Anbar Journal of Engineering Science (AJES)
P-ISSN: 1997-9428; E-ISSN: 2706-7440

Vol. 11 , No. 2 (2020) , pp. 154 ~ 161
DOI: 10.37649/aengs.2023.176830

Univiersty of Anbar

Anbar Journal Of Engineering Science©

journal homepage: http:// http://www.uoanbar.edu.iq/Evaluate/

New Quality Metric for Compresed Images

Fatimah S. Abdulsattar [a*], Maath Jasem Mahammad[b], Dhafer R. Zaghar[c]

[a] *Computer Engineering Department, Mustansiriyah University, 10047, Iraq*
[b] *Electrical Engineering Department, University Of Anbar, Iraq*
[c] *Computer Engineering Department, Mustansiriyah University, 10047, Iraq*

P A P E R I N F O

Paper history:
Received 18/9/2020
Received in revised form 16/10/2020
Accepted 29/10/2020

Keywords:

Image Quality Assessment, Image Compression, PSNR, MSE, SSIM, JPEG, JPEG2000.

A B S T R A C T

The field of image processing has several applications in our daily life. The image quality can be affected by a wide variety of deformations during image acquisition, transmission, compression, etc. Image compression is one of the applications where the quality of the image plays an important role since it can be used to evaluate the performance of various image compression techniques. Many image quality assessment metrics have been proposed. This paper proposes a new metric to assess the quality of compressed images. The principle idea of this metric is to estimate the amount of lost information during image compression process using three components: error magnitude, error location and error distribution. We denote this metric as MLD, which combines the objective assessment (error magnitude) and the subjective assessment (error location and error distribution). First, the metric is used to estimate the quality of compressed images using the JPEG algorithm as this is a standard lossy image compression technique. Then, the metric is used to estimate the quality of compressed images using other compression techniques. The results illustrate that the proposed quality metric is correlated with the subjective assessment better than other well-known objective quality metrics such as SSIM, MSE and PSNR. Moreover, using the proposed metric the JPEG2000 algorithm produces better quality results as compared to the JPEG algorithm especially for higher compression ratios.

1. Introduction

Image quality assessment has an important role in image processing applications. Image compression is one of the most important applications since it is used to create a new image file with a smaller size that is suitable for transmission over a communication channel. However, lossy compression can introduce several distortions to digital images such as blocking and blurring effects. Therefore, a tradeoff between image quality and compression ratio should be considered.

Image quality can be assessed subjectively by a human observer. However, the assessment is impractical and time-consuming. Automatic prediction of the image quality is called objective assessment. Several objective metrics for assessing image quality have been proposed. These metrics are classified into three groups [1]: full-reference, reduced-reference and no-reference. No-reference metrics estimate the image quality without any information about the original images. Reduced-referenced metrics use some information from the original images. Full-reference metrics, which are the most widely

Corresponding author: **Fatimah S. Abdulsattar** ; fatima.abdulsattar@gmail.com ; +9647721134599

used, assume the existence of the original images in the assessment process. The traditional objective full-reference metrics are Mean Square Error (MSE) and Peak-Signal-to-Noise Ratio (PSNR) [2]. Although these metrics are most widely used, they only measure error magnitude and they do not take into consideration the location and the distribution of the error.

Many other quality metrics have then been developed to overcome the limitations of traditional metrics. Structural similarity index (SSIM) [3] and Multi-Scale SSIM (MS-SSIM) [4] combine the effect of luminance, contrast and structure to evaluate the quality of the image. Information Fidelity Criterion (IFC) [5] and Visual Information Fidelity (VIF) [6] are two theoretic metrics that use mutual information to calculate an image quality score. Most Apparent Distortion (MAD) [7] models a visible distortion in the image based on two separate strategies. Several metrics in the literature were proposed by extracting information from edge regions, which are more sensitive to human eyes than flat regions [8, 9, 10]. Deep neural networks are also used as an efficient tool to assess the image quality [11, 12]. Mansouri, and Mahmoudi-Aznaveh [13] developed a new objective image quality metric based on a singular value decomposition. The final objective score is calculated by evaluating the structural information in the distorted image.

