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Noise Removal Using Histogram Equalized Based Contrast Masking For Image Quality Assessment

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Abstract

Image becomes the salient part, namely, watermarking, image enhancement, image compression, and etc. Similarly, the assessing the quality of the image also becomes an essential work of the users. In the last years, there are several advancements have been developed in analyzing the quality of the image. Considerably, Region-of-Interest (ROI) is used to assess the quality. ROI localization is a labor intensive process that takes multiple passes of sliding-window in search of proper ROI. Screen Content Image (SCI) comprises with picture regions and computer generated textual or graphical content. These are organized with statistical properties which lead to various behaviors. The SCI compression performance gets improved by the perceptual screen content coding scheme. Fetal US Image Quality Assessment (FUIQA) uses localization and classification to reduce the errors in the scanned images and enhances the quality of the image. Blind Image Quality Assessment (BIQA) predicts the quality of an image by showing the training data in the form of Discriminable image pairs (DIP) and then using the opinion-unaware BIQA model using RankNet Algorithms. This paper proposes a Noise Removal using Histogram Equalized based Contrast Masking scheme that reduced the time taken in ROI localization. The quality of the images is described using the features. ROI localization is performed using the Masking model which identifies masking and luminance value in parallel manner. The noise present in the image can be detected using the Finite Band Neighborhood Contrast measure.

Keywords: Image Quality Assessment, Region of Interest Localization, Histogram Equalization, Finite Band Neighborhood method.

INTRODUCTION

A digital image has significant part in the applications like satellite television, magnetic resonance imaging, computed tomography. Image Processing is type of signal processing where the input is an image such as a photograph or video frame. The output of image processing is an image or a number of features or parameters linked with the image. Image processing is a technique to transfer an image into digital form and presents some designs on it to obtain an improved image or to remove useful information from it. Image denoising and segmentation are the two major problems in image processing.

Data sets that are grouped with the help of image sensors are infected by noise. Faulty instrument problems with the data acquisition process and intrusive natural fact corrupt the data of interest. Additionally, noise is started by transmission faults and compression. Consequently, denoising is needed and it is an essential step performed before the data images are examined. It is essential to apply well-organized denoising technique to balance the data corruption. Image denoising is a main technique in image processing fields for both processes by itself and component in other processes. Many techniques are used for denoising an image or a group of data exists. The key aim of a good image denoising model extracts the noise while protecting the edges, corners and texture details. Image denoising is the key step in image preprocessing for achieving high–level vision tasks like recognition and scene interpretation.

The degradation of image quality can be during the image acquisition, compression, segmentation and / or transportation. Image Quality can assessed using the training and testing. The image assessment can be subject to full reference (FR), reduced-reference (RR) and no-reference (NR). FR method access the full image to the reference, RR method utilizes the features which are to be extracted from the reference image and NR method analyzes the image quality without any reference image. By using the waterloo database exploration [1], three evaluation criteria was presented to facilitate the future IQA research.

In the recent advancement on IQA for medical images, US scanning, CT Scanning and MRI scanning play a major role. But standards are not adopted due to various difficulties in designing the IQA. No Reference IQA is the one recommended for assessing the IQA for the medical images.

Screen Content Image (SCI) is has a statistical properties that are comprises of pictorial regions and computer generated textual content. An objective quality assessment [2] for SCI was developed for both visual field adoption and information content weighting into structural similarity based local quality assessment. A perceptual scheme was developed to assess the quality of the image.

The enormous growth of mobile devices results in a broader generation and usages of digital images. Therefore, it becomes an essential to address the quality of the images. A three-level representation [3] were analyzed to measure the retargeting image quality was proposed. An adaptive Singular Value decomposition (SVD) [4] which was based clutter flittering technique improves the signal-to-noise ratio (SNR) and contrast-to-noise (CNR) ratio.

In this paper, Histogram Equalization using ROI Localization scheme is proposed to improve the image quality with minimum processing time. Histogram Equalization is performed to mask the contrast of the reference image. The image features are extracted using Finite Band neighborhood Algorithm.

RELATED WORKS

The visual quality of the image depends on the several factors which brings the reality in the user's fact. Many researches were undergone to improve the quality of the images.

