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A Comparative Study on State of the Art Picture Coding Evaluation for Medical Image Compression

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ABSTRACT

The aim of this paper is to examine and evaluate a suitable image quality metrics as applied to medical image compression based on wavelet transform and figure out why a voluminous range of quality metrics are used ranging from simple objective mathematical assessment to complex subjective analysis. Wavelet based image compression is a cutting edge technology in the field of image processing. One of the main problems and challenges in the image compression schemes is the lack of a well defined and accepted metric for the prediction of image quality of the compressed images. The most commonly, regularly and frequently used image quality metrics for image compression system are remain simple and mathematically tractable such as peak signal to noise ratio (PSNR) or mean squared error (MSE). These simple objective based metrics do not accurately predict the visual quality of medical images which contain a large luminance variations such as edges and textured regions of complex systems of the human body. This study not only highlights how image quality metrics can be used to guide an image compression scheme in general but it also outlines the pros and cons of a number of quality metrics in particular and their limitations to medical images.

Keywords: Medical Image compression, Quality metrics, Image quality assessment performance, subjective quality assessment, objective quality measures

1. INTRODUCTION

It is well known that biomedical imaging technique has become one of the most important visualization and interpretation methods and procedures in the field of medicine for diagnostic of diseases and abnormalities [1]-[2]. The evaluation of picture quality is not only helpful, needful and useful but also crucial and indispensable in image coding because it plays important roles in a variety of images and video processing applications, such as compression, communication, printing, analysis, registration, restoration, enhancement and watermarking [3],[4],[6]. Noise, artifacts, and weak contrast are the cause of a decrease in image quality and make the interpretation of medical images very difficult. Poor image quality always leads to problematic and unreliable feature extraction, analysis, and recognition in many medical applications [5]-[7].

The picture quality evaluation can be done in two ways, namely, subjective assessment and objective measures [13]. It is no doubt that subjective assessment tests are commonly employed to evaluate the picture quality of coded images. However, careful subjective assessments of quality are experimentally difficult and lengthy, and the results obtained may vary depending on the test conditions [14]-[15]. Subjective assessments do not provide any constructive methods for performance improvement and are difficult to use as part of the design process. Major drawbacks of the subjective criteria are burdensome, inaccurate and inconsistent because it varies from person to person opinion [8]-[10].

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The objective picture quality evaluation is performed based on mathematical formula and also a part of the design process or coding part of the image software package [17]. There are basically two classes of objective quality or distortion assessment approaches. The first one are mathematically defined measures of error between the evaluated image and its ideal prototype. Typical examples of such measures are mean squared error (MSE), peak signal to noise ratio (PSNR), root mean squared error (RMSE), mean absolute error (MAE), and signal-to-noise ratio (SNR) [10]. The second classs of measurement methods considers human visual system (HVS) characteristics in an attempt to incorporate perceptual quality measures. Nowadays the most commonly and regularly used technique for quality metrics are mean squared error (MSE) and peak signal-to-noise ratio (PSNR) because they are simple to calculate and are mathematically easy to deal and tractable with for optimization purposes. However, they have been widely criticized for not correlating well with perceived quality measurement [8]–[12]. In the last three decades, a great deal of effort has been made to develop objective image and video quality assessment methods, which incorporate perceptual quality measures by considering human visual system (HVS) characteristics [15]. A reliable quality measure is much needed tool for determining the type and amount of image distortion specially on the medical images due to its purpose and characteristics [35]-[37]. The aim of this paper is to provide a complete quantitative performance evaluation of the state-of-the-art full reference image quality metrics over the available image quality measures.

The remainder of this paper is organized as follows: Section II is devoted to the literature survey and motivation of the proposed research work. In Section III, we address the mathematical treatise of quality measures for gray scale image compression and their limitations based on the various techniques that are incorporated and employed in the image coding system. Section IV deals with the experimental results and discussions of the study. Conclusion and future scope of the proposed research work are given in the Section V.

