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A Review of Image Quality Assessment (IQA): SNR, GCF, AD, NAE, PSNR, ME

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Wan Azani Mustafa [1,2,*], Haniza Yazid [1], Mastura Jaafar [3], Mustaffa Zainal [3], Aimi Salihah Abdul-Nasir [2], Noratikah Mazlan [1]

[1] School of Mechatronic Engineering, University Malaysia Perlis, 02600 Ulu Pauh, Arau, Perlis, Malaysia
[2] School of Engineering Technology, Kampus Sg. Chuchuh, Universiti Malaysia Perlis, 02100 Padang Besar, Perlis, Malaysia
[3] School of Environmental Engineering, University Malaysia Perlis, 01000 Kangar, Perlis, Malaysia

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ABSTRACT

Image quality assessment (IQA) is an objective way to measure the visual quality of an image, and it plays a crucial role in many image processing techniques. Recently, a lot of IQAs method was proposed based on their own direction and application. In this study, a few selected IQAs was reviewed such as Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), and others. The primary purpose is to study and explore the function and mathematical equation for each IQAs that was effected on non-uniform images. The findings of this survey will help the researcher to know and applied in their research.

1. Introduction

Measurement of the quality of image compression is important for image processing application [1–2]. In recent years, a large number of approaches have been developed to measure the perceptual quality of images [3–5]. Objective methods for assessing perceptual image quality traditionally attempted to quantify the visibility of errors (differences) between a distorted image and a reference image using a variety of known properties of the human visual system. An objective image quality metric can play a variety of roles in image processing applications. First, it can be used to dynamically monitor and adjust image quality. For example, a network digital video server can examine the quality of the video being transmitted in order to control and allocate streaming resources. Second, it can be used to optimize algorithms and parameter settings of image processing systems. For instance, in a visual communication system, a quality metric can assist in the optimal design of pre-filtering and bit assignment algorithms at the encoder and of optimal reconstruction, error concealment, and

* *Corresponding author.*
E-mail address: azani.mustafa@gmail.com (Wan Azani Mustafa)

post-filtering algorithms at the decoder. Third, it can be used to benchmark image processing systems and algorithms [6].

In this paper, the six types of IQA was calculated known as Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Global Contrast Factor (GCF), Normalised Absolute Error (NAE), Average Difference (AD), and Misclassification Error (ME). The primary goal of this review is to explore and study the effect of each IQA on tested images. The rest of this paper is as follows: Section 2.0 discussed an overview of the literature review. Section 3.0 explained a few details of IQA technique and Section 4.0 present a case study. Finally, section 5.0 described the conclusion of this research.

2. Background Review

An image quality assessment (IQA) is of crucial importance in image processing and analysis in practice. In 2012, He et al. suggested a universal blind image quality assessment (BIQA) metric based on sparse representation technique known as a sparse representation natural scene statistics (SRNSS) [7]. This method involved a few steps; (1) Natural Scene Statistics (NSS) features extraction, (2) Dictionary learning, (3) Sparse representation, and (4) Image quality quantification. Based on Linear correlation coefficient (LCC), the comparison result between others quality assessment technique was shown in table 1. The above finding is consistent with the study by Mittal et al. [8]. They also concentrated on natural scene statistics approach. However, this approach more complicated than SRNSS [7] because underlying features used to derive from the empirical distribution of locally normalized luminance and products of locally normalized luminance under a spatial natural scene statistic model. The performance more effective compared to the PSNR and SSIM [6]. Blind/referenceless image spatial quality evaluator (BRISQUE) has very low computational complexity, making it well suited for real time applications.

Table 1
The LCC of different metrics on other publicly available databases.

Database	TID [9]	CSIQ	IVC	MICT
PSNR	0.5643	0.8772	0.7192	0.6355
SSIM [6]	0.6387	0.8060	0.7924	0.7979
IFC [10]	0.5692	0.7482	0.8978	0.8387
VIF [11]	0.7496	0.9193	0.8966	0.9086
NSS [12]	0.2027	0.5667	0.4266	0.4541
BIQI [13]	0.4192	0.6601	0.5346	0.6853
BLINDS [14]	0.5086	0.7529	0.7013	0.7924
SRNSS [7]	0.7327	0.8157	0.7943	0.8094

In the same year, BIQA based on visual codebooks was studied by Ye and David [15]. A visual codebook consisting of Gabor-filter-based local features extracted from local image patches is used to capture complex statistics of a natural image. The codebook encodes statistics by quantizing the feature space and accumulating histograms of patch appearances.