A computerized Fetal US Image Quality Assessment (FUIQA) scheme was proposed to reduce the errors in the improper scanning of images. This scheme uses two convolutional neural network models, L-CNN and C-CNN respectively. The region of interest (ROI) localization was identified using L-CNN of the fetal abdominal region. C-CNN is used to classify the region of interest which in turn evaluates the image quality. The major drawback resides in the ROI localization that considered multiple passes of sliding-window scanning in search of proper ROI, increasing the average processing time.

An effective method [6] was proposed to evaluate the quality of the images which affected by symmetric distortions. A new 3D saliency map was developed that assigns the appropriate weights to the image and avoids the depth information calculations. The experimental results indicate that it is significant towards 2D and 3D quality images.

A learning blind image quality assessment model [7] predicts the quality of the image by accessing the pristine-quality counterpart as a reference. The large amount of reliable training data was shown in the form of quality-discriminable image pairs. An opinion-unaware Blind Image Quality Image Assessment uses RankNet to form a inferred quality index. The ListNet, learning model framework was proposed on quality-discriminable image. This index yields the performance gain on the quality of the image.

Intensity Histogram Equalization (IHE) [8] Pre-processing enhances the image contrast by changing the intensity values to improve the brightness. The Pre-processing step includes mask production, enlightenment equalization and colour normalization. These steps de-noise the image and hence image contrast gets improved but it does not address the quality of the image.

The Multi-Class Independent Component InfoMax Analysis [9] was developed to perform am efficient segmentation pattern by the watershed cuts principle and Minimal Spanning Forest. A richer quality texture image is segmented which is associated with regional minima to handle the poorly defined boundary images. This method attains the effective segmentation but fails to address the image quality assessment.

A no-reference image quality assessment [10] using RankIQA was proposed to address the problem of limited image quality assessment. A Siamese Network was used to rank images in terms of image quality by using synthetically generated distortions. A fine-tuning was used to transfer the knowledge represented in the Siamese Network to a traditional CNN that estimates the image quality from single image. The experiment results shows improvement by 5% while comparing with the state-of-arts method.

The Contrast-Enhanced Endoscopic Ultrasonography (CE-EUS) [11] method is used to achieve the subsequent patients having a pancreatic solid lesion and tumors are classified as various vascular patterns at more phases. The relationship among vascular patterns and histopathology of eradicated Pancreatic Cancer (PC) tissues are determined. The ultimate diagnoses of observe tumors such as inflammatory mass, autoimmune pancreatitis and neuroendocrine tumor. The Early-phase iso vascular PCs is possible to distinguish than other early phase hypo vascular. CE-EUS technique is very effective to characterize the PC from other solid pancreatic lesions for histological separation of PCs. An analysis of wide CE-EUS images is not shows that the different method to EUSFNA for the diagnosis of pancreatic tumors.

A novel algorithmic approach of image enhancement by optimal contrast-tone mapping [12] was developed by maximizing the expected contrast gain subject to an upper limit on the tone distortion. The contrast-tone optimization problem was solved by applying linear programming. This algorithm optimizes the transfer function such as sharp contrast and subtle tone according to the application requirements and user preferences.

A multi-band wavelet-based image fusion method [13] was presented to prove the performance in image fusion. The objective of the image fusion includes enhancing the image visibility, to improve the spatial resolution and spectral information of the original images. The qualities of the images are assessed using the set of qualities namely, intensity values, and standard deviation for assessing the details of the fused images.

HISTOGRAM EQUALIZED BASED CONTRAST MASKING FOR IMAGE QUALITY ASSESSMENT

The image features are mainly used for assessing the image quality. The image features vector can be design using the scalar values. These enumerated scalar set of values are analogous to an image feature vector. By using the vector values it is possible to measure the image quality.

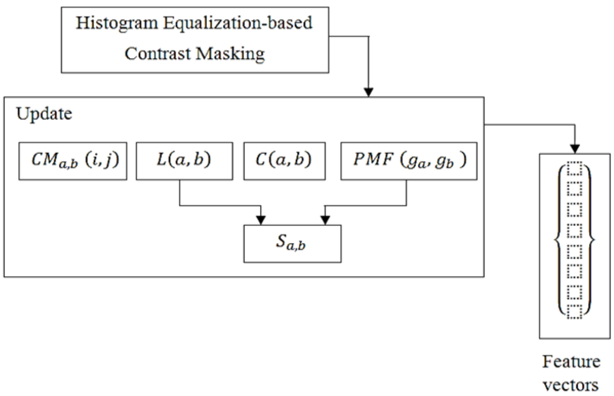


Figure 1. Block diagram of Histogram Equalization-based Contrast Masking

In Figure 1, $CM_{a,b}$ (i,j) is the contrast masking for the Histogram Equalization factor, which is calculated using the equation 1. Contrast Masking uses the Finite Band Neighborhood Contrast measure to evaluate the histogram equalized factors. This contrast value is based on the neighborhood values which standardize the sensitivity of the human into luminance dissimilarities with respect to the luminance mean values.

