IEM: A New Image Enhancement Metric for Contrast and Sharpness Measurements

Jaya V. L
Research scholar
Division of Electronics Engineering, School of Engineering,
Cochin University of Science And Technology, Kochi-22, Kerala, India

R. Gopikakumari
Professor
Division of Electronics Engineering, School of Engineering,
Cochin University of Science And Technology, Kochi-22, Kerala, India

ABSTRACT

Evaluation of images, after processing, is an important step for determining how well the images are being processed. Quality of image is usually assessed using image quality metrics. Unfortunately, most of the commonly used metrics cannot adequately describe the visual quality of the enhanced image. There is no universal measure, which specifies both the objective and subjective validity of the enhancement for all types of images. This paper is a study of the various quantitative metrics for enhancement against changes in contrast and sharpness of both general and medical images. A new metric is proposed that is useful for measuring the improvement in contrast as well as sharpness. It is computationally simple and can be used for all types of images.

Keywords:

Image enhancement, Image Quality Assessment(IQA), Full reference metric, Blind reference metric, Human Visual System(HVS), Image Enhancement Metric(IEM).

1. INTRODUCTION

Digital images are subjected to a variety of distortions or degradations at the time of acquisition, restoration, enhancement, compression and transmission. Removal of such degradations is very important for successive processing or analysis of images. In image compression and transmission, least changes are desired and metrics such as PSNR, MSE etc. are widely used as quantitative metrics for evaluating the amount of distortion with respect to the original image.

Image enhancement basically deals with improving the image quality for better vision. It is defined as the impression of its merit of excellence, as perceived by an observer. Contrast, brightness and sharpness are the three basic parameters that control the quality of an image.

Contrast enhancement is considered to be one of the important issues in image processing. Poor contrast may be due to poor illumination, lack of dynamic range in image sensor, wrong setting of lens aperture etc. during image acquisition. The idea behind contrast enhancement is to improve the dynamic range of the image pixels and thereby improving the visual quality of the image.

Brightness is the general intensity of the pixels in an image and its histogram gives an indication of the brightness. The image is darker when the histogram is confined to a small portion towards the lower end and is brighter when the histogram falls to the higher end.

Sharpness of an image refers to the amount of details present. Motion blur, out-of-focus, lossy compression, de-noising filtering are some of the causes that affect perceived image sharpness.

Even though a number of image enhancement techniques are available, development of a quantitative enhancement measure suitable for all types of images, is still a challenging area and newer metrics are being thought of every day [6] [16].

Existing Image Quality Assessment(IQA) [29] techniques can be categorized into subjective assessment, involving humans to evaluate the image quality and objective assessment, that measures the image quality automatically. Subjective quality evaluation is a reliable method since human beings are the ultimate users in most of the image processing applications. Mean Opinion Score (MOS) [13] has long been regarded as the best method for this purpose. But for applications such as medical image enhancement, this method requires the service of experts and is a time-consuming process. Hence it is not suitable for real time applications. Also, for small changes in the image, this evaluation is difficult.

The goal of objective quality evaluation is to obtain a quantitative measure which gives the quality of the image in a manner consistent with human perception and subjective analysis should match with objective assessment values. According to the availability of a reference image, objective evaluation techniques are classified as Full-Reference(FR), no or Blind-Reference(BR) and Reduced-Reference(RR) image quality metrics [30].

A distortion-less reference image of perfect quality is used in FR method to evaluate the quality of the modified image. Typically this comparison involves measuring the distance between the two signals in a perceptually meaningful way. Such methods are excellent for assessing the transmission and compression noise, but may not work for enhancement since good quality enhanced image is not known a-priori.

In BR method, quality is assessed without using any reference image. In the third method, the reference image is not fully available and some features based on statistical or texture properties extracted are employed for quality assessment.

This paper is a study about the full reference and blind reference IQA techniques for changes in contrast and sharpness. It also exposes the importance of image statistical features in quantitative evaluation of image enhancement. A full reference IQA metric, entitled IEM, capable of assessing contrast as well as sharpness of general and medical images is proposed.

2. REVIEW OF OBJECTIVE IQA METRICS

Many IQA metrics, both FR and BR, have been proposed over the past few decades. Each one has its own advantages and disadvantages in terms of accuracy, computational speed and application considered.

2.1 Full-reference IQA metrics

2.1.1 Conventional Quality metrics. A simple and widely used FR fidelity measure is the Peak Signal-to-Noise Ratio (PSNR), or the corresponding distortion metric, the Mean-Squared Error (MSE) [10] and are expressed as

$$MSE(r,e) = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(r(i,j)-e(i,j))^2 \tag{1}$$

$$PSNR(r,e) = 10log_{10}\left(\frac{(L-1)^2}{MSE(r,e)}\right)dB \tag{2}$$

where r and e denote the reference and enhanced images respectively, MN is the size of the image and L is dynamic range of pixel values (256 for 8-bit gray scale images). These methods directly measure the pixel-by-pixel differences between the images. They are attractive metrics for the loss of image quality due to its simplicity and mathematical convenience. But they are not well matched to perceive visual quality.