3. IQA Measurement Approach

In general, measurement of image quality usually can be classified into two categories, which are subjective and objective quality measurements. Subjective quality measurement such as Mean Opinion Score (MOS) is truly definitive, but too inconvenient, the more time taken, and expensive.

Therefore, objective measurements are developed such as MSE, MAE, PSNR, SC, MD, LMSE, and NAE that are the least time taken than MOS but they do not correlation well with MOS [3]. In this paper, we concentrated on the objective measurements only such as;

3.1 Signal to Noise Ratio (SNR)

SNR is defined as the ratio of the average signal value to the standard deviation of the signal value [16–17]. Higher SNR value showed a better quality image and low SNR indicates the certain region of image weakness relative to background noise [18–19]. The represent an input image and is the standard deviation of the image. The equation as follows

$$SNR = 10\log_{10} = \frac{Mean\left[I(x,y)\right]}{Std\left[I(x,y)\right]}$$

3.2 Peak Signal to Noise Ratio (PSNR)

The term peak signal-to-noise ratio (PSNR) is an expression for the ratio between the maximum intensity of an image and the distorting noise that affects the quality of its representation. PSNR is usually expressed in terms of the logarithmic decibel scale. The bigger the PSNR, the better the visual quality of the restored image [20–21].

$$PSNR = 10log10\frac{(2^n - 1)^2}{\sqrt{MSE}}$$

3.3 Global Contrast Factor (GCF)

The newly introduced Global Contrast Factor (GCF) corresponds closer to the human perception of contrast by computing the local contrast at various spatial frequencies and to use these local contrast for the computation of the global contrast factor. Lower GCF represents an image that is uniform [22].

$$GCF = \sum_{i=1}^{N} w_i * C_i$$

where, is the average local contrasts, is the weight factor and represents the size of the image.

3.4 Normalised Absolute Error (NAE)

The normalized absolute error is a measure of how far is the reconstructed image from the original image, with the value of zero being the perfect fit. A large value of Normalised absolute error indicates a poor quality image and a small value gives a good quality image [23].

$$NAE = \sum_{j=1}^{M}\sum_{k=1}^{N}\frac{\left|x_{(j,k)} - x'_{(j,k)}\right|}{\sum_{j=1}^{M}\sum_{k=1}^{N}\left|x_{(j,k)}\right|}$$

where, and is the row and column for the image size, is the input image and is the enhanced image.

3.5 Average Difference (AD)

Contrast defines the difference between the lowest and highest intensity level. AD is calculated based on the average difference intensity between the images. Small AD represents a good contrast image and the equation is denoted as the following [24].

$$AD = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}\left(x_{j,k} - x'_{j,k}\right)}{M \times N}$$

where, and is the row and column for the image size, is the input image and is the enhanced image.

3.6 Misclassification Error (ME)

Misclassification is defined as a variable for interpretation, analysis and leading to bias estimation if the misclassification is ignored. The misclassification error (ME) is used to evaluate the performance of the methods as depicted in:

$$ME = 1 - \frac{\left|B_0 \cap B_T\right| + \left|F_0 \cap F_T\right|}{\left|B_0\right| + \left|F_0\right|}$$

where and represent the foreground and background of the original image, while and is the foreground and background of the test image [25]. The ME reflects the percentages of background pixels incorrectly specify as the foreground, and conversely, the foreground pixels are not properly determined as the background. This can vary from 0 for a perfectly classified image to 1 for a totally wrong binarized image [26].

4. Case Study

In this paper, three (3) example images were experimented to test the Image Quality Assessment (IQA). The sample images are known as 'Square', 'Coin', and 'Block' from the online database [26], [27] and consist the illumination problem [28]. In order to improve the image quality based on contrast correction, the Homomorphic Butterworth method [29] was applied. Then, the segmentation using Otsu method [30] was performed to prove the effectiveness of image quality assessment in term of PSNR and ME. The resulting images as presented in Figure 1. As shown in the figure, the sample images are divided on 2 categorized which is contrast enhancement and segmentation. In this study, the IQA such as AD and NAE was obtained from the contrast enhancement result, while ME and PSNR were determined from the segmentation result. The original image was calculated using SNR and GCF. Table 2 presents the result of IQA on 3 sample images.