2. RELATED WORK

For the past two decades, efficient compression algorithms have been proposed and used in order to reduce transmission time and storage costs. The quality evaluation of medical image compression is an essential process in order to provide the cost effective services to the common men in the health care sector. One can find in the literature several variants of the original model with respect to the image fidelity and the compressed image. Most proposed quality assessment approaches in the literature are error sensitivity-based methods. There are a number of notable reviews of image quality metrics.

In particular, *Eskicioglu* et al. [11] present in-depth survey on a number of quality metrics that primarily on mathematical oriented. *Grgic* et al. [14],[20] elucidate a useful discussion of a number of visual factors which could be incorporated in a perceptual metric assessment to predict image quality. *Sakrison*, [22] propose a picture quality scale and gave an integrated view for image coding applications. *Tulu* et al. [24] intimate how an empirical investigation of objective and subjective video quality for the internet-based telemedicine. *Lukas* et a. [26] suggest a new technique for picture quality prediction based on a visual model for still images and video coding applications. *Kunt* et al. [31] comprehend a second-generation image-coding techniques and points out an empherical formula for quality assessment for video coding. *Miyahara* [33] presents quality assessments for visual service which covers only the basics of the picture evaluation.

In the above literature study, we have observed that the image quality measurement is still an unsolved problem today [6] -[10]. New studies exploiting certain aspects of the HVS report reasonable success in quantifying certain types of distortion based on subjective ranking. This issue is continuing to expand and has achieved a certain maturity level within the community of multimedia communication and multimedia computing [15]-[16].

3. IMAGE QUALITY MEASURES

This section gives a brief review of the different quality measures and objective assessment of the compressed image. Objective image quality assessment plays an important role in many image processing applications in general and image compression is particular [19]. Motivation of the proposed work is to examine how the image quality metrics are used in image compression schemes [11],[16],[17]. In general, the objective based image quality measures can be classified into two types, namely, univariate and bivariate.

3.1. Univariate measures

The univariate measures are used to assess the quality of the target image without the explicit use of a reference image. Some of the examples for the univariate measures are defocus blur, motion blur, off-angle, occlusion, specular reflection, lighting and pixel count [27], [28], [30]. The proposed paper does not cover anything about univariate measures of the quality assessment.

3.2. Bivariate measures based on Distortion Assessment

In bivariate measures, the quality of the target image is assessed based on a reference image. Major assessment techniques which are used for the bivariate measures are covered in this research work.

3.2.1. Mean Square Error (MSE)

The Mean Squared Error (MSE) is the simplest and most widely used image dissimilarity measure for image quality analysis. The MSE is easy to compute and has a number of desirable properties in real world applications, but it also suffers from several fundamental problems [10]. The least value of mean square means that image is in good quality. Mean square error between the reference image $p(i, j)$ and the compressed image q(i,j) is given in the following formula

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[p(i, j) - q(i, j)\right]^2$$

3.2.2. Peak Signal to Noise Ratio (PSNR)

The ratio between maximum possible power of the signal to the power of the corrupting noise that creates distortion of image via compression. The peak signal to noise ratio can be represented in decibels (db). The small value of Peak Signal to Noise Ratio (PSNR) means that image is poor quality The minimum value of PSNR should be above 30 db for better picture quality [13]. It can be calculated based on the following formula:

$$PSNR = 10\log\frac{\left(2^n - 1\right)^2}{MSE}$$

3.2.3. Average Difference (AD)

AD is the average of pixel difference between the reference image and compressed image. It can be calculated by the equation

$$AD = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[p(i, j) - q(i, j)\right]$$

3.2.4. Maximum Difference (MD)

Difference between any two pixels such that the larger pixel appears after the smallest pixel. The large value of maximum difference means that image is poor in quality. MD can be calculated by the following formula:

$$MD = Max\left(\left|p(i,j) - q(i,j)\right|\right)$$

3.2.5. Normalized Cross-Correlation (NK)

Normalized cross correlation is a measure of similarity of two waveforms as a function of the time lag applied to one of them. The cross correlation is similar in nature to the convolution of two functions.

$$NK = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[p(i,j) - q(i,j)\right]}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[p(i,j)\right]^2}$$

