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Image Quality Assessment For Various Medical Image Processing Applications

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Abstract— The features of the image degrade from the minute it is produced by device and processed for various applications. During the stages such as storing, processing, compressing, and transmitting, image quality is degraded by many factors. Most hospitals store medical image data in digital form using picture archiving and communication systems due to extensive digitization of data and increasing telemedicine use. Telemedicine application requires compressing data to save memory and transmission time and image enhancement during retrieving for correct decision making. With the expanding interest for therapeutic imaging framework, the proficient and dependable assessment of picture quality has expanded in significance. Estimating the picture quality is of principal significance for various picture preparing applications, where the objective of picture quality appraisal (IQA) strategies is to consequently assess the nature of pictures in understanding with human quality decisions. In this paper, the traditional image error based quality matrix like PSNR, MSE compared with information weighted image structural quality assessment technique for different processed set of images.

Index Terms— Image Quality assessment (IQA), Information weighted image quality assessment (IW-IQA), PSNR, MSE, SSIM, Medical Imaging, Image Enhancement, Image Compression, MATLAB.

1 INTRODUCTION

With the rapid development of multimedia technology, millions of digital images require to be processed and visual information is often a subject of many processing steps, e.g., acquisition, enhancement, compression, or transmission. After processing, some information carried by the content of the images is distorted [1], [2]. Image quality assessment (IQA) is employed to estimate the degree of distortion. That is, IQA plays a pivotal part in evaluating or monitoring the performance of an image processing system. The most accurate estimation method for image quality is subjective IQA carried out by human observers. However, subjective quality methods are costly, time-consuming, and impractical as they cannot be integrated within real-world systems for real-time visual quality monitoring and controlling [3], [4]. It triggers the need to develop reliable objective IQA methods that are consistent with subjective human evaluation.

There are three categories of image quality assessment (IQA) measures (metrics or models), depending on availability of a original reference, i.e., distortion-free, image: (1) full-reference, (2) no-reference, and (3) reduced-reference models. In this paper, the full-reference approach is considered, in which for each distorted image in a benchmark dataset its reference image is provided [5].

Conventional objective IQA methods like Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE) and structural similarity index (SSIM) are simple but in some cases their results are less accurate because they just measure the statistical information in images. Thereby, in recent decades, an increasing demands to make efforts to develop effective and efficient methods to evaluate the image quality automatically. Ideally, perceptual quality is obtained by the image perception mechanism of human visual system (HVS); nevertheless, due to the complexity and limited understanding of HVS, it is almost impossible to completely replicate HVS [6]. State-of-the-art methods turn to the other direction that manages to capture the statistical properties (features) which represent the information that HVS is interested in and are closely relevant to the image inherent quality and map them to the perceptual quality. Therefore, it is a significant problem for us to extract the effective image feature. Furthermore, in most cases, a single measurement cannot provide sufficient information for quality prediction.

2 REVIEW OF IQA MATRIX

The development in the research of IQA models started with FR image quality metrics.
Conventionally image fidelity metrics like Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) were used to evaluate quality of images. Though simple, they show certain limitations. They focus on global errors and ignore the local errors. In contrast to vision property of HVS, they operate on pixel by pixel basis. Spatial relationship among pixels is an important characteristic which is perceived by human eye. However, reordering the pixels does not change distortion measurement in case of these metrics. Therefore these conventional metrics fail to emulate human visual system.

Mean Structural Similarity Index Metric (M-SSIM) developed by Z. Wang et al [7], fascinated attention of entire IQA researcher community. It is based on the theory that human eye is subjected to extract structural action from any image. Luminance comparison, structure comparison and contrast comparison between original image and distorted image is done using mean, variance and covariance of the images. They all are combined as SSIM. Block wise quality score of the image is computed. Average of block wise SSIM values is called as M-SSIM, the final quality score. This metric is based on similarity measure and it quantifies any variation between the reference image and the degraded image. The metric performed much better than conventional image fidelity measures on image databases comprising of different distortions. It is well known that HVS is attracted by different image textures with different degrees. Therefore authors have suggested a modification in the metric. Spatially variant weighted average of SSIM index map can improve the HVS consistency of this approach.

