Image Quality Assessment Parameters : An Overview

Amanpreet Kaur, Ph.D Research Scholar, IK Gujral Punjab Technical University, Jalandhar, Punjab, India.

Jagroop Singh Sidhu, Department of Electronics and Communication Engineering, DAVIET, Jalandhar, Punjab, India.

Jaskarn Singh Bhullar, Department of Applied Sciences, MIMIT, Malout, Punjab, India.

Abstract: Image quality assessment parameters play an important role in the evaluation of digital image processing systems. Recent advancements in digital image processing technologies such as networking, storage capacity and bandwidth have resulted in the growth of images and videos processing. The primary objective of these technologies is to maintain an image quality without any loss of information. Sometime images are suffered from distortions during compression, acquisition and transmission. To enhance, control and to maintain the perceptual quality of an image, it is very important for image compression, acquisition, communication and management system to be adequate to measure the image quality degradations. The compression procedure degrades some contents from original image and therefore generating compression artifacts. To compare the performance of different post-processing techniques, image quality assessment metrics are required. Image quality evolution methods can be classified into two categories such as objective and subjective methods.

Keywords: Subjective, objective, compression, PSNR, MOS

I. INTRODUCTION

Digital images suffer a wide variety of distortions in many image processing applications from compression to printing. Because of these the perceptual quality of the images are degraded. Therefore perceptual image quality measurement is important in many image processing applications. The quality of an image can be generally measured objectively as well as subjectively. However, these data sets are used to evaluate the performance of several image compression techniques whist maintaining an acceptable image quality. In objective measures, several parameters have been used to evaluate decoded image fidelity automatically as well as accurately. However, in subjective measurement, some non-expert viewer's evaluate image directly and give their judgment based on the perceived quality and intelligibility. Nevertheless, a subjective method is very slow, time consuming and viewer's dependant on evaluation approach. Quality assessment methods are used to evaluate the effects of communication channels, bandwidth efficiency, wireless systems etc [1].

II. SUBJECTIVE EVALUATION METHODS

In these methods, the visual quality is estimated by using subjective method, where a group of persons evaluate various corrupted or compressed images with suitable methodologies. This method has the advantage that it is most reliable and effective and gives better understanding of mechanism underlying the quality perception. In order to obtain the results from subjective evaluation, several procedures and rules have been standardized for image quality assessment. The primary fidelity evaluation methods such as mean squared error (MSE), peak signal to noise ratio (PSNR) are very simple as well as widely used. However, these methods do not always correlate effectively along with image quality. These methods require original image to compare with reconstructed image and also at the same time fail to compare the different types of blocking artifacts such as artifacts of wavelet coders or sub-band verses block-based.

Mean Opinion Score (MOS)	Rating	Impairment
5	Excellent	Imperceptible
4	Very good	Perceptible
3	Good	Slightly annoying
2	Poor	Annoying
1	Very poor	Very annoying

Table 1: Rating for MOS

In subjective evaluation, the final user and functioning of human visual system (HVS) are directly involved. In addition to, the image must be evaluated objectively by using quantitative parameters. Moreover, the human eyes are sensitivity to luminance variations based on several components such as signal content, light level as well as spatial frequency [1]. Nevertheless, a subjective method is very slow, time consuming and quite cumbersome. The perception based subjective judgment is determined by

DOI : 10.18231/2454-9150.2018.0466

ISSN : 2454-9150 Vol-04, Issue-04, July 2018

mean opinion score (MOS). The MOS method is determined on the basis of five-grade impairment scale [2] with proper description considering every grade as shown in Table 1. The score five is given to an image with the best perceptual quality and score one to worst quality. The MOS values are calculated as follows:

$$MOS(y) = \frac{1}{n}\sum_{x=1}^{n} S(x,y) \quad (1)$$

Where n is number of human observers and $S(x,y)$ is the score given by the i^{th} observer to an image y. Subjective methods can be classified into three categories such as impairment test, quality test and comparison test [3]. In impairment test, the test subjects score the images in terms of how bad they are. In quality test, the test subjects rate the images in terms of how good they are. In comparison test, the images are evaluated on a side by side basis.