Recently, several full-reference metrics are proposed to evaluate an objective image score by fusing the effect of several measures into a single metric. Lie and et al. [14] used a regression method to calculate a weighted sum of a number of objective quality metrics for each type of image distortion. Another fusion strategy was also adopted in [15] where a number of existing image quality metrics was fused at a score level using a genetic algorithm as an optimization technique. Saha and Wu [16] assessed an objective image score by fusing the global and local distortion measures based on a pooling strategy.

This work proposes a new full-reference metric to assess the quality of compressed images by combining the effect of three different measures. The main idea of the proposed metric is to measure the amount of lost information during the compression process. Using the JPEG algorithm as a reference, the quality of other compression algorithms can be estimated accordingly. The relationship between the compression ratio and the quality of compressed images using JPEG and JPEG2000 algorithms is also studied. The outline of the rest of the paper is organized as follows: Section 2 explains the problem statement and the main contributions of this work. Section 3 describes the steps of computing the proposed metric in details. Section 4 discusses the results and section 5 lists the main conclusions.

2. Problem Statement and Contributions

JPEG and JPEG2000 are very popular and distinct image compression algorithms. The JPEG algorithm is implemented by partitioning the image into 8×8 blocks and applying Discrete Cosine Transform (DCT) on each block while the JPEG2000 algorithm is performed by partitioning the image into non-overlapping blocks and then applying Discrete Wavelet Transform (DTW) [17]. The proposed image quality metric is developed by combining the objective and subjective measurements to evaluate the compressed image quality based on JPEG and JPEG2000 [18]. Although several image quality metrics have been proposed as discussed in section 1. We noticed that these metrics have the following common technical problems:

1. The definition of image quality is fuzzy and general. In other words, no common definition for the quality is given especially in image compression field.
2. The efficiency of the metrics changes with the complexity of the compressed image.
3. Lack of the relationship between the image quality and the compression ratio (CR).

Therefore, the main contributions of our proposed metric are as follows: First, the metric suggests a clear definition for the compressed image quality assessment as will be discussed later. Second, the proposed metric will use a ratio of the difference between the original image and the distorted image to the original image in the main calculations to cope with the problem of the image complexity. Third, the metric will combine three measures (error magnitude, error location and error distribution) to overcome the limitations of using only a single measure. This metric uses the JPEG as a standard compression algorithm to estimate the quality of other compression algorithms such as JPEG2000.

3. The Proposed Image Quality Metric

This section will give a detailed description of the proposed image quality metric.

3.1 Compressed Image Quality Definition

In this work, we adopt the following definition for the quality of compressed images. If the difference between the original image and its compressed image is small, then the quality of the compressed image is high. This means that a little information is lost during the image compression process. Meanwhile, the quality of the compressed image is low when the difference between the original and the compressed image is high (i.e. substantial information is lost).

3.2 The Components of Our Proposed Metric

The proposed metric consists of three components: error magnitude (M), error location (L) and error distribution (D). The relationship between each of these components and the compression ratio (CR) will be analyzed to illustrate how they are related to the CR. After that, these components are combined to compute the final quality score. We hypothesize that the fusion of several different components could mitigate the shortages of using only a single component. The proposed metric will be denoted as *MLD* in the rest of the paper. The components of the *MLD* metric will be explained in the following subsection.

3.2.1 The M component

This component measures the magnitude of the error between two images. This component consists of two elements: rational mean square error (μ_r) and rational variance (σ_r). The correlation between these two elements is nearly one, so we can combine them in a single component. The following steps will illustrate how to compute each element.

