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Reduced Reference Image Quality Assessment for Gaussian Blur Distortion

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Abstract: In this study, a novel Reduced Reference Image Quality Assessment (RR-IQA) metric is proposed based on energy change in wavelet domain. In the first place, features of Gaussian blur images and their general properties in wavelet domain are analyzed, in terms of the corresponding significance they play on the representation of human visual system. Secondly, in accordance with some authoritative literatures, the change of image energy will evoke the change of human visual perceptual quality. Based on this fact, a series of features from Gaussian blur images which embody the change of image energy are extracted. Finally, we fuse these features based on the principal that we exert different importance in accordance with the different impact each individual sub-band plays on the visual perception. As far as the performance of the proposed metric for the Gaussian blur images is concerned, the proposed metric outperforms the state-of-the-art RR-IQA metrics and even two typical full-reference image quality assessment metrics.

Key words: Image quality assessment, reduced-reference, Gaussian blur, Wavelet transform

INTRODUCTION

It is a prevailing tendency that an explosion of information exchange, particularly in the form of image and video transmission tend to be a significant and changing task in the days to come (Lin and Kuo, 2011). For the reason that signal will be distorted as a consequence of the limited transmittal condition, we have to accurately evaluate the quality of the distorted images, to what extent it is distorted in comparison with the reference image. Human eyes are the ultimate receivers, hence the most accurate Image Quality Assessment (IQA) method is subjective evaluation method (Seshadrinathan *et al*., 2010; Zhai *et al*., 2008). However, in practical applications, subjective IQA is very inconvenient and time-consuming. A metric that can automatically measure image's perceptual quality should be formulated and ameliorated (Yu *et al*., 2002).

Objective IQAs can be sorted into three categories (Wang and Bovik, 2006) according to the amount of image features used for predicting the subjective quality. So far, most prevalent approaches are known as Full-Reference (FR) IQAs (Wang *et al*., 2004; Shnayderman *et al*., 2006; Chandler and Hemami, 2007; Liu *et al*., 2012), No-reference (NR) IQAs (Liang *et al*., 2010; Zhang *et al*., 2011) and Reduced-Reference (RR) IQAs (Wu *et al*., 2013; Ma *et al*., 2013; Soundararajan and Bovik, 2012; Rehman and Wang, 2012; Sheikh and Bovik, 2006).

FR-IQA metrics require the whole information of reference image. In practice, the requisition of reference image is of high costs. The simplest FR-IQA metrics are the Mean Square Error (MSE) and the Peak Signal-to-noise (PSNR). MSE and PSNR are prevalently adopted for its simplicity and manifest meaning. However, these two IQA indices purely evaluate the difference in terms of pixel intensity, in regardless of the perceptual properties of human eyes. That is why the overall performance is negative. The Structure Similarity (SSIM) index (Wang *et al*., 2004) was developed which considered that eyes are sensitive to the structural distortion and proved to earn superiority to some FR-IQA metrics. Shnayderman *et al*. (2006) utilized singular value decomposition to indirectly evaluate the quality of image and turned to be comparatively efficient but with somewhat high complexity. Chandler and Hemami (2007) advocated the Visual Siganl-to-Noise Ratio (VSNR) (Chandler and Hemami, 2007) to predict the perceptual quality in wavelet domain, the computaion complexity is unacceptable.

In most real-world cases, the reference image for quality assessment is not accessible. In this circumstance, NR-IQA indices play an momentous role for its independency on reference image and their evaluation object is constantly a specific distortion type. Liu *et al*. (2012) utilized statistical information in the form of a histogram representing the sharpness distribution of gradient profiles to evaluate JPEG 2000 distorion image and this feature proves to be highly sensitive and effective to predict the imag qaulity. Liang *et al*. (2010)

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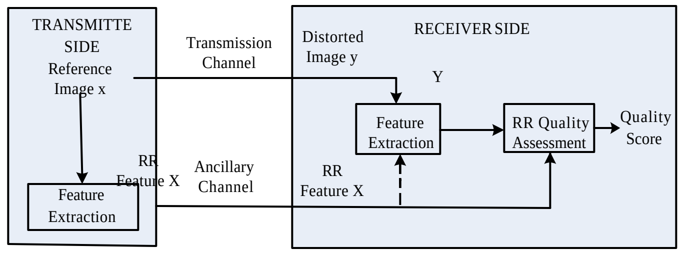

Fig. 1: Framework for the deployment of RR IQA system

made use of the edge activity, above all the weighting map was predicted so as to tell apart different importance in different areas.