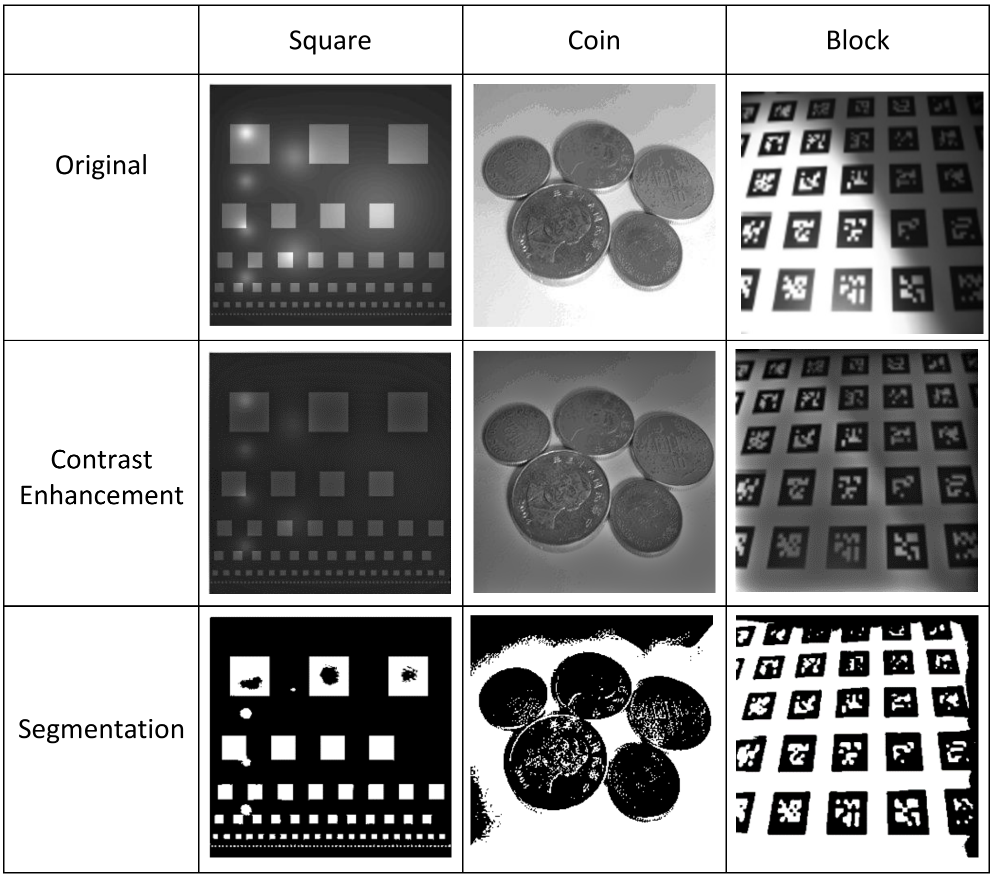

Fig. 1. Sample of experimented images

In mathematically, IQA performance represent different each other's, example the lowest of AD, NAE and ME and highest of SNR, PSNR and GCF shows the good performance. According to the table 2, its can be conclude that the square images achieved a higher performance (PSNR = 18.5652 and ME = 0.0351) compared to other.

Table 3
Comparison of 3 images based on IQA measurement.

	Square	**Coin**	**Block**
SNR	2.9258	4.2865	1.1887
GCF	5.6765	5.5985	10.7101
AD	28.0861	65.8963	48.0164
NAE	0.3709	0.4006	0.4870
PSNR	18.5652	7.8941	9.4174
ME	0.0351	0.2343	0.1934

4. Conclusion

Assessing the quality of visual information plays an important role in numerous image/video processing and computer vision applications. In this paper, we present an overview of the background and related work in the area of image quality assessment (IQA). Thus far, the majority of the published IQA methods based on objective quality measurements. The main target of the literature review was to study and explore the benefits of image quality assessment. From this experiment, we can decided that SNR, PSNR compatible for obtained the contrast image. However, ME measurement compatible for segmented image. This study was done by obtained the IQA on tested image and categorised them.

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