First, the μ_r can be computed as follows: Let $x = |I_o - I_c|$ where I_o and I_c are the original and the compressed images respectively. R and C are the dimensions of the image. Then, the μ_r can be defined as

$$\mu_r = \frac{\mu_d}{\mu_o} \qquad \textbf{(1)}$$

Where,

$$\mu_d = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C} x(i,j)}{R\times C} \quad \text{and} \quad \mu_o = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C} I_o(i,j)}{R\times C}$$

Second, the σ_r can be defined as

$$\sigma_r = \frac{\sigma_d}{\sigma_o} \qquad \textbf{(2)}$$

Where,

$$\sigma_d = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C}(x(i,j)-\mu_d)}{R\times C} \quad \text{and} \quad \sigma_o = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C}(I_o(i,j)-\mu_o)}{R\times C}$$

Finally, the M component can be defined as

$$M = (\mu_r + \sigma_r) \qquad \textbf{(3)}$$

The practical limits of this metric are in the range [0, 0.2] so it does not require any normalization. It should be noted that the limits of each component are estimated after applying the component on several images (more than 900 images). The relationship between the component M and the CR using the JPEG algorithm is demonstrated in Fig. 1 for Lena image. The relationship of each metric with the CR is plotted using log2(CR) for clarification. As can be seen, the M component increases steadily as the CR increases.

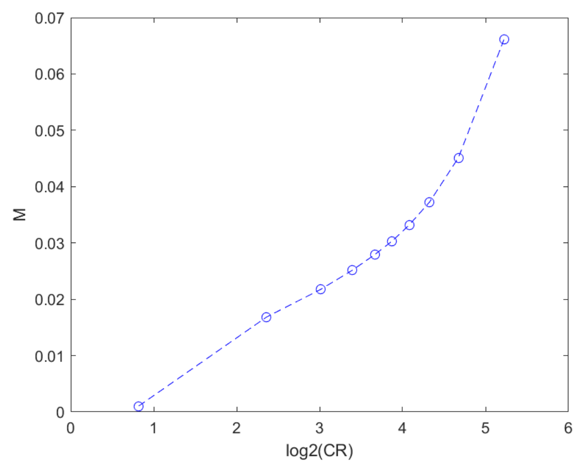


Figure 1 The M component versus CR using the JPEG algorithm for Lena.

3.2.2 The L component

The information distributed across the entire image does not have the same influence upon a human visual system since the human eye is more sensitive to errors in edgy areas than in smooth areas in the images. Therefore, the L component will compute the rational mean absolute error across the edgy points (i.e. the location of the error).

The L component can be computed as follows: Let $x_d = |x_o - x_c|$ where x_d and x_c are the edgy images after applying the canny edge detector [19] on the original and the compressed images respectively. Then, the L component can be defined as

$$L = \frac{E_d}{E_o} \qquad \textbf{(4)}$$

Where $E_d = \sum_{i=1}^{R}\sum_{j=1}^{C} x_d(i,j) \times \mu_r$

and $\quad E_o = \sum_{i=1}^{R}\sum_{j=1}^{C} x_o(i,j)$.

The practical limits for the ratio $\frac{E_d}{E_o}$ are in the range [0, 4]. Our hypothesis is that the larger values of L are due to shifted or rotated edges in the compressed images. This ratio should be normalized so that its range is between 0 and 1. Therefore, the normalized value of the L component can be calculated as

$$L = \frac{E_d}{4 \times E_o} \tag{5}$$

The normalization is computed for each component of our proposed metric if required so that their range is equal. The reason for the normalization process is to prevent the component with the higher value dominate the effect of components with the lower values in the calculation of the final quality assessment metric. Fig. 2 demonstrates the relationship between the L component and the CR using the JPEG compression algorithm. This component produces 0 for smaller compression ratios. However, its value increases sharply as the CR increases. This means that a high compression ratio can significantly degrade image edges.

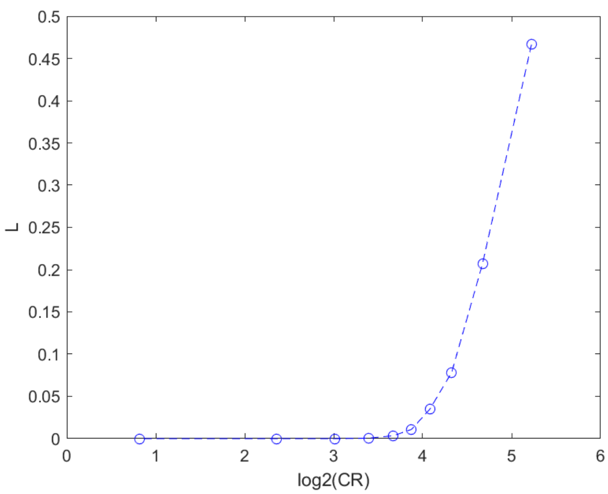


Figure 2 The L component versus CR using the JPEG algorithm for Lena.