3.2.6. Mean Average Error (MAE)

The large value of Mean Average Error (MAE) means that image is poor quality. MAE can be calculated by using the following formula:

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[p(i,j) - q(i,j)\right]$$

3.2.7. Normalized Absolute Error (NAE)

The large value of Normalized Absolute Error (NAE) means that image is poor quality. NAE can be defined and measured based on the following formula:

$$NAE = \frac{\sum_{i-1}^{M}\sum_{j=1}^{N}\left[p(i,j) - q(i,j)\right]}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[p(i,j)\right]}$$

3.2.8. Structural Content (SC)

It is one of the correlation based measures for quality assessment of the images. The correlation based measure is used to find the closeness (relationship) between two digital images which can also be quantified in terms of correlation function. This metric measures the similarity between two images. The large value of structural content SC means that image is poor quality. The Structural Content Metric (SCM) is based on the following equation.

$$SC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[p(i,j)\right]^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[q(i,j)\right]^2}$$

3.2.9. Image Fidelity (IF)

Image fidelity assessment is used to infer by the ability to discriminate between two images specially on original and compressed images. If we cannot detect the difference between an original and a compressed image, we conclude that the compression process was visually loss less. The image fidelity computational measure is done based on human vision models because these types of judgments depend upon our ability to detect differences between images [11], [12].

$$IF = 1 - \left(\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \left[p(i,j) - q(i,j) \right]^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} \left[p(i,j) \right]^2} \right)$$

3.2.10. Laplacian Mean Square Error (LMSE)

Laplacian mean square error is calculated based on the laplacian value of the expected and obtained data which is based on the importance of edges measurement. The large value of Laplacian Mean Square Error (LMSE) means that image is poor quality. LMSE is defined as follow:

$$LMSE = \frac{\sum_{i=1}^{M-1} \sum_{j=2}^{N-1} \left[O\{p(i,j)\} - O\{q(i,j)\} \right]^2}{\sum_{i=1}^{M-1} \sum_{j=2}^{N-1} \left[O\{p(i,j)\} \right]^2}$$

3.2.11. Peak Mean Square Error (PMSE)

Two commonly used measures are Mean-Squared Error and Peak Signal-to-Noise Ratio [6],[10]. The mean-squared error (MSE) between two images $g(x, y)$ and is: One problem with mean-squared error is that it depends strongly on the image intensity scaling.

$$PMSE = \frac{\frac{1}{MN} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \left[p(i,j) - q(i,j) \right]^2}{\left[Max\{p(i,j)\} \right]^2}$$

3.2.12. Normalized Mean Square Error (NMSE)

Normalized Mean Square Error (NMSE)) is used to estimate the overall deviations between predicted and measured values of original and compressed images.

$$NMSE = \frac{\sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \left[O\{p(i,j)\} - O\{q(i,j)\} \right]^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} \left[O\{p(i,j)\} \right]^2}$$

3.3. Image Quality Assessment based on SFM and SAM

3.1. Spatial Frequency Measure (SFM)

Spatial Frequency Measurement (SFM) is an image quality assessment method which is used to measure the overall activity level in an image. The human visual system is too complex to be fully understood with present physiological means but the use of spatial frequency has led to an effective objective quality index for image compression [ ]. The large value of SFM means that image contain components in high frequency area. The spatial frequency of an image block is defined as follows:

$$SFM = \sqrt{(RF)^2 + (CF)^2}$$

where the row (RF) and column (CF) frequencies of the image block are given by

$$RF = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=2}^{N} \left[p(i,j) - p(i,j-1) \right]^2}$$

where P(i, j) is the gray value of pixel at position (i, j) of image P.

$$CF = \sqrt{\frac{1}{MN}\sum_{j=1}^{N}\sum_{i=2}^{M}\left[p(i,j) - p(i-1,j)\right]^2}$$

M and N are numbers of pixels in horizontal and vertical directions, respectively.