Other frequently used metrics are Mean Absolute Error(MAE)[20], Signal-to-Noise Ratio(SNR) [25], [9], Absolute Mean Brightness Error(AMBE)[22], Contrast-to-Noise Ratio(CNR) [7] and are defined as

$$MAE(r,e) = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}|n(i,j)| \tag{3}$$

$$SNR(r,e) = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} r(i,j)^2}{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} n(i,j)^2} \tag{4}$$

$$AMBE(r,e) = |\mu_r - \mu_e| \tag{5}$$

$$CNR(r,e) = \frac{\mu_r - \mu_n}{\sigma_n} \tag{6}$$

where

$$n(i,j) = r(i,j) - e(i,j)$$

$$\mu_r = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} r(i,j)$$

$$\mu_n = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(n(i,j))$$

$$\sigma_n^2 = \frac{1}{MN-1}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(n(i,j)-\mu_n)^2$$

2.1.2 HVS based IQA metrics. HVS based methods take advantage of the known characteristics of Human Visual System and consider HVS characteristics to incorporate perceptual image quality metrics. In [27], Venkata et. al. developed a Distortion Measure(DM) and a Noise Quality Measure(NQM) to quantify the impact of frequency distortion and noise injection on the HVS. Universal Quality Index (UQI) is introduced[28] to successfully measure image similarity across distortion types and is expressed as

$$UQI(r,e) = \frac{4\mu_r\mu_e\sigma_{re}}{(\mu_r^2+\mu_e^2)(\sigma_r^2+\sigma_e^2)} \tag{7}$$

where

$$\sigma_{re} = \frac{1}{MN-1}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(r(i,j)-\mu_r)(e(i,j)-\mu_e)$$

.

In the same way as SNR is defined as the ratio of the average signal power to average noise power, Weighted Signal to Noise ratio(WSNR) [21] is defined as the ratio of average weighted signal power to average weighted noise power, where the weights are derived from the Contrast Sensitivity Function(CSF).

Natural image signals are highly structured exhibiting strong dependencies between spatially proximate pixels. They carry important information about the structure of the objects in the visual scene. Wang et.al.[30] introduced SSIM (Structural SIMilarity), an alternative framework, for quality assessment based on the degradation of structural information under the assumption that human visual perception is highly adapted for extracting structural information from a scene. The Mean SSIM (MSSIM) index, overall quality value, is expressed as

$$SSIM(r,e) = \frac{(2\mu_r\mu_e + C_1)(2\sigma_{re}+C_2)}{(\mu_r^2+\mu_e^2+C_1)(\sigma_r^2+\sigma_e^2+C_2)} \tag{8}$$

$$MSSIM(r,e) = \frac{1}{K}\sum_{i=1}^{K} SSIM(r_i,e_i) \tag{9}$$

where $C_1 = ((L-1)k_1)^2$, $C_2 = ((L-1)k_2)^2$, $k_1, k_2 \ll 1$ and K is the number of local windows in the image.
Sheikh et. al.[24] introduced information theory into image fidelity measurement and proposed a visual Information Fidelity Criterion(IFC) for IQA by using natural statistics models. Later IFC was extended to Visual Information Fidelity(VIF) [23] that

quantifies Shannon information shared between distorted image and the modified image. The Visual Information Fidelity in Pixel domain(VIFP) is derived from a quantification of two mutual information quantities: the mutual information between the input and the output of the HVS channel when no distortion channel is present and the mutual information between the input of the distortion channel and the output of the HVS channel for the test image [26].

A wavelet-based Visual Signal-to-Noise Ratio(VSNR) which operates by using both low-level and mid-level properties of HVS and quantifies the visual fidelity of enhanced images based on psychophysical findings is proposed by Chandler in [8]. A feature similarity metric, based on Riesz Transform (RFSIM)[31], can extract low level image features efficiently. The FSIM index proposed in [32] employs two features to compute the local similarity map, the phase congruency and the gradient magnitude. They play complementary roles in characterizing the image local quality.

2.2 Blind-reference IQA metrics

A number of blind-reference metrics have been proposed during the last decade. EME (measure of enhancement) and EMEE (measure of enhancement by entropy) have been developed by Agaian et. al. [3], [4], [17] give an absolute score to each image on the basis of image contrast processed with Fechner's Law relating contrast to perceived brightness or the well-known entropy concept.

$$EME(e) = \frac{1}{k_1 k_2} \sum_{m=1}^{k_1} \sum_{l=1}^{k_2} 20ln\left(\frac{I_{max}^{l,m}}{I_{min}^{l,m}}\right) \tag{10}$$

$$EMEE(e) = \frac{1}{k_1 k_2} \sum_{m=1}^{k_1} \sum_{l=1}^{k_2} \alpha\left(\frac{I_{max}^{l,m}}{I_{min}^{l,m}}\right)^{\alpha} ln\left(\frac{I_{max}^{l,m}}{I_{min}^{l,m}}\right) \tag{11}$$

where the image is divided into $k_1 k_2$ blocks, α is a constant, $I_{max}^{l,m}$ and $I_{min}^{l,m}$ are the maximum and minimum values of the pixels in each block of the enhanced image.

These metrics were improved based on Michelson contrast law and AME and AMEE were introduced [5]. Later Panetta et. al. developed logAME and logAMEE [18] for better assessment of images.

$$AME(e) = -\frac{1}{k_1 k_2} \sum_{m=1}^{k_1} \sum_{l=1}^{k_2} 20ln\,(X) \tag{12}$$

$$AMEE(e) = -\frac{1}{k_1 k_2} \sum_{m=1}^{k_1} \sum_{l=1}^{k_2} \alpha\,(X)^{\alpha}\, ln\,(X) \tag{13}$$

where $X = \frac{I_{max}^{l,m} - I_{min}^{l,m}}{I_{max}^{l,m} + I_{min}^{l,m}}$. All these metrics divide an image into $k_1 k_2$ blocks and calculate the average value of the measured results of all blocks in the entire image.