3.2.3 The D component

This component measures the distribution of the error over image blocks. In order to compute this metric, the image is first divided into non-overlapping blocks of equal size *z×z*. A typical value for *z* is 8. The selection of block size is not critical in this metric and other values can be selected. Then, a ratio between the sum of the highest mean square error blocks and the sum of the mean square error for all blocks is calculated. Therefore, the D component can be defined as

$$D = \frac{\sum_{i \epsilon a} MSE_i(b_o(i), b_c(i))}{\sum_{j=1}^{N} MSE_j(b_o(j), b_c(j))} \tag{6}$$

Where $a = \lfloor \sqrt{N} \rfloor$ represents the indices of the highest mean square error blocks. N is the total number of blocks in the image. b_o and b_c are the original and the compressed image blocks respectively. The practical limits of this metric are in the range $[1/a, 1]$, so Eq.(6) will be normalized. Therefore, the final value of the D component will be calculated as

$$D = (D - 1/a) \times \frac{\mathrm{a}}{\mathrm{a} - 1} \tag{7}$$

Fig. 3 show the relationship between the D component and the CR using the JPEG algorithm. From this figure, we can notice that the value of this component increases as the compression ratio increases until its value is just over 0.35, then it begins to decreases slightly.

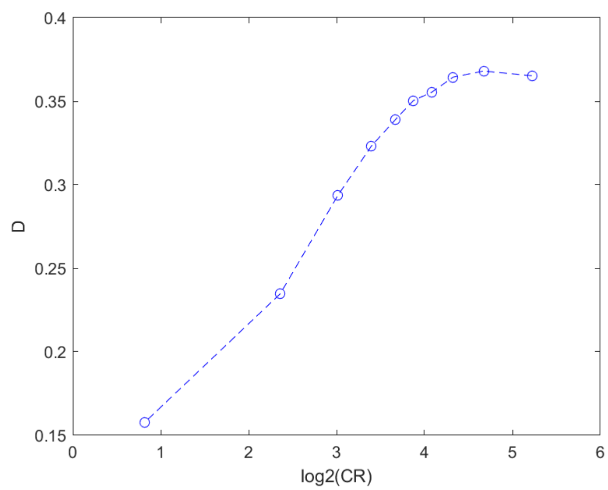


Figure 3 The D component versus CR using a logarithmic scale.

3.3 The MLD Components Combination

Fig. 4 demonstrates the steps of computing the *MLD* metric. In the beginning, each of the M, L and D components will be calculated using the original and the distorted images as inputs. After that, the resulting values will be combined using as a weighted sum to compute the final value of the *MLD* metric using Eq.(8).

$$MLD = w1 \times M + w2 \times L + w3 \times D \tag{8}$$

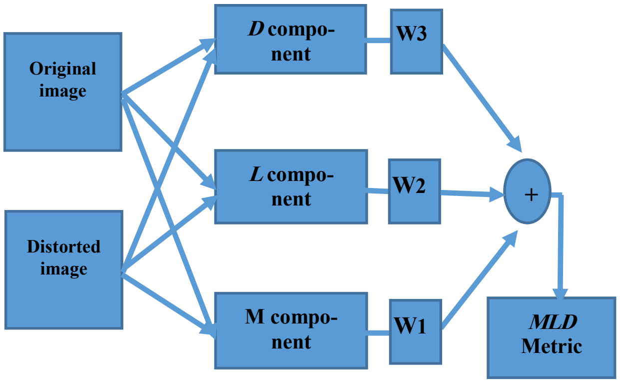


Figure 4 The steps for calculating the *MLD* metric.