$$CM_{a,b}\,(i,j) = \frac{L_{a,b}\,(i,j)}{\sum_{c=1,d=1}^{m} L_{c,d}^{a}\,(i,j)} \tag{1}$$

In addition, it is said to be a Finite Band as the degradation perception depends on its spectral location.

From (1), '$L_{a,b}\,(i,j)$' and '$CM_{a,b}\,(i,j)$' represents the luminance and contrast masking present at the coordinates '(i,j)' of the ath channel and them bth angular sector. In addition 'd' represent the angular sector of the cth band respectively.

In the proposed scheme, an input test image is represented in the form of vector in an image space with contrast masking as specified in Equation (1). In that case, any image distortion is interpreted in such a way by including a distortion vector to the training image vector. In this space, the two vectors that represent luminance and contrast changes the span a plane that is adapted to the training image vector.

$$L(a,b) = \frac{2\mu_a\mu_b + \beta_1}{\mu a^2 \mu b^2 + \beta_1} \tag{2}$$

From (2), the luminance value 'L(a,b)' is a measure of mean intensities of image 'μ_a' and 'μ_b', where 'β_1' denotes the constant circumventing uncertainty factor.

$$C(a,b) = \frac{2\,\sigma_a\sigma_b + \beta_2}{\sigma_a^2 + \sigma_b^2 + \beta_2} \tag{3}$$

From (3), the contrast changes 'C(a,b)' is a measure of standard deviation of image 'σ_a' and 'σ_b', where 'β_2' denotes the constant circumventing uncertainty factor with respect to images 'a' and 'b', respectively. With the obtained luminance and contrast changes, pre-processing is performed using Histogram Equalization Factor (HEF). In order to perform HEF, Probability Mass Function 'PMF' and Cumulative Distributive Function 'CDF' is measured. This function is measured for 'N' number of images with 'g_a' gray level for an image 'I_a', 'g_b' gray level for an image 'I_b'.

$$PMF\,(g_a, g_b) = \frac{I_a}{N} * \frac{I_b}{N} \tag{4}$$

$$CDF(I_a) = \sum_{i=1}^{n} Prob(g_a, g_b) \tag{5}$$

The Histogram Equalization (HEQ) gray level value 'S_a' to gray level 'g_a' and 'g_b' for each input testing image is calculated using equation as given below,

$$S_{a,b} = L(a,b) * PMF\,(g_a, g_b) \tag{6}$$

The pseudo code representation for noise removal using Finite Band Neighborhood Contrast is as given below.

Input: Testing images '$\{I = I_1, I_2, \dots, I_n\}$', coordinates '$(i,j)$', constant circumventing uncertainty factor 'β_1'
Output: Feature vectors '$S_{a,b} = f_{a1b1}, f_{a2b2}, \dots, f_{anbn}$'
1: Begin 2: For each testing images 'I' 3: Obtain Contrast Masking for spatial histogram equalization factors using eq. (1) 4: Measure luminance factor using eq. (2) 5: Measure contrast changes using eq. (3) 6: Measure Probability Mass Function using eq. (4) 7: Measure Cumulative Distributive Function using eq. (5) 8: Measure HE using eq. (6) 9: End for 10: End

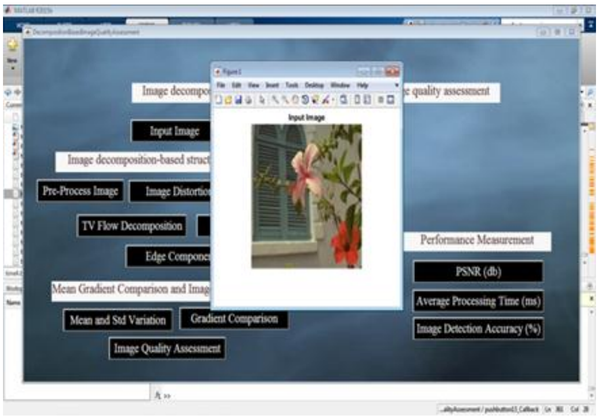
Algorithm 1. Finite Band Neighbourhood Contrast algorithm