As a compromise between FR and NR, RR-IQA indices are formulated to evaluate the perceptual quality by means of using partial information of the reference image. Fig. 1 shows the basic framework of the RR-IQA model. An image x is transmitted to the receiver side via a transmission channel which makes reference image x be the corresponding distorted image y. The feature which denoted as X from x extracted at the sender side is sent to the receiver side with auxiliary channel, then extract the feature denoted Y from yat the receiver side, the distance of X and y indicates the change in image perceptual quality. Ultimately, the predicted quality score is estimated.

In most cases, an efficient RR-IQA metric should achieve a good tradeoff between the information amount and prediction accuracy. To a great extent, the more the amount of reference image information RR-IQA indice acquires, the higher the accuracy will be.

The Visual Information Fidelity (VIF) (Wu *et al*., 2013) for Gaussian blur (Gblur) distorted images advocated that image understanding was mainly caused by the distortions on primary visual information, hence, they computed the quantities of the decisive visual information and residual uncertainty to predict the subjective quality, the result of Gaussian blur image proved to be excellent. IQA indice, named Reorganized Discrete Cosine Transform (RDCT) (Ma *et al*., 2013), extracted the feature by calculating city-block distance, mutual information and the ratio of different frequency information and the experimental result showed excellent performance, particular for the third feature it was appropriate to evaluate the Gaussian blur images. Soundararajan and Bovik (2012) measured the difference of Wavelet entropy and has achieved good result. Recently, statistical significant analysis has been carried out based on variance-based hypothesis testing. Rehman and Bovik extracted statistical features from a multi-scale multi-orientation divisive normalization transform and a distortion measurement (Rehman and Wang, 2012) to estimate the SSIM index of the corresponding distorted image is formulated.

Inspired by the significance of the image energy to human visual perception, a novel RR-IQA is developed by measuring the energy change in wavelet domain for the reference image and the corresponding distorted image. As a Multiresolution processing, image wavelet transform decomposes an image into three sets of coefficients details with three different orientation information-the horizontal, vertical ,and diagonal information (Toufik and Mokhtar, 2012). what is more, wavelet transform matches with multi-channel model of human visual system in the form that eyes are sensitive to image’s vertical and horizontal information at a similar level and comparatively insensitive to that of image’s diagonal informatin (Rezazadeh and Coulome, 2013). Hence, from the perspective of visual perception, an appropriate approach to measure the energy change derived from these three orientation information will become an efficient IQA indict.

The remainder of this study is organized as follows. In part two, we give the detailed explanation of the proposed metric and then extensive experimental invalidation and related analysis is followed in part three. Ultimately, conclusions are drawn in part four.

PROPOSED RR-IQA INDEX

Gaussian blur image: The preliminary target of image blurring is to alleviate image noise which also impairs the original image’s texture or edge regions. In certain circumstance, this processing operation will bring the images to be better. However, if an image is unduly blurred, the image will be taken as an obviously distorted one. The visual effect of blurred image is like that we look at an image by a translucent screen. From the perspective of mathematical analysis, a Gaussian blur image is derived as a result of the original image which is operated as a