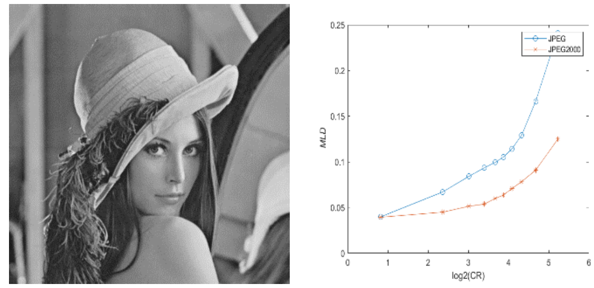
Where $w1$, $w2$ and $w3$ are the weights for the *M*, *L* and *D* components respectively, which can be used to control the effect of the *MLD*. We suppose that the component *M* is similar in its behavior to the objective measure while the components *L* and *D* are similar to the subjective measure. Also, we suppose that the sum of the weight values is equal to 1 so that the range of the *MLD* metric is between 0 and 1. Therefore, we will use 0.5, 0.25 and 0.25 for the values of $w1$, $w2$ and $w3$ respectively in Eq.(8).

4. Results and Discussion

This section demonstrates the performance of our proposed metric in estimating the quality of compressed images, which ultimately leads to evaluate the performance of the compression algorithms. We first computed JPEG as a standard lossy image compression algorithm. Then, we compared its performance with other compression algorithms. The compression was implemented using MATLAB's imwrite command for standard Lena image. The CR was varied from 1.76 to 40. In order to compute the proposed metric, we first computed the *M*, *L* and *D* components on each compressed image using Eqs. (3), (5) and (7) respectively. Then, the *MLD* can be computed using Eq. (8).

4.1 MLD test for JPEG and JPEG2000

Fig. 5 demonstrates the result of applying the *MLD* metric on compressed Lena image using JPEG and JPEG2000 algorithm for a number of compression ratios. As can be illustrated in Figure 4 (b), the two algorithms have the same quality performance for a low CR using the proposed metric. The JPEG2000 algorithm outperforms the JPEG as the CR increases. The possible reason for this behavior of the two algorithms is that more information has been lost using the JPEG than that using the JPEG2000 for a higher compression ratio.



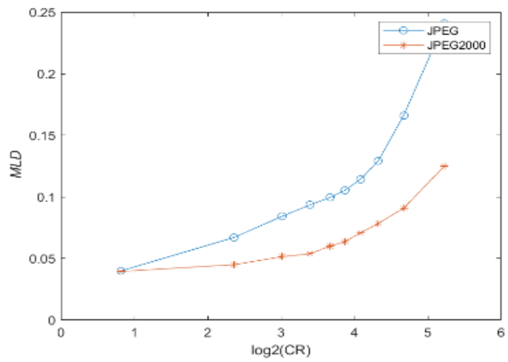
(a) (b)

Figure 5 (a) Standard image (Lena), (b) The relationship between the *MLD* metric and the CR using JPEG and JPEG2000 algorithms.

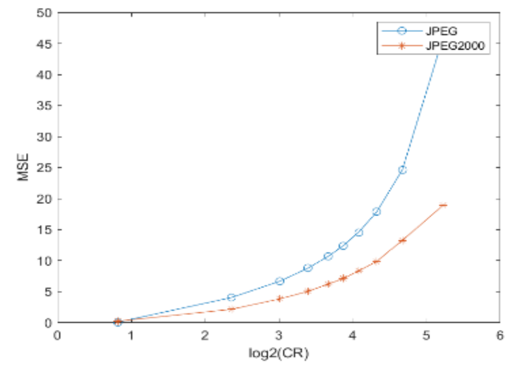
4.2 Assessment Test for JPEG and JPEG2000

Fig. 6 demonstrates the values of the *MLD, MSE, SSIM and PSNR* metrics on compressed Lena image using JPEG and JPEG2000 algorithm for a number of compression ratios. The four metrics show that the JPEG2000 algorithm outperforms the JPEG as the CR increases but the *MLD* is more sensitive to the error difference. The possible reason for this behavior of the two algorithms is that *MSE, SSIM and PSNR* detect the error from one point while *MLD* detects the error using three elements as described previously.