In the above algorithm, features are selected and / or noise removal is accomplished. To measure the noise present in the input image, initially, luminance and contrast measure has to be detected. In order to detect luminance and contrast measure in a grey image, the Histogram Equalization is expressed in the Finite Band Neighbourhood Contrast measure. Then Histogram Equalization (HEQ) grey level value 'S_a' is applied on the resulting feature vectors in order to remove both noise and non-important edges.

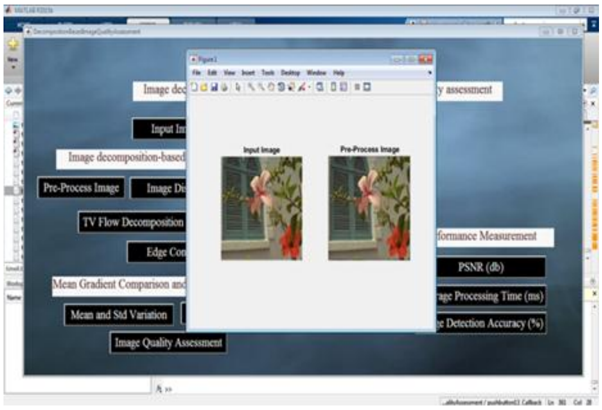
EXPERIMENT EVALUATION

Histogram Equalization-based Contrast Masking for noise removal on Public-Domain Subjective Image Quality Database is developed in MATLAB platform. HE-HALR scheme uses the LIVE Public-Domain Subjective Image Quality Database [14] for image quality assessment. The idea of this model is to define a database with a test image used as benchmark images for Image Quality Assessment.

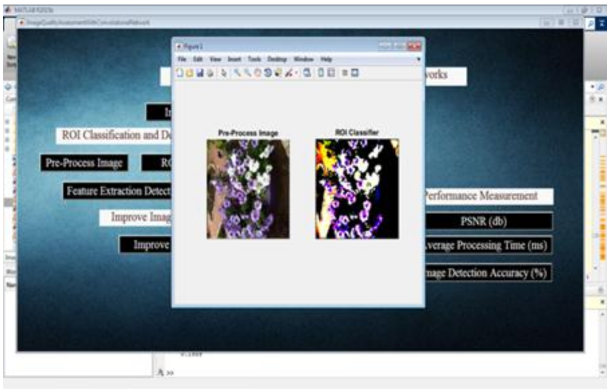
The IQA research heavily depends upon subjective experiments to provide with both the calibration data and testing mechanism, as because the objective of IQA research is to make quality predictions, agreement with subjective opinion of human observers. In order to calibrate IQA algorithms and perform test, a data set including images and videos whose quality has been ranked by human subjects is required. Using LIVE Public-Domain Subjective Image Quality Database, an extensive experiment was conducted to obtain scores from human subjects for a number of images distorted with different distortion types. These images were acquired in support of a research project on generic shape matching and recognition.



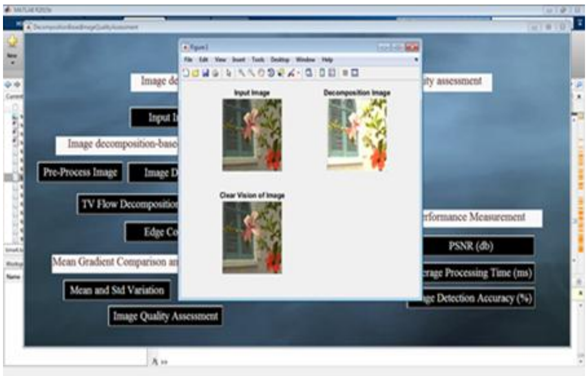
(a)



(b)



(c)



(d)

Figure 2 (a) An Input image for Histogram Equalization **(b)** Output of the Pre-processing Process **(c)** ROI Localization Process for noise removal **(d)** Output of the Histogram Equalization using ROI Localization.