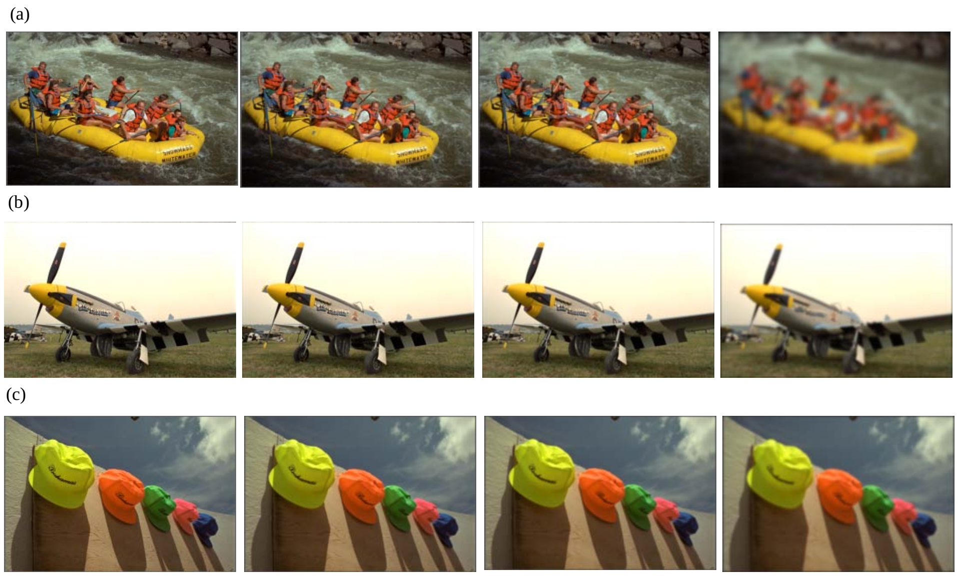

Fig. 2(a-c): Three original images and their three Gaussian blur images with different degrees of distortion, (a) rapids, (b) plane and (c) caps

convolution with a fixed Gaussian distribution window (Gedraite and Hadad, 2011). The elements in this template window obey Gaussian distribution. Fig. 2 shows three images which are Gaussian blur, the extent of blur distortion is gradually becoming higher from the first original image to the right most one.

If f_0 (i, j) is a reference image and its blurred version denoted f_b (i, j) is expressed as follows:

$$\begin{aligned} f_b(i,j) &= f_0(i,j) * h(i,j) \\ &= f_0(i,j) * \frac{1}{2\pi\alpha^2}\exp\left(-\frac{i^2+j^2}{2\alpha^2}\right) \end{aligned} \tag{1}$$

where h (i, j) is the distribution function of the filter. Moreover, the Fourier transform of h (i, j) can be expressed as:

$$H(w,v) = \exp\left(-\frac{1}{2}\rho^2 a^2\right) = \exp\left(-\frac{1}{2}\sqrt{w^2+v^2}\,a^2\right) \tag{2}$$

where w and v are two frequency variables. Generally, many optical imaging systems can be described as a low-frequency Pass Filter (LPF). The cut-off frequency in LPF reflects the blurring degree.

Wavelet analysis of image: In the Fourier analysis of image, an image is expressed as a sum, theoretically infinite, of sines and cosines, making the FT suitable for infinite and periodic signal analysis. However if it succeeded in providing image frequency information it failed to provide any information of image's occurrence time. Fortunately, wavelet analysis of image is defined as a mathematical technique in which an image is analyzed (or synthesized) in time domain and frequency domain by utilizing different versions of a dilated and translated basis function named the wavelet prototype or the mother wavelet (Toufik and Mokhtar, 2012). In view of the advantages, paricular in time-scale localisation and multirsolution capacity, wavelet transform is employed to describe the energy of an image.

Feature extraction: In human visual perception, the luminance of image is more decisive compared with chrominance. Consequently, we convert images into luminance space. In this study, four level of wavelet transform is to be performed (Fig. 3). The coefficient matrix S_0 in the upper left corner represent the average greyscale value of the whole image and is called DC (direct current) coefficient.

The sub-bands S_1, S_4, S_7 and S_{10} indicate the image's horizontal information, the sub-bands S_2, S_5, S_8 and S_{11} indicate the image's vertical information and finally the sub-bands S_3, S_6, S_9 and S_{12} indicate image's diagonal information (Mannos and Sakrison, 1974).

Sub-band S_0, S_1, S_2, S_3 mainly contain the information of image low frequency information. Sub-bands S_4, S_5, S_6 and sub-bands S_7, S_8, S_9 collectively contain the information of image median frequency. Sub-bands

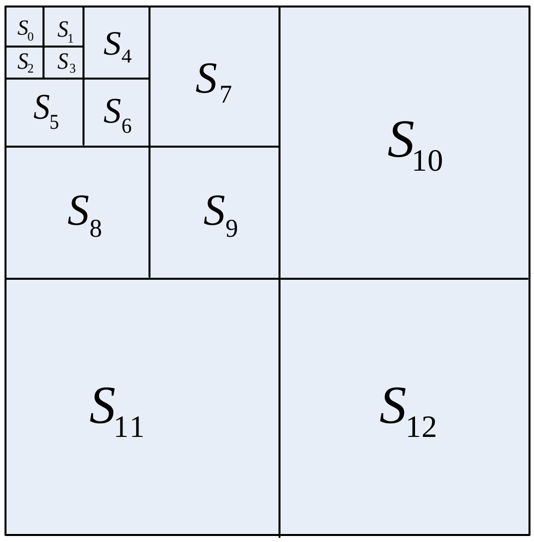

Fig. 3: Distribution of wavelet subband

S_{10}, S_{11}, S_{12} contain the high information. Fig. 4 shows the wavelet decomposition of *Lena*.