3.2. Spectral Activity Measure (SAM)

Spectral Activity Measure (SAM) is a measure of image predictability and it is evaluated in frequency domain based on the following formula [11], [21], [23].

$$SAM = \frac{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|F(i,j)\right|^2}{\left[\prod_{i=1}^{M}\prod_{j=1}^{N}\left|F(i,j)\right|^2\right]^{\frac{1}{MN}}}$$

where F(i, j) is DFT spectrum and its coefficients. SAM has a dynamic range from 1 to . For active images, the SAM value is close to 1. Higher values of SAM imply higher predictability.

3.3. Image Quality Measures based on UIQI

The Universal Image Quality Index (UIQI) metric was developed and introduced by Bovik and Wang [32]. Instead of using traditional error summation methods such as MSE or PNSR, the UIQI is designed by modeling any image distortion as a combination of three factors: loss of correlation, luminance distortion and contrast distortion. If x and y are the reference (original image) and the test image signals (compressed image), the UIQI is defined as

$$Q = \frac{4\sigma_{xy}x'y'}{\left(\sigma_x^2+\sigma_y^2\right)\left[(x')^2+(y')^2\right]}$$

where

$$x' = \frac{1}{N}\sum_{i=1}^{N} x_i, \qquad y = \frac{1}{N}\sum_{i=1}^{N} y_i, \qquad \sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - x'\right)^2,$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - y'\right)^2, \qquad \sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - x'\right)\left(y_i - y'\right)$$

A product of three components is given below in order to understand and implement in the programming aspects.

$$Q = \frac{\sigma_{xy}}{\sigma_x\sigma_y}\cdot\frac{2x'y'}{(x')^2+(y')^2}\cdot\frac{2\sigma_x\sigma_y}{\sigma_x^2+\sigma_y^2}$$

The UIQI is better correlated with the quality perception of the HVS than the conventional objective quality metrics of the image compression system. The UIQI index values vary between 0 and 1. The values close to 1 show the highest correspondence with the original images.

3.4. Image Quality Assessment Based on SSIM

The motivation behind the structural similarity approach for measuring image quality is that the HVS is not designed for detecting imperfections and errors in images [9]. SSIM is used for measuring the similarity between two images and a full reference metric. The measurement of image quality is based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods such as peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human visual perception. This index was proposed by Wang et al. [7]-[9]. The SSIM index computes the quality of a distorted image by comparing the correlations in luminance, contrast, and structure locally between the reference and distorted images and averaging these quantities over the entire image. It is an improved version of the universal image quality (UIQI) index proposed before by Wang et al. [6]. The SSIM index values vary between 0 and 1. The values close to 1 show the highest correspondence with the original images [18].

The Structural Similarity (SSIM) Index quality assessment index is based on the computation of three terms, namely the luminance term, the contrast term and the structural term. The overall index is a multiplicative combination of the three terms.

$$SSIM(x,y) = \left[l(x,y)\right]^{\alpha} . \left[c(x,y)\right]^{\beta} . \left[s(x,y)\right]^{\gamma}$$

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}, \qquad C(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}, \qquad S(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

where μ_x, μ_y, σ_x, σ_y, and σ_{xy} are the local means, standard deviations, and cross-covariance for images x, y.

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i, \qquad \mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i, \qquad \sigma_x = \left(\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)^2\right)^{\frac{1}{2}},$$

$$\sigma_y = \left(\frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \mu_y\right)^2\right)^{\frac{1}{2}}, \qquad \sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)\left(y_i - \mu_y\right)$$

If $\alpha = \beta = \gamma = 1$ (the default for Exponents), and C3 = C2/2 (default selection of C3) the index simplifies to:

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}$$

4. EXPERIMENTAL 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. Experiments were done on a large number of

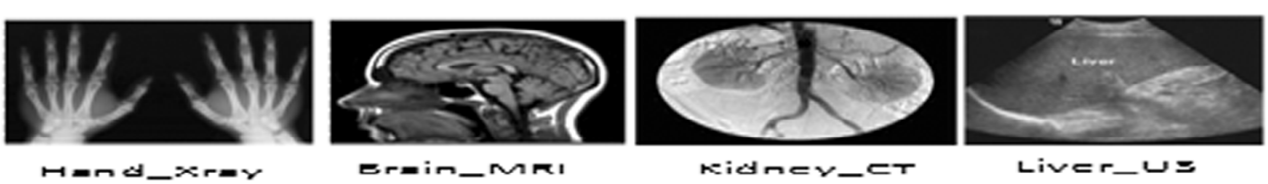


Figure 1: Test Medical Images of JPEG Format

Figure 2: Test Medical Images of PNG Format

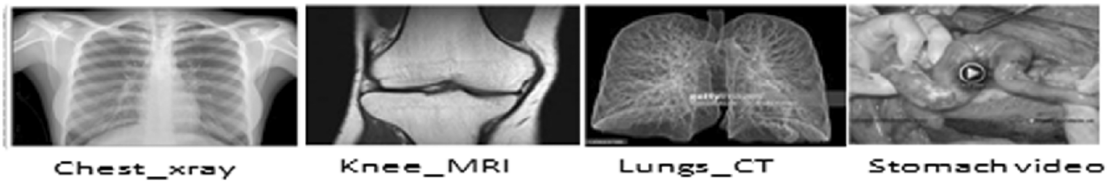


Figure 3: Test Medical Images of GIF Format

medical images of different modalities. These test images are grouped into three categories based on its storage format such as JPEG (Fig. 1), PNG (Fig. 2) and GIF (Fig. 3) form. These include X ray lung, X ray hand, retinal images, MRI brain, liver ultra sound, CT spine, skull and video clipping in order to assess the performance of the proposed algorithm.

The proposed method is implemented in the MATLAB (2014 a) and the operating system used here is windows OS 7. The MATLAB wavelet toolbox function 'wavedec2' is used to perform wavelet transform. The image is decomposed into its coefficients using the 'wavedec2' function. The decomposition depends on the type of wavelet and the level of decomposition. Many image quality assessment algorithms have been shown to behave consistently when applied to compressed images created from the same original image. As shown in the tables (Table 1- 4), in our experiments, the SSIM values of the compressed medical images for JPEG format are from 0.759 to 0.9997. The MSE values also reduce when the quality factors are

Table 1
Quality performance of Brain_MRI of JPEG format

Quality Factor	*MSE*	*PSNR (db)*	*AD*	*MD*	*NK*	*MAE*	*NAE*	*SC*	*SSIM*
10	111.1	27.67	-0.1573	87	0.9861	-0.1573	0.1082	1.014	0.857
20	61.35	30.25	-0.03279	69	0.9903	-0.03279	0.08087	1.012	0.9068
30	44.23	31.67	-0.04031	53	0.9928	-0.04031	0.06871	1.009	0.9304
40	35.19	32.67	-0.2716	47	0.9935	-0.2716	0.06533	1.009	0.912
50	28.74	33.55	0.001404	38	0.9945	0.001404	0.05595	1.007	0.951
60	23.6	34.4	-0.01906	37	0.9956	-0.01906	0.05103	1.006	0.9581
70	18.37	35.49	-0.2806	27	0.9965	-0.2806	0.04898	1.005	0.9354
80	12.16	37.28	-0.04579	24	0.9973	-0.04579	0.03761	1.004	0.9727
90	5.43	40.78	-0.01405	14	0.9987	-0.01405	0.02515	1.002	0.9874
100	0.06915	59.73	-0.00116	1	1	-0.00116	0.001145	1	0.9997