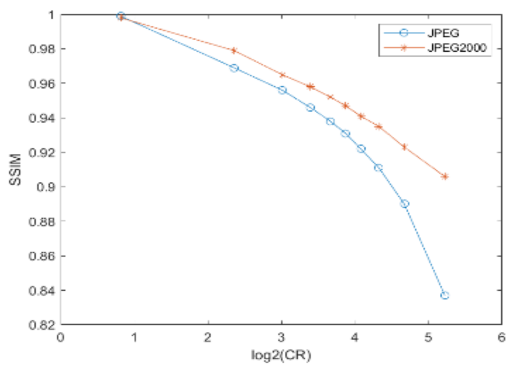
To magnify this difference, we choose two cases that have similar values for the classical factors (*MSE, SSIM* and *PSNR*) but they are different in terms of subjective quality and *MLD* metric values as shown in Fig. 7 and Table 1.



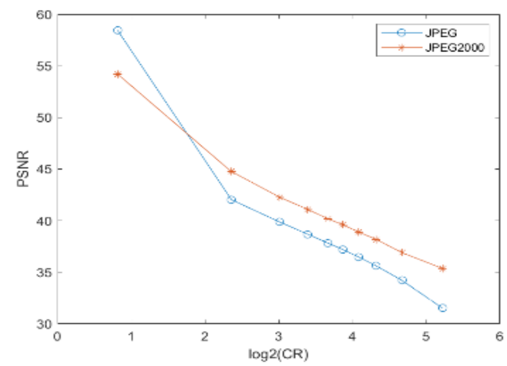
(a)



(b)



(c)



(d)

Figure 6 The values of objective metrics (a) *MLD*, (b) *MSE*, (c) *SSIM* and (d) *PSNR* using the JPEG and JPEG2000 algorithm for a number of compression ratios.

(a) J1

(c) J3

(b) J2

(d) J4

Figure 7 The subjective assessment for compressed Lena image (a) J1 is compressed using JPEG at a high CR, (b) J2 is compressed using JPEG2000 at a high CR, (c) J3 is compressed using JPEG at a mid CR, (d) J4 is compressed using JPEG2000 at a mid CR.

Table 1 Objective assessment values for the compressed images in Fig. 7.

Image	J1	J2	J3	J4
CR	39.2902	104.844	29.9627	64.573
MLD	0.2485	0.2283	0.1889	0.1830
SSIM	0.8250	0.8380	0.8700	0.8760
MSE	51.4890	51.098	31.4910	31.451
PSNR	31.0140	31.047	33.1490	33.154

Four compressed images are shown in Figure 7. The images in the first row (J1 and J3) are compressed using JPEG algorithm at high and medium CR values respectively while the images in the second row (J2 and J4) are compressed using JPEG2000 algorithm at high and medium CR values. The images compressed using the JPEG2000 algorithm have a better subjective appearance as compared to these compressed using the JPEG algorithm at similar CR values.

Table 1 show that the compressed images J1 and J2 in the first and second columns have approximately similar classical assessment metrics for the JPEG and JPEG2000 but they have different *MLD* values and subjective quality. The compressed images J3 and J4 in the third and fourth columns have similar tendency. The possible reason for this behaviour is because the JPEG saves the low frequency information while the JPEG2000 saves all the information in the low and high frequencies.

5. Conclusions

This paper proposed a new objective metric for assessing the quality of compressed images. The proposed metric combines the effect of three parameters: error magnitude, error location and error distribution. The main idea of this metric is to estimate the amount of lost information during image compression. To isolate the effect of the detailed complexity in the original image, all the calculations are based on the difference between the original and the distorted images with respect to the original image. The results demonstrate that the quality of compressed images using the JPEG2000 algorithm is better than that using the JPEG algorithm. For small CRs, the performance of the two compression algorithms is similar. However, the performance of the JPEG2000 algorithm outperforms the JPEG algorithm as the CR increases. The possible explanation is that more information is lost using the JPEG algorithm as compared to the JPEG2000 algorithm. The gap in performance becomes more prominent for higher CRs. In general, the proposed quality metric has a better correlation with the subjective assessment than other well-known objective quality metrics such as *SSIM*, *MSE* and *PSNR*.