For Gaussian blur images shown in Fig. 2, the loss of high-frequency components smoothens the image and decreases the energy of each subband. Here, the energy of the wavelet sub-bands of an image is defined as follows:

$$e_k = \frac{1}{m \times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\log_2(|c|+1) \tag{3}$$

where e_k indicates the energy information of the k^{th} sub-band, c indicates the coefficient in the k^{th} sub-band and k = {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10}. As we know, the change of image energy will reflect the change of image quality. Actually, there are plenty of approaches to measure the distance of two features of reference and distorted images, the choice of the corresponding approach is mainly based on the properties of the features. The distance here is defined as:

$$d_k = \frac{e_k^{dis}}{e_k^{org}} \tag{4}$$

where e_k^{org} and e_k^{dis} indicate the energy information of the k^{th} sub-band of the reference and distorted images, respectively. When looking at an image, eyes constantly attach great importance to the horizontal and vertical information at the similar level. While the implication that the diagonal information plays is minor. Based on this fact, the diagonal information is eliminated on the purpose of less information. Thus the average energy of the horizontal and vertical information works on behalf of the l^{th} level as below:

Fig.4(a-b): Lena under Wavelet decomposition (a) Original Lena and (b) Decomposed *Lena*

$$f_l = \frac{e_{lh}+e_{lv}}{2} = \frac{1}{2mn}\left(\sum_{i=1}^{m}\sum_{j=1}^{n}\log_2(|c_{lh}+1|)+\sum_{i=1}^{m}\sum_{j=1}^{n}\log_2(|c_{lv}+1|)\right) \tag{5}$$

where e_{lh} and e_{lv} indicate the horizontal and vertical energy in the l^{th} level, m and n are the height and width of the corresponding subband, respectively c_{lh} and c_{lv} are the coefficient in the in the l^{th} level sub-band respectively and l = {1, 2, 3, 4}. Four features of the reference image and its distorted one are extracted from their four levels decomposition and are denoted as two vectors

$$\vec{F}_{org} = \{f_{1org}, f_{2org}, f_{3org}, f_{4org}\}$$

and

$$\vec{F}_{dis} = \{f_{1dis}, f_{2dis}, f_{3dis}, f_{4dis}\}$$

In the study of IQA, a variety of data fusion approaches are widely applied. Recently, a strategy based on Support Vector Regression (SVR) (Charrier *et al*., 2012) is utilized to fuse. But the underlying principal is of high complexity and its performance is not so suitable in some cases. As a result, a fine approach to fuse these four features is linear weighted method and the ratio of the fused feature acts as the objective quality. Thus, the final objective assessment criterion can be defined as:

$$Q = \frac{W \cdot F_{org}}{W \cdot F_{dis}} = \left(\sum_{i=1}^{4} \omega_i f_i^{org}\right)^{-1} \cdot \sum_{i=1}^{4} \omega_i f_i^{dis} \quad (6)$$

where, Q is the objective quality of distorted image; W is the weighting vector denoted as W $\{\omega_1, \omega_2, \omega_3, \omega_4\}$. The value of ω_i denotes the i^{th} level's contribution to image visual perception and it conforms to the rule:

$$\sum_{i=1}^{4} w_i = 1.$$

EXPERIMENTAL RESULTS

Database and performance criterion: In this section, to demonstrate the efficieny of the proposed metrics for evaluating the image perceptual quality, We conduct experiments on the authoritative image quality database, namely Laboratory for Image and Video Engineering (LIVE) image database (Sheikh *et al*., 2005). LIVE database contains 29 original images and five different distortion types including JPEG, JP2K, additive white Gaussian noise (WN), Gaussian blur (Gblur) and bit errors due to the transmission of JP2K image in a Fast Fading channel (FF). There are 779 images across all the distortion categories in total. In this study, we merely utilize the sub-base consisting of 145 Gaussian blur images. Each Gaussian blur image has a subjective index, called DMOS which is derived from subjective experiment. The criterion of objective assessment performance is to measure the consistency between objective quality and subjective quality. We follow the performance evaluation procedure introduced in the Video Quality Experts Group (VQEG) HDTV test.