For better image quality assessment, a Second Derivative like MEasurement (SDME) [33], [19] was introduced and this measure is shown to have better performance than other measures in evaluating the image visual quality after enhancement.

$$SDME(e) = -\frac{1}{k_1 k_2} \sum_{m=1}^{k_1} \sum_{l=1}^{k_2} 20ln\left|\frac{I_{max}^{l,m} - 2I_{cen}^{l,m} + I_{min}^{l,m}}{I_{max}^{l,m} + 2I_{cen}^{l,m} + I_{min}^{l,m}}\right| \tag{14}$$

where $I_{cen}^{l,m}$ refers to the center pixel value of each block.

2.3 Statistical feature metrics

A feature is a characteristic that can capture visual properties of an image either globally for the entire image or locally for regions or objects. The visual characteristics of homogeneous regions of real-world images are often identified as texture. Since an image is made up of pixels, texture can be defined as an entity consisting of mutually related pixels or group of pixels and thus leading to visual quality of images.

An image can be described by means of first order statistics of gray values of the pixels inside a neighborhood. Examples of such features extracted from the image histogram are mean, standard deviation(SD) and entropy.

The second order features are based on gray level co-occurrence matrix (GLCM)[11] and it is one of the most popular methods for pixel variation statistics. Some of the second order statistical features are entropy, contrast, homogeneity, energy and correlation of the gray level pixels, defined as [12].

$$Entropy = -\sum_i \sum_j P(i,j) log P(i,j) \tag{15}$$

$$Contrast = \sum_i \sum_j (i-j)^2 P(i,j) \tag{16}$$

$$Homogeneity = \sum_i \sum_j \frac{P(i,j)}{1+|i-j|} \tag{17}$$

$$Energy = \sum_i \sum_j P(i,j)^2 \tag{18}$$

$$Correlation = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j} P(i,j) \tag{19}$$

where i and j are two different gray levels of the image, P is the number of the co-appearance of gray levels i and j.

Entropy is used to measure the content of an image with higher value indicating an image with richer details. Contrast returns a measure of the intensity difference between a pixel and its neighbor over the whole image. Homogeneity measures the similarity of gray-scale levels across the image. Thus, larger the changes in the gray-scale, the higher the GLCM contrast and lower the homogeneity. GLCM energy measures the overall probability of having distinctive gray-scale patterns in image. Correlation returns a measure of how correlated a pixel is to its neighbor over the whole image and it measures the joint probability of occurrence of the specified pixel pairs.

3. NEW IMAGE ENHANCEMENT METRIC(IEM)

Changes in sharpness and contrast reflect intensity difference between a pixel and its neighbors. Therefore, it is a straightforward idea to compare the absolute value of intensity difference between a pixel and its neighbors corresponding to the reference and enhanced images.

The proposed IQA metric, IEM, approximates the contrast and sharpness of an image by dividing an image into non-overlapping blocks. Average value of the absolute difference between the center pixel and its eight neighbors for all local windows corresponding to the reference and enhanced image will give an indication of the change in contrast and sharpness. Window size of 3×3 is enough as the metric uses only eight neighbors.

Full-reference metric, IEM is defined as the ratio of sum of absolute values of the difference of each pixel from its 8-neighbors of the enhanced image to the reference image and is mathematically expressed as

$$IEM_{8n} = \frac{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\sum_{n=1}^{8}\left|I_{e,c}^{l,m} - I_{e,n}^{l,m}\right|}{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\sum_{n=1}^{8}\left|I_{r,c}^{l,m} - I_{r,n}^{l,m}\right|} \quad (20)$$

where the image is divided into k_1k_2 blocks of size 3×3 and $I_{e,c}^{l,m}$, $I_{r,c}^{l,m}$ are the intensity of the center pixel in (l, m) block of the enhanced and reference images respectively. $I_n^{l,m}, n = 1, 2, , 8$ indicate the 8 neighbors of the center pixel.

When the reference image and enhanced image are identical, IEM=1. $IEM > 1$ indicates that the image is enhanced whereas there is deterioration otherwise. Higher the value of IEM, better the improvement in image contrast and sharpness.

The metric can also be defined by taking the difference of each pixel from its four neighbors to reduce the computational overhead.

$$IEM_{4n} = \frac{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\sum_{n=1}^{4}\left|I_{e,c}^{l,m} - I_{e,n}^{l,m}\right|}{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\sum_{n=1}^{4}\left|I_{r,c}^{l,m} - I_{r,n}^{l,m}\right|} \quad (21)$$

It can be defined alternatively to understand the prominence of vertical or horizontal edges in an image by taking only the horizontal neighbors or vertical neighbors alone as shown below.

$$IEM_{v} = \frac{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\left|I_{e,c}^{l,m} - I_{e,l}^{l,m}\right| + \left|I_{e,c}^{l,m} - I_{e,r}^{l,m}\right|}{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\left|I_{r,c}^{l,m} - I_{r,l}^{l,m}\right| + \left|I_{r,c}^{l,m} - I_{r,r}^{l,m}\right|} \quad (22)$$

$$IEM_{h} = \frac{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\left|I_{e,c}^{l,m} - I_{e,t}^{l,m}\right| + \left|I_{e,c}^{l,m} - I_{e,b}^{l,m}\right|}{\sum_{m=1}^{k_1}\sum_{l=1}^{k_2}\left|I_{r,c}^{l,m} - I_{r,t}^{l,m}\right| + \left|I_{r,c}^{l,m} - I_{r,b}^{l,m}\right|} \quad (23)$$

where $I_{e,l}^{l,m}$, $I_{e,r}^{l,m}$, $I_{e,t}^{l,m}$ and $I_{e,b}^{l,m}$ are the intensity of the pixels in the left, right, top and bottom of the center pixel in (l, m) block of the enhanced image.