References

[1] Okarma, K., Extended hybrid image similarity–combined full-reference image quality metric linearly correlated with subjective scores. Elektronika ir Elektrotechnika 2013; 19(10); 129-132.

[2] Umme Sara, Morium Akter, Mohammad Shorif Uddin, Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study, Journal of Computer and Communications 2019; 7: 8-18.

[3] Wang, Z., Bovik, A. C., Sheikh, H.R. and Simoncelli, E.P., Image quality assessment: from error visibility to structural similarity. IEEE transactions on image processing 2004; 13(4): 600-612.

[4] Wang, Z., Simoncelli, E.P. and Bovik, A.C., November. Multiscale structural similarity for image quality assessment. In the IEEE Thirty-Seventh Asilomar Conference on Signals, Systems & Computers 2003; 2: 1398-1402.

[5] Sheikh, H.R., Bovik, A.C. and De Veciana, G., An information fidelity criterion for image quality assessment using natural scene statistics. IEEE Transactions on image processing 2005; 14(12): 2117-2128.

[6] Sheikh, H.R. and Bovik, A.C., May. Image information and visual quality. In IEEE International Conference on Acoustics, Speech, and Signal Processing 2004; 3: iii-709.

[7] Larson, E.C. and Chandler, D.M., Most apparent distortion: full-reference image quality assessment and the role of strategy. Journal of Electronic Imaging 2010; 19(1); pp.011006(1-21).

[8] Mou, X., Zhang M, Xue W, Zhang L. Image quality assessment based on edge. In Digital Photography VII, International Society for Optics and Photonics 2011; 7876: pp. 78760N(1-9).

[9] Attar, A., Shahbahrami, A., Rad, R.M. Image quality assessment using edge-based features. Multimedia Tools and Applications 2019; 75(12): pp.7407-7422.

[10] Shi Z, Zhang J, Cao Q, Pang K, Luo T. Full-reference image quality assessment based on image segmentation with edge feature. Signal Processing 2018; 145: pp. 99-105.

[11] Bosse, S., Maniry, D., Wiegand, T., Samek, W. A deep neural network for image quality assessment2016; In IEEE International Conference on Image Processing (ICIP); pp. 3773-3777.

[12] Talebi H, Milanfar P. NIMA: Neural image assessment. IEEE Transactions on Image Processing 2018; 27(8): pp.3998-4011.

[13] Mansouri, A. and Mahmoudi-Aznaveh, A., SSVD: Structural SVD-based image quality assessment. Signal Processing: Image Communication2019; 74: pp.54-63.

[14] Liu, T.J., Lin, W. and Kuo, C.C.J., Image quality assessment using multi-method fusion. IEEE Transactions on image processing 2013; 22(5), pp.1793-1807.

[15] Oszust, M., Decision fusion for image quality assessment using an optimization approach. IEEE Signal Processing Letters 2016; 23(1): pp.65-69.

[16] Saha, A. and Wu, Q.J., Full-reference image quality assessment by combining global and local distortion measures. Signal Processing 2016; 128: pp.186-197.

[17] Hamid R. Sheikh, Zhou Wang, Lawrence Cormack and Alan C. Bovik, Blind, Quality Assessment for JPEG2000 Compressed Images, Conference Record of the Thirty-Sixth Asilomar Conference on Signals, Systems and Computers, DOI: 10.1109/ACSSC.2002.1197072, IEEE Pacific Grove, CA, USA, USA, 2002.

[18] Ratchakit Sakuldee, and Somkait Udomhunsakul, Objective Performance of Compressed Image Quality Assessments, World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering 2007; 1(11).

[19] Walaa Khalaf, Dhafer Zaghar, and Noor Hashim, Enhancement of Curve-Fitting Image Compression Using Hyperbolic Function, MDPI Symmetry 2019; 11,291.