After the raw quality metric q is derived, we utilize a non-linear regression to map the calculated objective quality to its predicted subjective quality. The regression process can be expressed as:

$$DMOS_p = \frac{b_1 - b_2}{1 + \exp\left(-\frac{q - b_3}{|b_4|}\right)} + b_2 \quad (7)$$

where, $DMOS_p$ denotes the representative of perceptual quality index of the corresponding distorted image. The four parameters in the function denoted as vector $\{b_1, b_2, b_3, b_4\}$ is utilized to map q into $DMOS_p$. And these four parameters can be determined by the minimizing the sum squared differences between $DMOS_p$ and its corresponding subjective quality.

To qualify the performance of objective assessment metric, VQEG recommended a series of assessment criterion (ITU-T SG09, 2001)

The prediction accuracy measure of Pearson Correlation Coefficient (CC) which evaluates the accuracy of predicted quality. It is computed as:

$$CC_{X,Y} = \frac{\sum_{j=0}^{N-1}(X_j - \bar{X})(Y_j - \bar{Y})}{\sqrt{\sum_{j=0}^{N-1}(X_j - \bar{X})^2}\sqrt{\sum_{j=0}^{N-1}(Y_j - \bar{Y})^2}} \quad (8)$$

Spearman Rank Order Correlation Coefficient (SROCC) which evaluates the prediction monotonicity.

The compression is shown as follows:

$$SROCC_{X,Y} = 1 - \frac{6 \times \sum_{i=0}^{N-1}(R_{X_i} - R_{Y_i})^2}{N \times (N^2 - 1)} \quad (9)$$

Root Mean Square Error (RMSE) which measures the difference between the realistic subjective value and the predicted subjective quality after nonlinear regression. It is computed as:

$$RMSE_{X,Y} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2} \quad (10)$$

where X_i and Y_i refer to be the j^{th} original subjective quality score and predicted quality, $\bar{X}$ and $\bar{Y}$ refers to the mean data of variable X and Y. R_X and R_y are the order of i^{th} variable.

Selection of parameters: In this study, we utilize the wavelet 'bior 4.4' which is a Biorthogonal wavelet. It earns the superiority in property of its linear phase. As mentioned in previous part, we choose to linearly weight

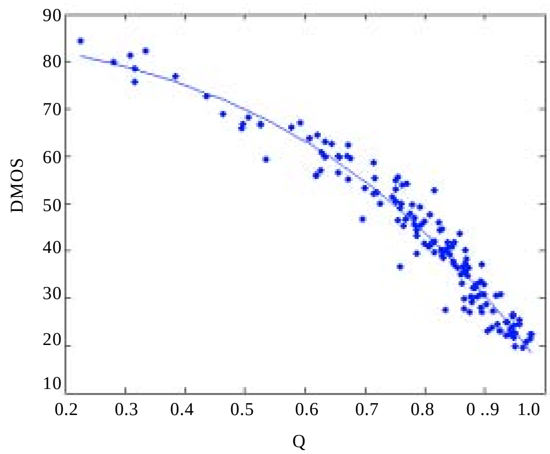

Fig. 5: Scatter of $DMOS_P$ and DMOS

each sub-band's energy in the representation of perceptual quality change in wavelet domain. Plenty of literatures in image processing have demonstrated that eyes are comparatively sensitive to areas with median frequency and comparatively insensitive to ares with low and high frequency information (Mannos and Sakrison, 1974). From the perspective of image structure itself, plat and texture areas represent low and high frequency information, while edge represents image's median information. And the edges of an image are more decisive for the understanding of the image. As a result, big weighting coefficients to energy with median frequency information are allocated and the other two kinds of energy are allocated with smaller weighting coefficients. It is presented in Table 1.

Performance and comparison: The performances of the proposed metric for Gaussian blur images are shown in Table 2. To provide background comparisons, we also incite six others objective IQA indices, among which four are RR-IQA indices and two are FR-IQA indices. It is manifest from the criteria that our proposed metric is able to accurately evaluate the quality of Gaussian blur images. On the whole, two classic full-reference metrics and five existing Reduced-reference metrics are inferior to our proposed metric. According to the investigation of existing Gaussian blur RR-IQA indices, the existing metrics do not have the performance that their CC and SROCC are bigger than 0.97 but the CC and SROCC of the proposed metric are 0.9735 and 0.9702, respectively and accompanying a very low RMSE of being 3.5892. Moreover, the number of its required features extracted from eight sub-bands is only eight that is smaller than many RR-IQA metrics. It greatly alleviates the burden of system in practical applications. SSIM fails to acurately predict the quality of Gaussian blur image for its low efficiency of estimating the distortion degree by pixel local statistical property. the performance of IQA algorithm based on SVD is excellent. But it is inefficient for the requirement of reference image. RDCT (Ma *et al*., 2013) utilized the DCT transform to reconstuct a new decomposition approach which is similar to wavelet decomposition in terms of its implication on visual perception and yields satisfactory result. The model of primary visual information and residual uncertainty in VIF(Wu *et al*., 2013) works good but what exact are these two information still deserve to be studied. RRED (Soundararajan and Bovik, 2012) and RR-SSIM (Rehman and Wang, 2012) perform well in IQA.