III. OBJECTIVE IMAGE ASSESSMENT METHODS

The objective quality methods evaluate perceived quality of images and videos and report their fidelity accurately. The idea behind the objective perceptual methods for image quality is to measure the difference between two images [4]. Here, one of image is original or uncorrupted which is used as reference and second image is distorted, reconstructed or modified in some sense. So, these measures are good for compression techniques and provide better results when applied to evaluation of non-structured analogical distortion. The perception based objective measurement is determined by picture quality scale (PQS). Objective assessment methods play a fundamental role in image and video processing applications including for real time quality monitoring, for the optimization of image and video coding and control in displays [5].

3.1 Classification of Objective Image Assessment Methods

Objective image assessment methods can be classified into three different categories as follows:

- Objective Full-Reference Quality Assessment (FRQA)
- Objective No-Reference quality Assessment (NRQA)
- Objective Reduced-Reference Image Quality Metrics (RRQA)

3.1.1 Objective Full-Reference Quality Assessment (FRQA)

Objective full-reference quality assessment metrics measure the similarity between perfect quality image (original image) and distorted image. In other words, the quality of an image may be measured by comparing it against reference image. The standard objective distortion measures indices that can be used to evaluate the perceived image quality as follows:

- Peak Signal to Noise Ratio (PSNR)
- Peak Signal to Noise Ratio including Blocking Effects (PSNR-B)
- Mean Structural Similarity Index Measure (MSSIM)
- Similarity Factor (SF)

i. Peak Signal to Noise Ratio (PSNR)

PSNR is the simplest and most widely used full-reference quality assessment metric which compares the original (reference) image with distorted (test) image. This metric is commonly used for performance evaluation, although it's well-known limitation because of its simplicity. PSNR can be determined as follows:

$$PSNR = 10 \times log_{10}\frac{1}{N}\sum_{i=1}^{N}\frac{255^2}{(m_i - n_i)} dB \quad (2)$$

Where N is the total number of samples and m_i, n_i are the grey levels of original and reconstructed image. PSNR is measured in decibels (dB).

ii. Peak Signal to Noise Ratio including Blocking Effects (PSNR-B)

Yim *et al.* [6] proposed a new image quality assessment approach named peak signal to noise ratio including blocking effects (PSNR-B). Based on PSNR, PSNR-B designed for a blocking effect factor (BEF) is used to calculate the blocking effects of test images, which is more efficient for estimating the quality of deblocking images than PSNR. PSNR-B can be estimated on the basis of two parts, firstly calculating mean square error (MSE) of original image and reconstructed image. Secondly, calculating blocking effect factor (BEF) of test images. BEF can be defined as follows:

$$BEF_{Tot}(n) = \sum_{k=1}^{K} BEF_k(n) \quad (3)$$

Where $BEF_{Tot}(n)$ is over all block sizes. With the help of PSNR-B, the image quality evaluation can be determined as:

$$\text{MSE-B}(m,n) = MSE(m,n) + BEF_{Tot}(n) \quad (4)$$

$$\text{PSNR-B}(m,n) = 10 \times log_{10}\frac{255^2}{MSE-B(m,n)} \text{dB} \quad (5)$$

MSE-B (m,n) measures mean squared error containing blocking effects (MSE-B) for reference image 'm' and test image 'n', while BEF measures the amount of blocking artifacts in test image 'n'. The MSE calculates the distortion between reference image 'm' and test image 'n'. PSNR-B is measured in decibels (dB).

iii. Structural Approaches

Wang *et al.* [7] deigned an objective method which is based on quality measures from perspective of image formation. Structural Similarity (SSIM) is measured similarity on the basis of three components: luminance, contrast and structure. First, luminance of all signals is compared. Second, the mean intensity from signal is removed. Third, signal is divided by standard deviation.

 DOI : 10.18231/2454-9150.2018.0466

ISSN : 2454-9150 Vol-04, Issue-04, July 2018

Let 'm' and 'n' are two non-negative image signals which have been aligned with each other. If one of the signals is to have perfect quality, then the similarity measure can be used as a quantitative measurement of the quality of the second signal [8].

$$SSIM\ (m,n) = \frac{(2\mu_m\mu_n+C_1)(2\sigma_{mn}+C_2)}{(\mu^2{}_m+\mu^2{}_n+C_1)(\sigma^2{}_m+\sigma^2{}_n+C_2)} \qquad (6)$$

