standard deviation of the pixel values of the images are distributed with respect to mean square error of the reconstructed images. It is observed that there is strong negative correlation exists between the mean squared error (MSE) and the standard deviation (std dev).

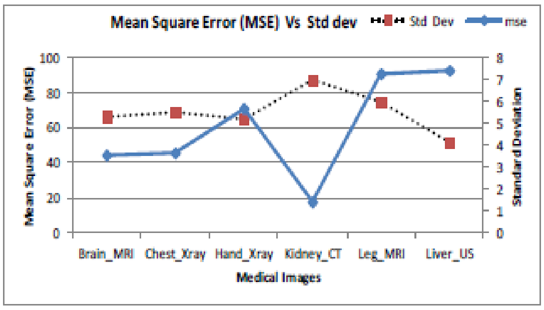

Fig.8 MSE vs Std Dev

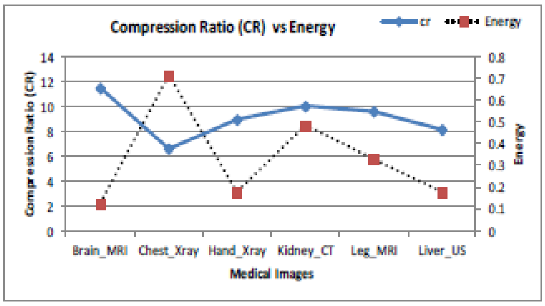

Fig 9 CR vs Energy

The compression ratio (CR) with respect to energy distribution of the images are displayed in the Fig. 9. It shows that a positive correlation exist between energy values of pixel elements of the images and compression ratio.

VI. CONCLUSIONS AND FUTURE WORK

We conducted a simple, yet effective statistical based metric function for medical image compression and investigated the correlation between the image characteristics and coding performance based on certain image statistics like entropy, energy, edges, image gradient, skewness and kurtosis. In conclusion, we comprehend that statistical characterization of medical images is at the prime focuses of many challenging problems in image compression, image processing and analysis, computer vision, and digital image forensics. The work elucidated in this paper reveals just a small fraction of the tremendous potential of these image statistics and image features. Although a lot of room for improvement can be made using evolutionary computation such as Fuzzy logic, rough set and Genetic Algorithms (GAs), they can serve as a well-posed starting point for future exploration in this direction.

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REFERENCES

[1] Bostanci, E., Kanwal, N., and Clark, A.F. ,“Spatial Statistics of Image Features for Performance Comparison", IEEE Trans. on Image Processing, vol. 23, no.1, pp 153-162, 2014

[2] Czajka, A., and Bowyer, K.W., “Statistical analysis of multiple presentation attempts in iris recognition”, IEEE – 2nd Int. Conf. on Cybernetics (CYBCONF), pp. 483–488, 2015

[3] Yap. V.V., and Rahman, S., “ The Implications of Image Statistics and Image Features on Coding Performance of Synthetic Images”, Proc.of Int. Conf. on SCI-2003, Orlando, Florida, July 2003

[4] Saha, S., and Vemuri, R,, “How do image statistics impact lossy coding performance?", Proc. IEEE Int. Conf. on Information Technology: Coding and Computing, 2000, pp. 42-47.

[5] Sheikh, H.R. and Bovik, A.C, “Image information and visual quality", IEEE Trans. On Image Processing, vol. 15, no.2, pp. 430-444, 2006

[6] Li, D and Loew, M, “Closed-form quality measures for compressed medical images: statistical preliminaries for transform coding", Proc. 25th IEEE- Annual Int. Conf. of the IEEE-Engineering in Medicine and Biology Society, 2003. pp. 837-840.

[7] Haralick, R.M., Shanmugan,K., and Dinstein, I., "Textural Features for Image Classification", IEEE Transactions on Systems, Man, and Cybernetics, Vol. SMC-3, pp. 610-621, 1973.

[8] Field, D.J., “ Relations between the statistics of natural images and the response properties of cortical cells”, Journal of Optical Soc. Am. A, Vol. 4, No. 12, pp. 2379-2392, Dec 1987.

[9] Haralick, R.M., and L.G. Shapiro. Computer and Robot Vision, vol 1, Addison-Wesley, 1992.

[10] Gonzalez, R.C., R.E. Woods, and S.L. Eddins, Digital Image Processing Using MATLAB, New Jersey, Prentice Hall, 2003, Chapter 11.

[11] Hyvärinen. A, Hurri. J, and Hoyer, P. O., Natural Image Statistics - A probabilistic approach to early computational vision, Springer-Verlag, 2009