B. Wang et al [8] proposed HVS based SSIM metric based on frequency and spatial characteristics of human eye. It is based on the hypothesis that human eye does not pay equal attention to all regions in the image. Frequency sensitivity weight is calculated using DCT coefficients. To mimic the foveated vision of human eye spatial affect weight is calculated in spatial domain. These weights are used in the calculation of M-SSIM. This metric gives HVS consistent results especially for badly blurred images.

W. Xue et al [9] proposed a creative methodology in gradient magnitude similarity metric. It depends on the idea that picture gradient is influenced due to picture contortions. Distinctive nearby structures in a misshaped picture endure by various sum because of corruptions. The measurement figures pixel-wise closeness between the gradient extent maps of reference and misshaped pictures and furthermore nearby quality map for by and large picture quality forecast in the wake of pooling. The measurement predicts perceptual picture quality precisely and proficiently.

H. W. Chang et al [10] proposed an excellent full-reference quality metric using sparse correlation coefficient. This model is based on bottom-up approach and simulates the receptive fields of simple cells found in primary visual cortex. Sparse coding is used to correlate the test image with original image. Sparse correlation coefficient is calculated to capture the correlation between the two sets of outputs obtained from a sparse model of simple cell in receptive fields. Fixed point Independent Component Analysis (ICA) algorithm is used to get the sparse codes of the image. This metric correlates well with human visual system. However, use of bottom up approach makes it complex.

A. Shnayderman et al [11] proposed a new SVD based multidimensional image quality measure. Singular values of an image represent relationship among the pixels of underlying matrix. Hence they are used to measure dissimilarity between images. Original image and test image are divided in small blocks and SVD is applied to each block. Error value between the corresponding blocks of the two images is calculated and such error scores are combined to predict the overall image quality. To minimize the computational burden, block size of 8*8 is preferred. Distortion maps are presented for six types of distortions, each with 5 levels. They are used as graphical measure.

All these metrics have exhibited good performance. However, all individual IQA matrix work only with specific characteristic of image. Today in this era of multimedia and internet, it is required to develop IQA matrix which work well in all situation or distortion.

3 IMAGE QUALITY ASSESSMENT ALGORITHM

Generally, the fundamental principle of IQA is to measure the degree of perceptual quality degradation by assessing the difference or dissimilarity between the distorted image and its reference image. The scheme of a basic IQA method is shown in Figure 1, where there are three stages. In the first stage, features that can reflect the image quality are extracted by different algorithms. Then, difference or dissimilarity of each feature between the distorted image and its corresponding reference is quantified in the second stage. Such differences or dissimilarities are regarded as the distortion indices to measure the degradation of image quality. Finally, in the third stage, all the distortion indices are fused together and mapped into an objective quality score.

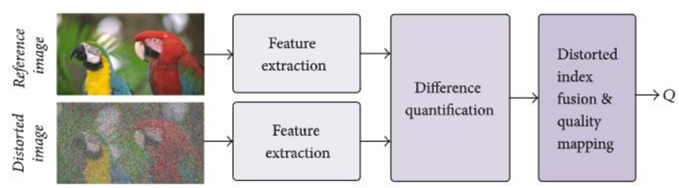

Fig-1 Basics of IQA

3.1 Mean square error (MSE)

The MSE is used in measuring the difference in the predicted outcome with that of expected outcome. This metric is the dispersion metric and it can be used to measure the quality of the image enhancement algorithm in which it is applied to removal of noise and blur. Also in real time this metric can be applied to satellite, seismic and medical applications. If the MSE value increases, then the image degradation increases. When MSE value reaches zero then pixel by pixel matching of images becomes perfect.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j) - y(i,j))^2 \qquad (1)$$

Where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, x (i, j) is the filtered image at i and j co-ordinates and y(i, j) is the noisy image at i and j co-ordinates.

3.2 Peak signal to noise ratio (PSNR)

The PSNR is the important metric which is used to measure the quality of the restored image when it is corrupted due to noise and blur. This metric performs well in LAND-SAT images. Higher the value of PSNR, indicates higher the quality rate. The MSE decides the PSNR value.

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When comparing the two images, PSNR is calculated by taking the Mean Squared Error (MSE) between the pixel intensities and taking the ratio of the maximum possible intensity to the result of the calculation. The standard value of PSNR is 35 to 40 db. In general, a higher PSNR value corresponds to a better quality image. The PSNR standard value is subjected to correlative analysis and is depends on MSE. MSE is indirectly proportional to the PSNR. The histogram represents the frequency of differences in intensity between the two compared images. The histogram values spread from 30 to 40 db shows more signal.