4. SIMULATION

This study focuses on enhancement of natural as well as medical images. Eight images each, having adequate diversity in contrast, shape and spread in histograms are selected for analysis. These images include standard images like *Lena, barbara, cameraman, pelicans, pepper, boat, aeroplane, goldhill* and eight medical images of *lung, brain, prostate, breast and bone* and are shown in Figs.1 and 2.

Primary objectives of the analysis are

(1) To find the importance of the new metric, IEM, in sharpness and contrast improvement of general and medical images.

Fig. 1. Eight general images

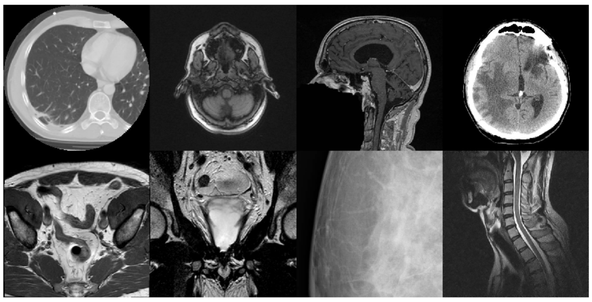

Fig. 2. Eight medical images

(2) To compare the performance of IEM with existing IQA metrics for image enhancement.

(3) To identify metrics suitable for quantifying enhancement of both general and medical images.

(4) To study the role of statistical parameters of an image in enhancement.

Variations in image contrast and sharpness are derived by modifying the images in Figs.1 and 2 and a data set of five images each are formed for all 16 images. The five contrast and sharpness differed images of *Lena*, as example, with their histograms are shown in Figs.3 and 4 respectively. In Fig.3, the contrast of the image is varied by compressing the image histogram to its center. The image is smoothened successively by using averaging filter as in Fig.4. Image Quality level1 (IQ1) signifies the poorest quality image while IQ5 stands for the best quality image. Since optimal enhanced image is not known a-priori for image enhancement, most degraded image of the data set IQ1 is considered as the reference image.
For the calculation of full reference metrics, IQ1 is considered as the reference image and IQ2, IQ3, IQ4 and IQ5 as progressively enhanced images with IQ5 as the most enhanced image. For BR metrics and statistical features, the five images are considered separately for finding the metrics.

To find the significance of IEM for image enhancement, most commonly used metrics for image processing applications, as mentioned in section II, are considered for analysis.

5. RESULTS AND DISCUSSION

The usefulness of the new metric, IEM for image enhancement applications is explored by comparing its performance with other popular IQA metrics with respect to contrast and sharpness.

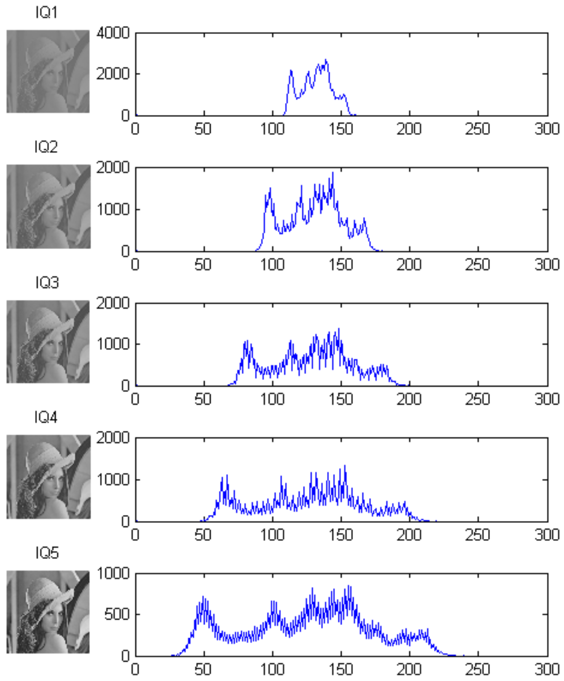

Fig. 3. Lena images of varying contrast and their histograms

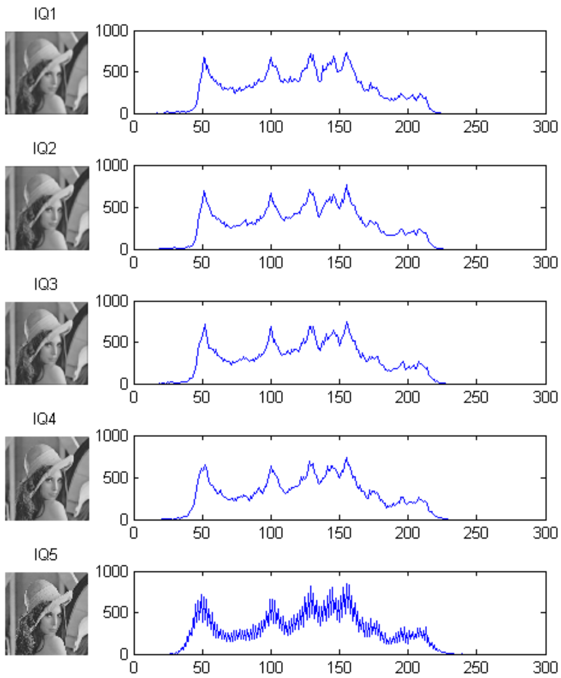

Fig. 4. Lena images of varying sharpness and their histograms

PSNR, SSIM, MSSIM, VSNR, VIF, VIFP, UQI, IFC, NQM, WSNR, SNR metrics are calculated based on [15]. FSIM and RFSIM metrics are found using the on-line code available[1], [2].