Table 2
Quality performance of Hand_X ray of JPEG format

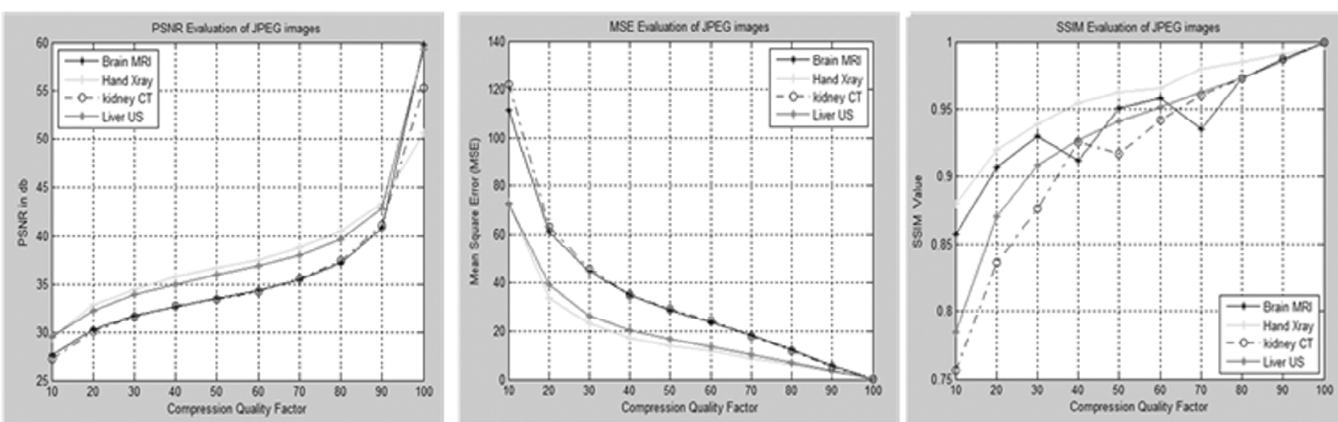
Quality Factor	*MSE*	*PSNR (db)*	*AD*	*MD*	*NK*	*MAE*	*NAE*	*SC*	*SSIM*
10	73.17	29.49	0.0542	66	0.9916	0.0542	0.1032	1.008	0.8795
20	33.95	32.82	0.2257	56	0.9975	0.2257	0.0715	1.001	0.9197
30	23.07	34.5	-0.05076	31	1.001	-0.05076	0.05922	0.9959	0.9392
40	17.16	35.79	-0.1497	29	0.9988	-0.1497	0.05106	1	0.9543
50	13.73	36.75	0.1127	25	0.9994	0.1127	0.04526	0.9995	0.9624
60	11.5	37.52	-0.06701	24	0.9989	-0.06701	0.04293	1.001	0.965
70	8.395	38.89	0.02304	24	0.9986	0.02304	0.0338	1.002	0.9798
80	5.769	40.52	-0.01968	16	0.9998	-0.01968	0.02767	0.9997	0.9852
90	2.978	43.39	-0.00571	12	0.9996	-0.00571	0.01961	1	0.9909
100	0.5579	50.67	-0.00907	5	0.9998	-0.00907	0.006807	1	0.9977

Table 3
Quality performance of Kidney_CT of JPEG format

Quality Factor	*MSE*	*PSNR (db)*	*AD*	*MD*	*NK*	*MAE*	*NAE*	*SC*	*SSIM*
10	122.3	27.26	0.9686	83	0.9846	0.9686	0.07174	1.025	0.7559
20	63.39	30.11	-0.8949	65	0.9982	-0.8949	0.05351	1	0.8359
30	45.49	31.55	-0.1475	59	0.9978	-0.1475	0.04479	1.002	0.8758
40	34.93	32.7	-0.2207	65	0.9987	-0.2207	0.03689	1.001	0.9261
50	29.21	33.48	-0.00097	48	0.9981	-0.00097	0.03546	1.002	0.9167
60	24.21	34.29	-0.1779	50	0.9988	-0.1779	0.03112	1.001	0.942
70	18	35.58	-0.1575	33	0.9994	-0.1575	0.02676	1	0.96
80	11.62	37.48	-0.01315	29	0.9993	-0.01315	0.02126	1.001	0.9727
90	4.987	41.15	-0.05796	16	0.9999	-0.05796	0.01385	1	0.9871
100	0.1903	55.34	0.003031	4	1	0.003031	0.001369	1	0.9993