In Figure 2 an input image is considered for the pre-processing stage using the Histogram Equalization Contrast Masking model. In this stage Region of Interest localization is done to remove the noise present in the images. The contrast masking factors are obtained to evaluate the features vectors. The contrast value is based on the luminance dissimilarities with respect to the luminance mean value. With this value Histogram Equalization Factors is calculated using Probability Mass Function and Cumulative Distributive Function. These results are produced the Figure 2 (a) to 2 (d).

RESULT AND DISCUSSION

The performance of the proposed scheme for assessing the image quality is conducted using the LIVE Public-Domain Subjective Image Quality Database. The proposed scheme is investigated based on the Peak-to-Signal Noise Ratio (PSNR) with FUIQA.

In order to computer the Peak-to-Signal Noise Ratio Mean Square Error (MSE) is calculated. This can be evaluated by,

$$MSE = \frac{1}{N}\sum_{i=0}^{N}[a(i,j) - b(i,j)]^2 \qquad (7)$$

The values ‘a’ and ‘b’ represents the two finite length discrete signals with the rows ‘i' and the columns ‘j’. The value ‘N’ refers the number of signal samples.

The PSNR can be expressed as,

$$PSNR = 10\log\left[\frac{(2^B - 1)^2}{MSE}\right] \qquad (8)$$

Here ‘MSE’ refers to Mean Square Error and ‘B’ refers to number of bits per pixel of the image.

Table 1. Tabulation for PSNR using LIVE database

No. of Images	PSNR (using LIVE database)	
	Histogram Equalized Using ROI	FUIQA
10	0.73	0.68
20	0.78	0.73
30	0.82	0.77
40	0.75	0.70
50	0.80	0.75
60	0.84	0.79
70	0.88	0.83
80	0.85	0.80
90	0.92	0.87
100	0.95	0.90

Table 1 presents the PSNR rate with respect to number of images used. From this table one can observe that the PSNR rate is quite always improved when the contrast masking is used to reduce the noise present in the images, whatever the number of images used.

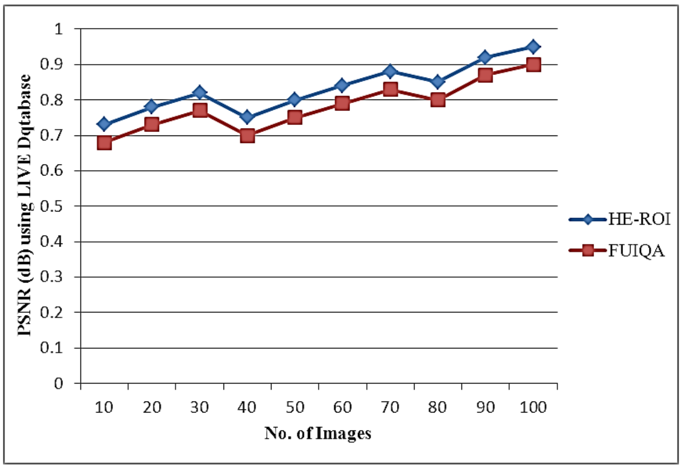


Figure 3. PSNR rate results obtained employing the LIVE database

Figure 4 shows the graphic representation of PSNR using LIVE database. The database consists of 779 images, whereas in figure 4, 100 images are taken for observation. To this, a negative result with high PSNR is useful for image quality assessment. Furthermore, a high PSNR value is reliable. The PSNR is found to be higher when applied with the proposed HE-ROI scheme than FUIQA [5] respectively. ROI localization using Histogram Equalization-based Contrast Masking in the HE-HALR scheme improves the rate of PSNR.

ROI localization involves a series of uncertainties and accurate features being extracted may result in the appropriate classification of features. This is because of the ROI localization which has to be carefully analyzed; otherwise the extracted results will be inappropriate or irrelevant features. The main advantage of the proposed procedure is that it gets a good performance without having to extract different types of features using the Finite Band Neighborhood Contrast measure. With regard to the obtained results, the experiment with the best performance is HE-ROI scheme achieving PSNR greater than 6% compared to FUIQA [5].

CONCLUSION

In this paper, Histogram Equalization is applied as the pre-processing step to remove the noise with the help of region of interest. This work uses the Finite Band neighbourhood algorithm for the contrast masking. Further, a machine learning technique will applied to assess the image quality. We noted that our proposal using the ROI localization for improving image quality achieved better results compared to the state-of-the-art methods.