However, the PSNR result is unbounded. PSNR can be computed by using the following relation:

$$PSNR = 10\log_{10}\frac{Max^2}{MSE} \qquad (2)$$

Where n is the maximum pixel value of the image.

3.3 Structural similarity index matrix (SSIM)

In order to bring betterment to these metrics SSIM is introduced. SSIM is defined as a function of luminance comparison, contrast and structural comparison term. The value lies from 0 to 1. SSIM is a perception-based model that considers the image degradation as perceived change in structural information where, structural information is the idea that the pixels have strong interdependencies especially when they are spatially close. The linear dependence factor is computed using the correlation coefficient in SSIM index. Blurring operation on an image causes fading of the sharp edges of an image. SSIM has a high significance on blurred images with high consistency. In real time, this metric can be widely used in bio-medical applications especially in mammographic diagnosis and cancer detection fields. It is the universal metric where we can apply this metric to assess the quality of any images. Since this metric is operating on luminance, contrast and structural information in images.

N is the total number of pixels in the image. is the filtered image at i and j co-ordinates and is the noisy image at i and j co-ordinates.

$$SSIM = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \qquad (3)$$

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

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*. c1, c2 and c3 are constants.

4 IMAGE QUALITY MEASURE BASED ON ERROR

MSE, PSNR have many attractive features:
1) It is simple to calculate. It is parameter free and inexpensive to compute. It has complexity of only one multiplication and two additions per pixel.
2) It is memory less. The squared blunder can be assessed at each example, free of other example.
3) It has clear physical significance. It characterizes the vitality of the blurr picture. The vitality is protected considerably subsequent to applying direct change, for example, Fourier Transform on the picture. Thus this guarantees the vitality of the bending stays same for change space.

There are a number of reasons why MSE or PSNR may not correlate well with the human perception of quality [4][5].
1] Digital pixel values, on which the MSE is typically computed, may not exactly represent the light stimulus entering the eye.
2] Simple error summation, like the one implemented in the MSE formulation, may be markedly different from the way the HVS and the brain arrives at an assessment of the perceived distortion.
3] Two distorted image signals with the same amount of error energy may have very different structure of errors, and hence different perceptual quality.

5 IMAGE QUALITY MEASURE BASED ON STRUCTURE SIMILARITY

Z. Wang proposed a new philosophy assuming that the human visual system (HVS) is highly adapted to extract structural information from the visual scene [12]. The new concept is very different from the previous error sensitivity philosophy, which considers image degradations as perceived changes in structural information instead of perceived errors. Why human visual system is adopted for image quality assessment? Human visual system is a part of the central nervous system, which enable organisms to deal with visual details from the eyes of observer [13], [14]. Applying human visual system to image quality assessment is more appealing to human eyes. The luminance of an object's surface observed from human eyes is the product of the illumination and the reflectance, but the structures of an object are independent of the illumination. For the above reason, defines the image structure information is independent of the average luminance and contrast calculating from the local luminance and contrast. The structural similarity measurement system divides the measurement into three mutually independent components: luminance, contrast and structure. Result analysis of various image compression technique is shown