Changes in the values of IQA metrics for variations in contrast and sharpness are tested. A high value is expected for IEM, PSNR, SNR, CNR, WSNR, VSNR, NQM, UQI, IFC, SSIM, MSSIM, FSIM, RFSIM, VIF, VIFP, EME, EMEE, AME, AMEE and SDME metrics. MAE and AMBE should be as small as possible for better similarity between images.

Table 1. Full-reference IQA metric values of Lena image for contrast

Metrics	IQ1,IQ2	IQ1,IQ3	IQ1,IQ4	IQ1,IQ5
PSNR(dB)	28.86	22.85	19.33	16.83
SNR(dB)	23.10	17.08	13.56	11.06
CNR	14.29	7.06	4.64	3.44
WSNR(dB)	23.47	17.45	13.93	11.43
VSNR(dB)	05.40	-0.62	-4.06	-6.47
NQM	23.69	17.67	14.15	11.65
UQI	0.83	0.66	0.53	0.44
IFC	9.44	9.45	9.74	10.17
SSIM	0.96	0.89	0.81	0.73
MSSIM	0.93	0.81	0.70	0.62
FSIM	0.96	0.88	0.81	0.74
RFSIM	0.50	0.17	0.07	0.03
VIF	1.55	2.01	2.40	2.74
VIFP	1.42	1.72	1.95	2.15
MAE	7.50	14.99	22.48	29.97
AMBE	1.68	3.37	5.06	6.75
IEM	1.94	2.79	3.63	4.47

The metric values are tabulated for all 16 images and their variations with sharpness and contrast are noted. Values in respect of contrast for the FR and BR metrics obtained for *lena* image are listed in Tables 1 and 2 respectively and the corresponding sharpness metrics are listed in Tables 3 and 4. A comparative evaluation of IQA metrics and statistical features for sharpness and contrast corresponding to the general and medical images are shown in Table 5.1. Based on this, following observations are made.

5.1 Analysis of IQA metrics for contrast

Observations

(1) Values of Mean, PSNR, SNR, CNR, WSNR, VSNR, NQM, UQI, SSIM, MSSIM, FSIM, RFSIM and AME decrease with increase in image quality for medical as well as general images.

(2) IFC, VIF, VIFP, MAE, AMBE, IEM, EME, EMEE, AMEE, SDME, Entropy and SD give increasing values with increase in image quality.

(3) Statistical parameters like Contrast and Correlation values increase whereas Homogeneity, energy values decreases with image quality for general images and there is no fixed variation pattern for medical images.

(4) Objective scores obtained for IEM, VIF, VIFP, EMEE, Entropy and SD are highly consistent with subjective measures for natural as well as medical images. Hence these metrics can be used for measuring the contrast improvement of all types of images. A plot of the above metrics for contrast variations is shown in Fig.5

5.2 Analysis of IQA metrics for sharpness

Observations

(1) Scores obtained for Correlation, Homogeneity, PSNR, SNR, CNR, WSNR, VSNR, NQM, UQI, IFC, SSIM, MSSIM,

Table 2. Blind-reference and statistical feature IQA metric values of Lena image for contrast

Metrics	IQ1	IQ2	IQ3	IQ4	IQ5
EME	0.74	1.36	2.06	2.90	3.98
EMEE	0.04	0.08	0.13	0.21	0.35
AME	87.11	76.17	68.45	62.45	57.31
AMEE	0.07	0.10	0.13	0.16	0.18
SDME	11.03	13.72	14.30	15.63	16.60
Entropy	5.43	6.21	6.69	7.07	7.45
Contrast	0.04	0.07	0.11	0.14	0.21
Correlation	0.91	0.90	0.93	0.94	0.95
Homogeneity	0.98	0.97	0.95	0.93	0.91
Energy	0.49	0.39	0.24	0.20	0.15
Mean	130.80	129.12	127.43	125.74	124.06
SD	11.76	20.77	29.80	38.83	47.85

Table 3. Full-reference IQA metric values of Lena image for sharpness

Metrics	IQ1,IQ2	IQ1,IQ3	IQ1,IQ4	IQ1,IQ5
PSNR(dB)	35.48	35.59	30.55	26.63
SNR(dB)	27.74	29.84	24.81	20.88
CNR(dB)	28.81	29.22	16.37	10.45
WSNR(dB)	31.44	33.71	27.84	24.77
VSNR(dB)	25.42	26.49	20.02	16.31
NQM	23.59	26.59	20.62	17.49
UQI	0.91	0.88	0.78	0.56
IFC	4.42	4.32	2.71	1.93
SSIM	0.98	0.96	0.92	0.80
MSSIM	0.99	0.99	0.97	0.94
FSIM	0.98	0.98	0.95	0.92
RFSIM	0.76	0.80	0.64	0.52
VIF	0.72	0.78	0.58	0.48
VIFP	0.74	0.76	0.60	0.45
MAE	2.29	2.22	3.97	6.54
AMBE	0.13	0.26	0.38	0.69
IEM	1.08	1.19	1.38	2.36