REFERENCES

[1] Kede Ma, Zhengfang Duanmu, Qingbo Wu, Zhou Wang, Hongwei Yong, Hongliang Li, and Lei Zhang, February 2017, "Waterloo Exploration Database: New Challenges for Image Quality Assessment Models", IEEE Transactions on Image Processing, VOL. 26, NO. 2, pp 1004 – 1016.

[2] Shiqi Wang, Ke Gu, Kai Zeng, Zhou Wang, and Weisi Lin, "Objective Quality Assessment and Perceptual Compression of Screen Content Images", IEEE Computer And Graphics Application.

[3] Yichi Zhang, King Ngi Ngan, Lin Ma, and Hongliang Li, Dec. 2017, "Objective Quality Assessment of Image Retargeting by Incorporating Fidelity Measures and Inconsistency Detection", IEEE Transactions on Image Processing, Volume: 26, Issue: 12. pp. 5980 - 5993.

[4] Pengfei Song, Armando Manduca, Joshua D. Trzasko, Shigao Chen, Jan. 2017, "Ultrasound Small Vessel Imaging with Block-Wise Adaptive Local Clutter Filtering", IEEE Transactions on Medical Imaging, Volume: 36, Issue: 1,pp. 251 - 262.

[5] Lingyun Wu, Jie-Zhi Cheng, Shengli Li, Baiying Lei, Tianfu Wang, and Dong Ni, May 2017,"FUIQA: Fetal Ultrasound Image Quality Assessment with Deep Convolutional Networks", IEEE Transactions on Cybernetics, Volume: 47, Issue: 5..

[6] YunLiu, JiachenYang, QinggangMeng, Zhihan Lv, Zhanjie Song, Zhiqun Gao, August 2016, "Stereoscopic image quality assessment method based on binocular combination saliency model", Signal Processing, Volume 125, Pages 237-248.

[7] Kede Ma, Wentao Liu, Tongliang Liu, Zhou Wang, and Dacheng Tao, August 2017," dipIQ: Blind Image Quality Assessment by Learning-to-Rank Discriminable Image Pairs", IEEE Transactions On Image Processing, VOL. 26, NO. 8, pp. 3951 – 3964.

[8] N.Balakrishnan , S.P.Shantharajah , June 2014, "Image Denoising and Contrast Via Intensity Histogram Equalization Method", International Review on Computers and Software (I.RE.CO.S.), Vol. 9, N. 6, pp.988 – 996.

[9] Balakrishnan, N & Shantharajah, S P, 2016, 'An effective segmentation pattern using multi-class independent component analysis on high quality color texture images', Research Journal of Applied Sciences, Engineering and Technology, vol. 12, no. 9, pp. 916-925.

[10] Xialei Liu, Joost van de Weijer, and Andrew D. Bagdanov,2017, " RankIQA: Learning from Rankings for No-reference Image Quality Assessment", Computer Vision and Pattern Recognition, https://arxiv.org/abs/1707.08347v1.

[11] Yasunobu Yamashita, Jun Kato, Kazuki Ueda, Yasushi Nakamura, Yuki Kawaji, Hiroko Abe, Junya Nuta, Takashi Tamura, Masahiro Itonaga, Takeichi Yoshida, Hiroki Maeda, TakaoMaekita, Mikitaka Iguchi, Hideyuki Tamai & Masao Ichinose, 2015, 'Contrast-enhanced endoscopic ultrasonography for pancreatic tumors', Biomedical Research International, http://dx.doi.org/10.1155/2015/491782

[12] Xiaolin Wu, 2011, 'A linear programming approach for optimal contrast-tone mapping', IEEE Transactions on Image Processing, vol. 20, no. 5, pp. 1262-1272.

[13] WenzhongShi, Chang Qing Zhu,YanTian, Janet Nichol, 2005, ,Wavelet-based image fusion and quality assessment, International Journal of Applied Earth Observation and Geoinformation, Volume 6, Issues 3–4, pp. 241-251.

[14] .R. Sheikh, M.F. Sabir and A.C. Bovik, "A statistical evaluation of recent full reference image quality assessment algorithms", *IEEE Transactions on Image Processing,* vol. 15, no. 11, pp. 3440-3451, Nov. 2006.