Where μ_m, μ_n and σ_m, σ_n are mean intensities and standard deviation for m and n. C_1 and C_2 are constant. σ_{mn} can be defined as:

$$\sigma_{mn} = \frac{1}{N-1}\sum_{i=1}^{N}(m_i-\mu_m)(n_i-\mu_n) \qquad (7)$$

a. Mean Structural Similarity Index Measure (MSSIM)

A mean $SSIM$ ($MSSIM$) index to measure the overall quality of an image is calculated as:

$$MSSIM\ (m,n) = \frac{1}{M}\sum_{i=1}^{M} SSIM\ (m_i,n_i) \qquad (8)$$

Where 'm' and 'n' are reference and reconstructed images respectively m_i and n_i are the image contents at the i^{th} local window and M is the number of local windows of the image. The mean structural similarity ($MSSIM$) value is equal to one when two images are identical.

b. Similarity Factor (SF)

If the difference in MSSIM values for reference (original) and reconstructed image is small then it is difficult to recognize. SF is used to calculate the similarity of two $MSSIM$:-

$$SF(m,n) = 100 \times log_2\left(\frac{MSSIM_m}{MSSIM_n}\right) \qquad (9)$$

Where 'm' is testing signal and 'n' is a original signal. MSSIM describes the similarity between testing image and original image. If a testing image 'm' is exactly same as JPEG image then SF is equal to zero. If SF is positive for test image, the perception quality of an image is more identical to original image than JPEG signal. If SF is negative for test image, the quality of an image is recognized as more degraded [7].

3.1.2 Objective No-Reference Quality Assessment (NRQA)

In various practical applications, image quality assessment systems do not access reference image. So, no reference (NR) or blind model has been used which accesses the quality of the distorted image. In this technique the quality of image is evaluated without the knowledge of reference signal. Although, human observer can reliably and effectively evaluates the perceived quality of reconstructed image without needing any reference signal [9].

3.1.3 Objective Reduced-Reference Quality Assessment (RRQA)

In reduced-reference quality assessment method, the information regarding reference signal is partially available. Alternately, some characteristics are extracted from reference signal and based on various characteristics the quality of distorted signal is determined [10].

IV. CONCLUSION

In this paper, image quality assessment metrics have discussed. Quality assessment methods are classified into two different categories such as subjective and objective image quality assessment methods. Objective quality assessment methods are based on human observation whereas subjective methods predict perceived quality of reconstructed image accurately. The primary objective of these quality assessment methods is to evaluate image fidelity i.e. how close a reconstructed image to a given reference or original image. Subjective evaluation methods are reliable and effective but these are expensive and quite cumbersome, way to evaluate image fidelity.

REFERENCES

[1] Alan Conrad Bovik, *Handbook of Image and Video Processing*, Academic Press, San Diego, California, USA. 2000.

[2] Sonja Grgic and Mislav Grgic, "Reliability of objective picture quality measurement," *Journal of Electrical Engineering*, vol. 55, no.1-2, pp. 3-10, 2004.

[3] A.J. Hussain, Ali Al Fayadh and Naeem Radi, "Image compression techniques: A survey in lossless and lossy algorithms", *Neurocomputing*, Vol. 300, pp. 44-69, July 2018.

[4] H. R. Sheikh, "Image quality assessment using natural scene statistics," Ph.D. dissertation,University of Texas, Austin, May 2004

[5] Zhou Wang and Alan Conrad Bovik, *Modern Image Quality Assessment*, Morgan & Claypool, USA, 2006.

[6] Changhoon Yim and Alan Conrad Bovik, "Quality assessment of deblocked images," IEEE *Transactions on Image Processing*, vol. 20, no. 1, pp. 88-98, January 2011.

[7] Zhou Wang, Alan Conrad Bovik , H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no.4, pp. 1-14, April 2004.

[8] R. C. Gonzales, and R. E. Woods, Digital Image Processing. 3rd edition, New Delhi, Pearson Education, 2003.

[9] Y. F. Hsu, and Y. C, Chen, "A new adaptive separable median filter for removing blocking effects," IEEE Transactions on Consumer Electronics, vol. 39, issue 3, pp. 510-513, 1993

[10] D. Zhang, "Information theoretic criteria for image quality assessment based on natural scene statistics," M.Sc. thesis, University of Waterloo Ontario, Canada, 2006.

 DOI : 10.18231/2454-9150.2018.0466