Table 4. Blind-reference and statistical feature IQA metric values of Lena image for sharpness

Metrics	IQ1	IQ2	IQ3	IQ4	IQ5
EME	1.88	2.063	2.25	2.63	3.98
EMEE	0.124	0.142	0.161	0.201	0.351
AME	73.53	73.38	72.39	69.79	57.31
AMEE	0.11	0.12	0.13	0.14	0.18
SDME	12.74	13.10	13.60	14.39	16.60
Entropy	7.39	7.40	7.41	7.42	7.45
Contrast	0.08	0.09	0.12	0.12	0.21
Correlation	0.98	0.97	0.97	0.96	0.94
Homogeneity	0.96	0.95	0.95	0.94	0.91
Energy	0.18	0.17	0.16	0.15	0.14
Mean	122.36	122.49	122.62	123.74	124.05
SD	45.78	46.14	46.58	46.97	47.85

Table 5. Comparison of IQA metrics and statistical features in Proper order for changes in sharpness and contrast

Metrics	Sharpness		Contrast	
	General	Medical	General	Medical
PSNR	D *	D *	D	D
SNR	D *	D *	D	D
CNR	D *	D *	D	D
WSNR	D *	D *	D	D
VSNR	D *	D *	D	D
NQM	D *	D *	D	D
UQI	D	D	D	D
IFC	D	D	I *	I *
SSIM	D	D	D	D
MSSIM	D	D*	D	D
FSIM	D	D*	D	D
RFSIM	D *	D*	D	D
VIF	D *	D *	I	I
VIFP	D *	D *	I	I
MAE	I *	I*	I	I
AMBE	I	NP	I	I
IEM	I	I	I	I
EME	I	I *	I	I *
EMEE	I	I*	I	I
AME	D*	D*	D	D *
AMEE	I	I*	I	I*
SDME	I	I *	I *	I *
Entropy	I*	NP	I	I
Contrast	I	I	I	NP
Correlation	D	D	I *	NP
Homogeneity	D	D	D	NP
Energy	D *	NP	D*	NP
Mean	I	NP	D *	D
SD	I	I	I	I
D-decreases, I-Increases, NP-Changes not Predictable				

Note:*Mentioned variation not true for all values.

FSIM, RFSIM, VIF, VIFP and AME decrease with increase in image quality.

(2) IEM, MAE, EME, EMEE, AMEE, SDME and statistical parameters, Contrast and SD increase with increase in image quality.

(3) Entropy, mean and AMBE increases while energy decreases for general images and vary in an order for medical images.

(4) Objective scores obtained for IEM, SDME and for statistical parameters Contrast, Correlation, Homogeneity and SD are highly consistent with subjective measures for medical and general images. A plot of the above metrics with sharpness variations is shown in Fig.6.

5.3 Analysis of IQA metrics for contrast and sharpness

VIF, VIFP, IEM, EMEE, Entropy and SD are useful for evaluating the contrast of the enhanced images. IEM, SDME and statistical parameters Contrast, Correlation, Homogeneity and SD are useful for assessing the sharpness of both medical and general images.

A list of the useful FR and BR IQA metrics and statistical features are listed in Table 6. A measure which is capable of assessing both contrast and sharpness of general as well as medical images is the new FR metric, IEM. Statistical feature, SD also increases with increase in contrast and sharpness. So, IEM along with SD can

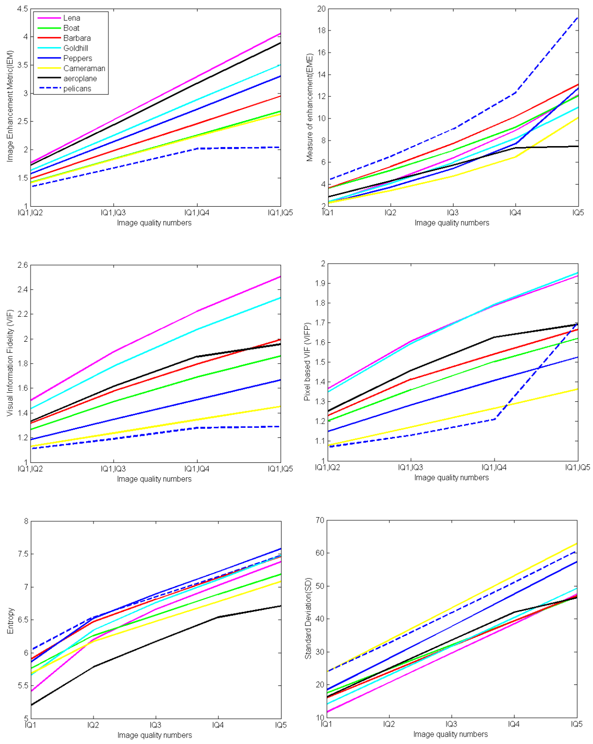

Fig. 5. Variation of IEM, EME, VIF, VIFP, Entropy and SD metrics for contrast variations