Table 4
Quality performance of Liver_US of JPEG format

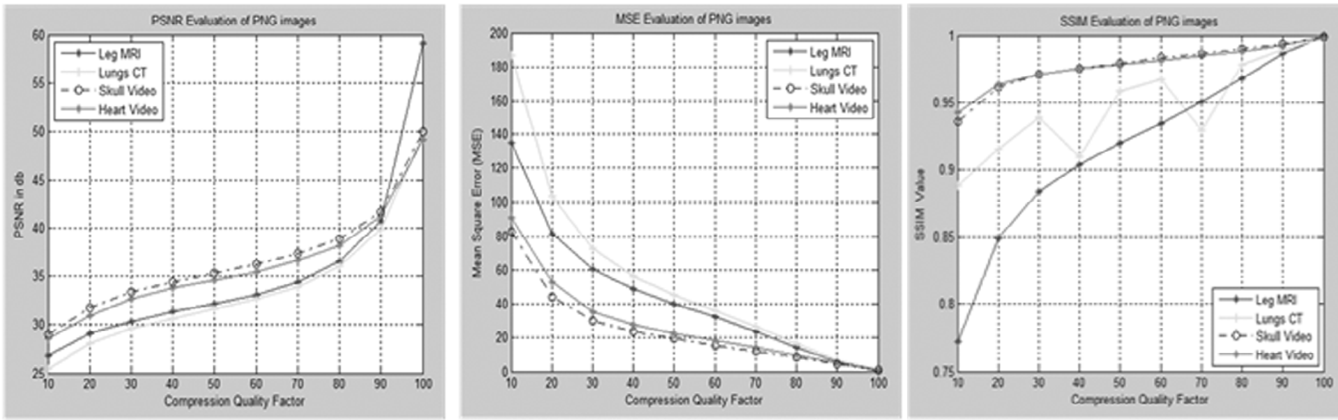
Quality Factor	*MSE*	*PSNR (db)*	*AD*	*MD*	*NK*	*MAE*	*NAE*	*SC*	*SSIM*
10	72.5	29.53	0.2702	83	0.9954	0.2702	0.0722	1.002	0.7845
20	39.11	32.21	0.0898	55	0.9979	0.0898	0.05346	1	0.8702
30	26.41	33.91	-0.02658	46	0.9984	-0.02658	0.04352	1	0.9083
40	20.46	35.02	0.1084	47	0.9983	0.1084	0.0381	1.001	0.9276
50	16.41	35.98	0.09367	36	0.9993	0.09367	0.03446	0.9997	0.941
60	13.22	36.92	0.03238	38	0.999	0.03238	0.0294	1.001	0.9515
70	10.12	38.08	-0.00234	26	0.9995	-0.00234	0.02578	1	0.9621
80	6.921	39.73	0.002945	21	0.9997	0.002945	0.02141	0.9999	0.9729
90	3.353	42.88	0.002151	12	0.9999	0.002151	0.01477	0.9999	0.9858
100	0.07596	59.33	0.002014	1	1	0.002014	0.000909	1	0.9996



(a) (b) (c)

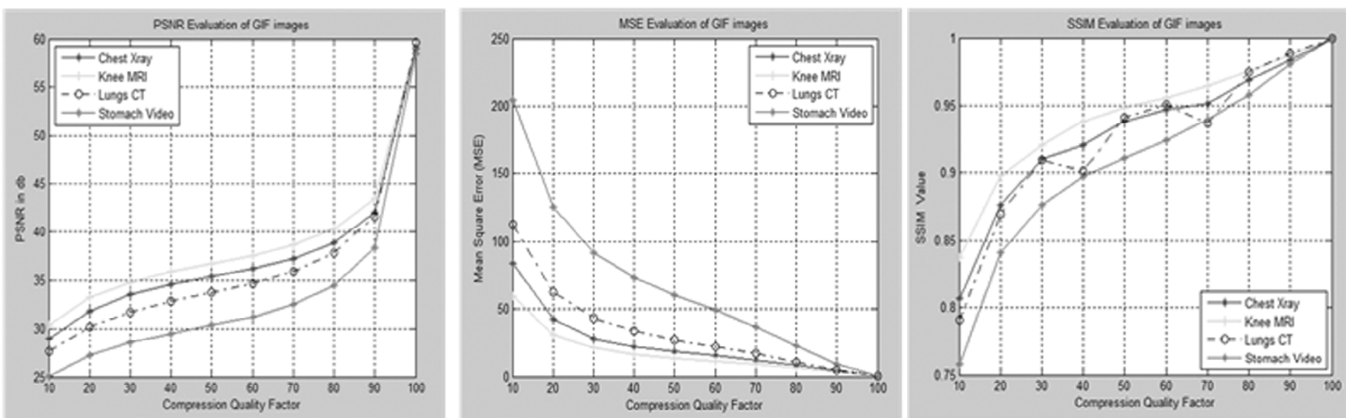
Figure 4: (a-c) Objective Quality performance of JPEG images (PSNR, MSE and SSIM)