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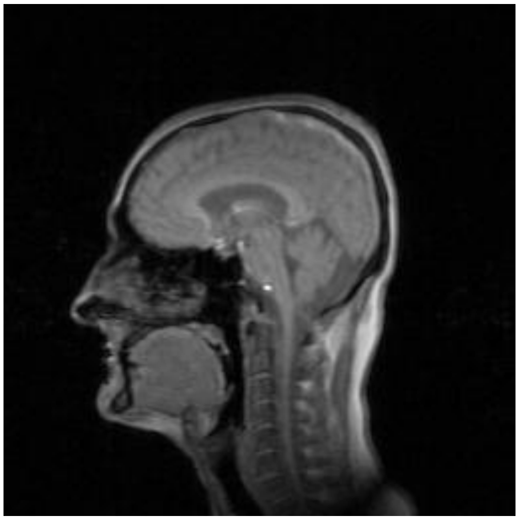
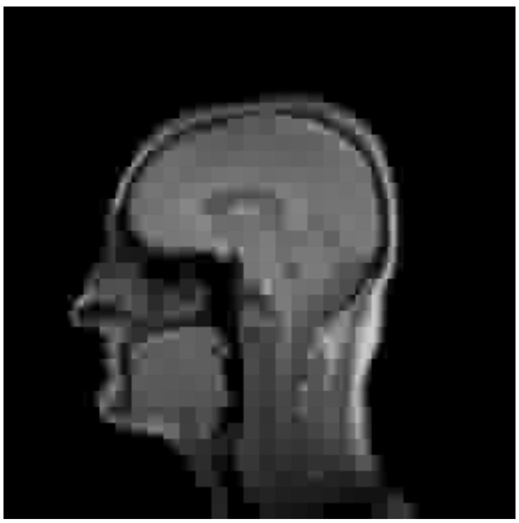
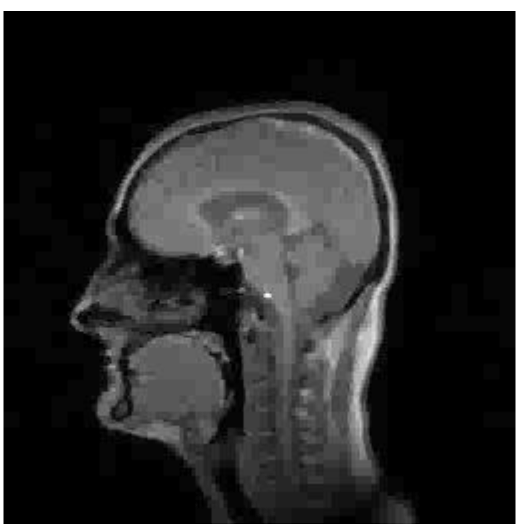