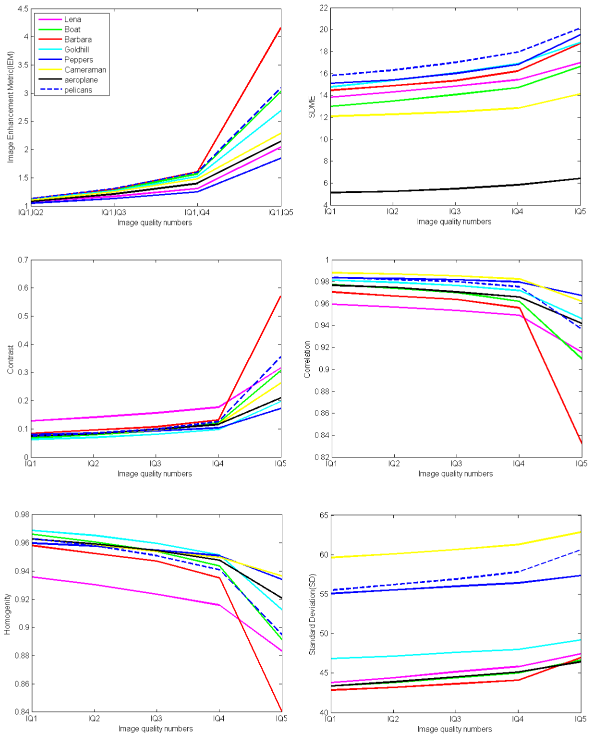

Fig. 6. Variation of IEM, SDME, Contrast, Correlation, Homogeneity and SD for Sharpness changes

Table 6. Usefulness of IQA metrics and statistical features for image enhancement

Metrics	Sharpness		Contrast	
	General	Medical	General	Medical
VIF	-	-	Yes	Yes
VIFP	-	-	Yes	Yes
IEM	Yes	Yes	Yes	Yes
EMEE	Yes	-	Yes	Yes
SDME	Yes	Yes	-	-
Entropy	-	-	Yes	Yes
Contrast	Yes	Yes	Yes	-
Correlation	Yes	Yes	-	-
Homogeneity	Yes	Yes	Yes	-
SD	Yes	Yes	Yes	Yes

be used for assessing the contrast and sharpness of the enhanced images of all types.

6. VALIDATION

Live Image Quality Assessment Database, Categorical Image Quality database(CISQ)[14] is used for the validation of the above study for general images and to find the usefulness of the new metric. It consists of 30 general images, each at four levels of contrast and five levels of sharpness variations. The images are natural images from animal, landscape, people, plants and urban categories. They are subjectively rated based on a linear displacement of the images across four calibrated LCD monitors placed side by side with equal viewing distance to the observer.

Table 7. Validation results of useful IQA metrics and statistical features

Metrics	Sharpness	Contrast
VIF	-	True
VIFP	-	True
IEM	True	True
EMEE	-	True
SDME	False	-
Entropy	-	True
Contrast	True	-
Correlation	True	-
Homogeneity	True	-
SD	True	True

Validation of medical images is done by deriving 5 contrast and sharpness varying images each from 30 medical images of abdomen, brain, teeth, prostate, bone and breast.

All metrics listed in Table 6 are used for validation and the results are shown in Table 7. On comparison, the only change is with SDME. This shows that the above generalization that IEM along with SD can be used for measuring contrast and sharpness of enhanced images is correct.

7. CONCLUSION

In this paper, a new FR metric, Image Enhancement Metric(IEM) is proposed. Study of 17 FR IQA(including the proposed metric), 5 BR IQA and 7 statistical feature metrics is done for image enhancement applications. It has been observed that the only IQA metric that can be used for general and medical images for assessing improvement in contrast and sharpness is IEM. Standard Deviation also increases with increase in contrast and sharpness. So IEM together with SD may be considered useful for assessing quality of the enhanced image with respect to contrast and sharpness variations.

8. REFERENCES

[1] Fsim matlab code [online]. available :. http://www.comp.polyu.edu.hk/ c̃slzhang/IQA/FSIM/FSIM.htm.

[2] Rfsim matlab code [online]. available:. http://www.sse.tongji.edu.cn/linzhang/IQA/RFSIM/RFSIM.htm.

[3] S. S. Agaian, K. P. Lentz, and A. M. Grigoryan. A new measure of image enhancement. In *IASTED 2000: Proceedings of the Int. Conf. Signal Processing and Communication*, pages 19–22, 2000.

[4] S. S. Agaian, K. Panetta, and A. Grigoryan. Transform based image enhancement with performance measure. *IEEE Tran. Image Processing*, 10:367–381, March 2001.

[5] S. S. Agaian, B. Silver, and K. A. Panetta. Transform coefficient histogram-based image enhancement algorithms using contrast entropy. *IEEE Trans. Image Process*, 16:741758, Mar. 2007.

[6] Ali A. Al-Zuky, Salema S.Salman, and Anwar H. Al-Saleh. Study the quality of image enhancement by using retinex technique which capture by different lighting (sun and tungsten). *International Journal of Computer Applications*, 73:31–38, July 2013. Published by Foundation of Computer Science, New York, USA.

[7] B. Bechara, C. A. McMahan, W. S. Moore, M. Noujeim, H. Geha, and F. B. Teixeira. Contrast-to-noise ratio difference in small field of view cone beam computed tomography machines. *Journal of Oral Science*, 54:227–232, 2012.