increased. Due to paucity of space, we have included only the JPEG simulation tables. The MSE, PSNR and SSIM measurement results are given in the figure caption. MSE performs very poorly in this case. The SSIM values exhibit much better consistency with the qualitative visual appearance. However, the effectiveness of these models degrades significantly when applied to a set of images originating from different reference images, and/or including a variety of different types of distortions [15].



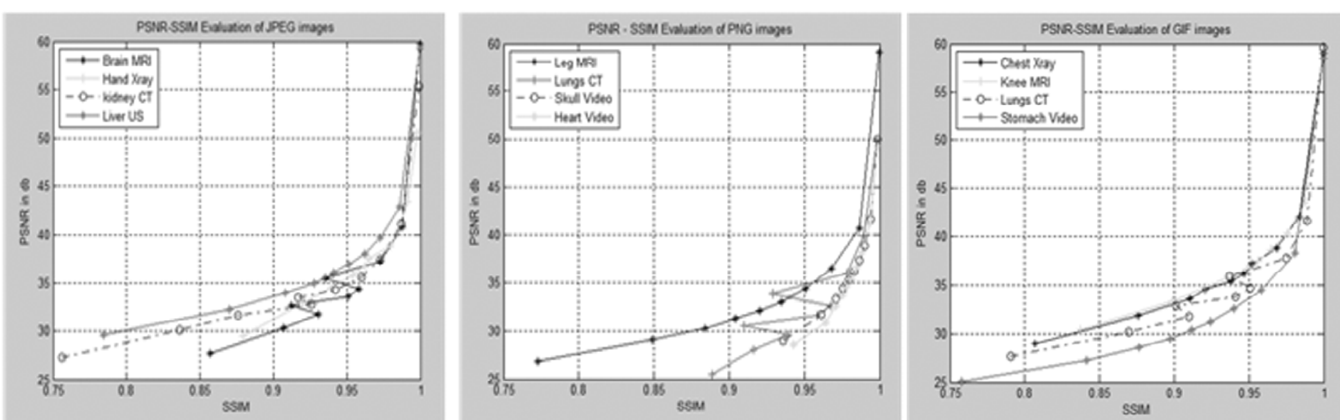
(d) (e) (f)

Figure 5 (d-f) Objective Quality performance of PNG images (PSNR, MSE and SSIM)



(g) (h) (i)

Figure 6 (g-i) Objective Quality performance of GIF images (PSNR, MSE and SSIM)



(a) (b) (c)

Figure 7 (a-c) Quality performance based on PSNR vs SSIM (JPEG, PNG, GIF)

V. CONCLUSION AND FUTURE WORK

In this paper, we have investigated how the image quality metrics have been used in image compression schemes and discussed some of the visual factors which are incorporated in the metrics. We have also described a number of quality metrics commonly used by image compression researchers and elucidated the difficulties associated with validating them in psycho-physical experiments. From the above investigation, we comprehend that there is no single reliable objective criterion for measuring the quality of a compressed image. One cannot make a complete evaluation of various compression techniques [6]. Though we have tried several widely and commonly used metrics to evaluate their performance on medical images, but there are still some limitations. First, there is still room for investigating by other metrics. Second, the good performance metrics are all need reference image which is hard to obtain sometime. Last but not least, we do not use the information in each modalities view, separately. Therefore, in the future, we plan to investigate more image quality assessment metrics to evaluate the quality of medical image and to build a system for systematic evaluations of the quality of performance on compressed medical images.

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