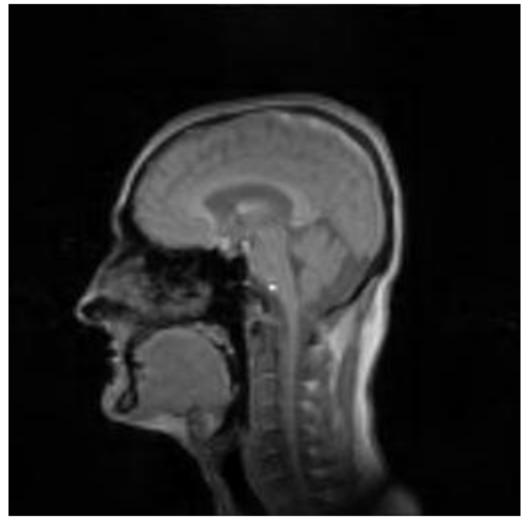
(a) Original Head MR Image



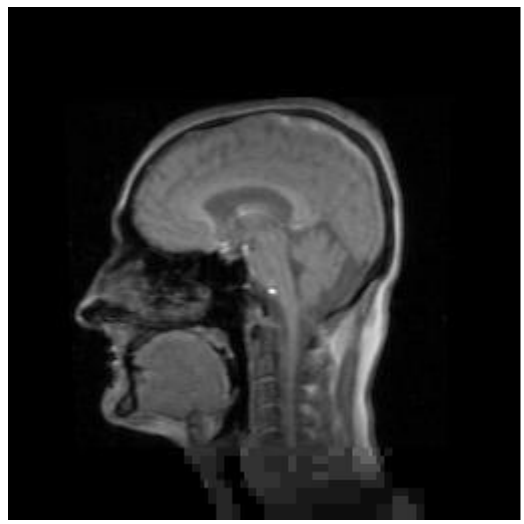
(b) DCT Compressed Image



(c) DWT Compressed Image



(d) Modified SPIHT Compressed Image

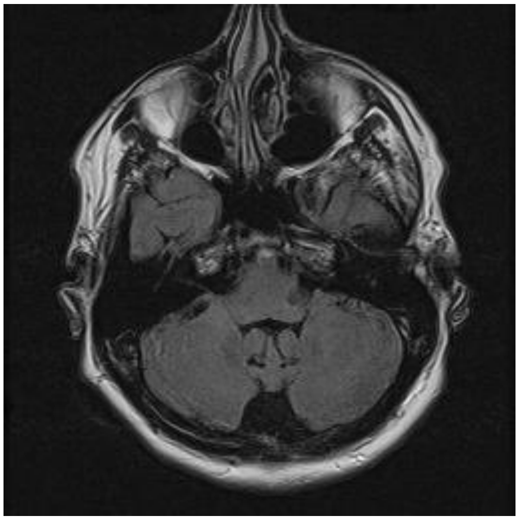


(e) ROI based Compressed Image

Fig. 1 Compression of Head MR Image

Table 1
IQA for Head MR Image

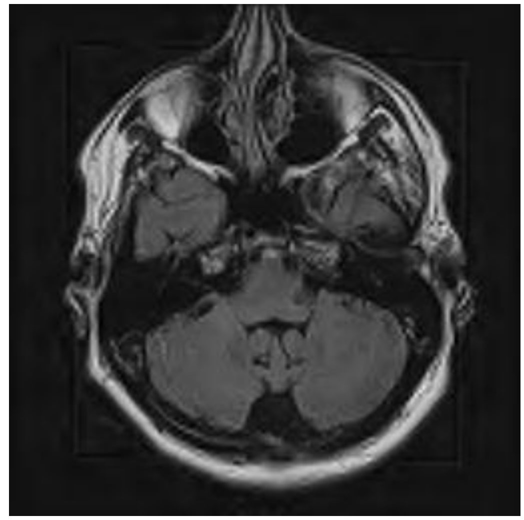
Image	CR	MSE	PSNR	SSIM
DCT Compressed Image	0.956	197.69	25.17	0.2685
DWT Compressed Image	0.851	80.73	29.60	0.4151
Modified SPIHT Image	0.916	85.32	28.82	0.4590
ROI based Compressed Image	0.889	50.29	31.11	0.5455



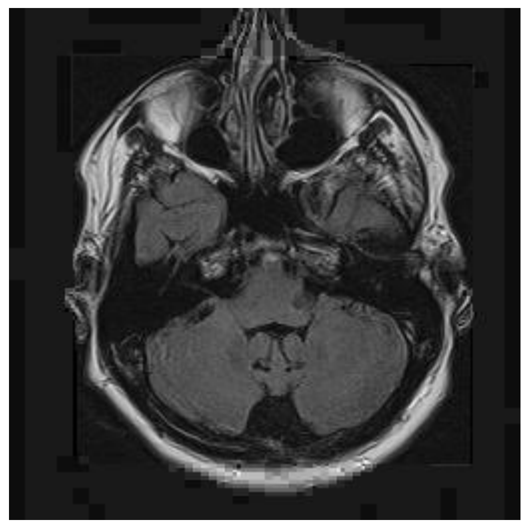
(a) Original Head MR Image

(b) DCT Compressed Image

(c) DWT Compressed Image



(d) Modified SPIHT Compressed Image



(e) ROI based Compressed Image

Fig. 2 Compression of Head MR Imag

Table 2

IQA for Heart MR Image

Image	CR	MSE	PSNR	SSIM
DCT Compressed Image	0.968	70.92	29.62	0.2135
DWT Compressed Image	0.916	35.21	32.66	0.3114
Modified SPIHT Image	0.916	14.71	36.45	0.4262
ROI based Compressed Image	0.889	12.87	37.03	0.4641

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By analyzing results of IQA matrix, MSE and PSNR of some distorted images is irrespective of its quality, but the appearance or distortion level of each of the distorted image is quite related with SSIM.

6 CONCLUSION

In this paper we discussed, The ordinary picture quality evaluation dependent on error affectability and its restrictions in therapeutic pictures. We have additionally examined about the strucutral methodologies of picture quality estimation. We exhibit the upsides of strucutral methodology over the traditional methodology. Nonetheless, because of the weaknesses of the basic methodologies numerous analysts have attempted to beat these deficiencies by build up another picture quality metric especially for ultrasound pictures. As most of the images are ultimately viewed by human observers, the only reliable test to assess the quality of an image is by visually evaluating the image. Subjective picture quality evaluation takes quite a while, yet additionally is over the top expensive and not viable continuously applications. Further, there can be singular factors that may impact the apparent picture quality. In this way, it is important to assess the picture quality impartially, keeping the human visual framework as a reason for such an assessment. Any target IQA calculation will have a nearby relationship with the human impression of vision and it must have reliable execution over a wide range picture types. There is no general purpose metric has been settled upon, to supplant the abstract or the target quality measurements. Henceforth there is still a lot of left to be wanted, and leave the entryway open to attempt to build up another model that can improve the expectation of picture quality measure exactness in medical pictures.

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