[8] D. M. Chandler and S. S. Hemami. Vsnr: A wavelet-based visual signal-to-noise ratio for natural images. *IEEE Trans. Image Process*, 16:2284–2298, Sep. 2007.

[9] Deniz Erdogmus, Erik G Larsson, Rui Yan, Jose C Principe, and Jeffrey R Fitzsimmons. Measuring the signal-to-noise ratio in magnetic resonance imaging: a caveat. *Signal processing*, 84:1035–1040, 2004.

[10] B. Girod. *Whats wrong with mean-squared error?*, chapter Digital Images and Human Vision. Cambridge, MA: MIT Press, 1993.

[11] R.M Haralick. Statistical and structural approaches to texture. *Proceedings of the IEEE*, 67:786–804, 1979.

[12] Yong Hu, Chun xia Zhao, and Hong nan Wang. Directional analysis of texture images using gray level co-occurrence matrix. In *PACIIA '08: Pacific-Asia Workshop on Computational Intelligence and Industrial Application*, pages 277 – 281, 2008.

[13] ITU-T Recommendation,. Methods for subjective determination of transmission quality., 1996.

[14] E. C. Larson and D. M. Chandler. Most apparent distortion: full-reference image quality assessment and the role of strategy. *Journal of Electronic Imaging*, 19:1–21, March 2010.

[15] M. Gaubatz. Metrix mux visual quality assessment package'[online] available :. http://www.foulard.ece.cornell.edu/gaubatz/metrix _ mux.

[16] Ankita Pandey, Sarbjeet Singh, and Ankur Pandey. Review : On performance metrics for quantitative evaluation of contrast enhancement in mammograms. *International Journal of Computer Applications*, 75:40–45, August 2013. Published by Foundation of Computer Science, New York, USA.

[17] K Panetta, S Agaian, Yicong Zhou, and E.J. Wharton. Parameterized logarithmic framework for image enhancement. *IEEE transactions on Systems, Man, Cybernetics*, 41:460–473, 2011.

[18] K. A. Panetta, E. J. Wharton, and S. S. Agaian. Human visual system based image enhancement and logarithmic contrast measure. *IEEE transactions on Systems, Man, Cybernetics*, 38:174188, Feb. 2008.

[19] K. A. Panetta, Yicong Zhou, S. S. Agaian, and Hongwei Jia. Nonlinear unsharp masking for mammogram enhancement. *IEEE Trans. on information technology in biomedicine*, 15:918 – 928, Nov. 2011.

[20] Planitz and A. Maeder. Medical image watermarking: A study on image degradation. In *APRS '05: Proceedings of Australian Pattern Recognition Society(APRS) Workshop on Digital Image Computing*, pages 8–13. U.S.A. IEEE Society, Feb.2005.

[21] Schmidt, R.L. Haskell, B.G. Eng, and K.Y. O'Riordan. An experimental time-compression system for satellite television transmission. *Proceedings of the IEEE*, 73:789–794, 1995.

[22] S.D.Chen and A.R.Ramli. Minimum mean brightness error bi-histogram equalization in contrast enhancement. *IEEE Transactions on Consumer Electronics*, 49:1310–1319, 2003.

[23] H.R. Sheikh and A.C. Bovik. Image information and visual quality. *IEEE Transactions on Image Processing*, 15:430–444, Feb. 2006.

[24] H.R. Sheikh, A.C. Bovik, and G. de Veciana. An information fidelity criterion for image quality assessment using natural scene statistics. *IEEE Trans. IP*, 14:2117–2128, Dec. 2005.

[25] J. Sijbers, P. Scheunders, N. Bonnet, D. Van Dyck, and E. Raman. Quantification and improvement of the signal-to-noise ratio in a magnetic resonance image acquisition procedure. *Magn. Reson. Imag*, 14:11571163, 1996.

[26] N. Thakur and S. Devi. A new method for color image quality assessment. *Internatinal Journal of Computer Applications*, 15:10–17, Feb. 2011. Published by Foundation of Computer Science, New York, USA.

[27] N. Damera Venkata, T.D. Kite, W.S. Geisler, B.L. Evans, and A.C. Bovik. Image quality assessment based a on degradation model. *IEEE Trans. IP*, 4:636–650, 2000.

[28] Z. Wang and A. C. Bovik. A universal image quality index. *IEEE Signal Proces. Lett*, 4:81–84, Sept. 2002.

[29] Z. Wang and A. C. Bovik. *Modern image quality assessment*, chapter Introduction, pages 1–15. Morgan and Claypool, New York, 2006.

[30] Z. Wang, A. C. Bovik, H.R. Sheikh, and E. P. Simoncelli. Image quality assessment: From error visibility to structural similarity. *IEEE Trans.Image Process*, 13:600–612, 2004.

[31] L. Zhang, L. Zhang, and X. Mou. Rfsim: A feature based image quality assessment metric using riesz transforms. In *ICIP '10: Proceedings of IEEE Internatinal conference on image processing*, pages 321–324, Hong Kong, 2010.

[32] L. Zhang, L. Zhang, X. Mou, and D. Zhang. Fsim: a feature similarity index for image quality assessment. *IEEE Trans. Image Process*, 20:2378–2386, Sep. 2011.

[33] Yicong Zhou, Karen Panetta, and S. S. Agaian. Human visual system based mammogram enhancement and analysis. In *IPTA, '10: 2nd International Conference on Image Processing Theory Tools and Applications*, pages 229–234, 2010.