Table 1: Distribution of weight vector W

	Weighting Factors			
	ω_1	ω_2	ω_3	ω_4
Value	0.3	0.2	0.4	0.1

Table 2: Performance of IQA metrics for Gaussian blur on live database

	Criteria			
Metric	CC	SROCC	RMSE	No. of Features
Proposed	0.9735	0.9702	3.5892	8
FR-SSIM	0.8969	0.9144	6.9818	----
FR-SVD	0.95	0.9368	6.5821	----
RR-VIF	0.955	0.9611	4.6601	30
RR-RDCT	0.9459	0.9525	5.8801	15
RRED	0.9531	0.953	5.6221	32
RR-SSIM	0.9154	0.8632	7.3412	36

Scatter plots shown in Fig. 5 represent a satisfactory result. The predicted quality is well fitted shown in the full line. It means it has pretty good accuracy and monotonicity for this specific type of distortion. All the performance shown in Table 2 and the Fig. 5 have demonstrate our proposed IQA index is highly consistent with perceptual quality and exhibit highly competitive performance in the Reduced-reference evaluation of Gaussian blur image.

CONCLUSION

In this study, the change of energy in wavelet domain is introduced to develop a novel RR-IQA method. For the properties of eyes to wavelet decompositon with different orientation and frequency sensitivity for human visual perception, four energy features are extracted with proper weighting sheme to predict the perceptual quality. The experimental results on LIVE database show the proposed metric exhibits satisfactory correlation with subjective evaluation for the evaluation of Gaussian blur image. Above all, the complexity of the proposed metric and the amount of feature information it needs are superior to most of the existing RR metrics. However its function is still deserved to be studies further in terms of the specific impact each wavelet sub-band plays on visual perception. The change of energy in wavelet domain will be further applied to the research of NR-IQA and video quality assessment.

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REFERENCES

Chandler, D.M. and S.S. Hemami, 2007. VSNR: A wavelet-based visual signal-to-noise ratio for natural images. IEEE Trans. Image Proc., 16: 2284-2298.

Charrier, C., O. Lezoray and G. Lebrun, 2012. Machine learning to design full-reference image quality assessment algorithm. Signal Process.: Image Commun., 27: 209-219.

Gedraite, E.S. and M. Hadad, 2011. Investigation on the effect of a gaussian blur in image filtering and segmentation. Proceedings of the 53th International Symposium ELMAR, September 14-16, 2011, Zadar, Croatia, pp: 393-396.

ITU-T SG09, 2001. Final report from the video quality experts group on the validation of objective models of video quality assessment, phase II (FR-TV2). http://www.itu.int/md/T01-SG09-C-0060/en

Liang, L., S. Wang, J. Chen, S. Ma, D. Zhao and W. Gao, 2010. No-reference perceptual image quality metric using gradient profiles for JPEG2000. Signal Process.: Image Commun., 25: 502-516.

Lin, W. and C.C. Jay Kuo, 2011. Perceptual visual quality metrics: A survey. J. Visual Commun. Image Represent., 22: 297-312.

Liu, A., W. Lin and M. Narwaria, 2012. Image quality assessment based on gradient similarity. IEEE Trans. Image Process., 21: 1500-1512.

Ma, L., S. Li and K.N. Ngan, 2013. Reduced-reference image quality assessment in reorganized DCT domain. Signal Process.: Image Commun., 28: 884-902.

Mannos, J.L. and D.J. Sakrison, 1974. The effects of a visual fidelity criterion of the encoding of images. IEEE Trans. Inform. Theory, 20: 525-636.

Rehman, A. and Z. Wang, 2012. Reduced-reference image quality assessment by structural similarity estimation. IEEE Trans. Image Process., 21: 3378-3389.

Rezazadeh, S. and S. Coulombe, 2013. A novel discrete wavelet transform framework for full reference image quality assessment. Signal Image Video Process., 7: 559-573.

Seshadrinathan, K., R. Soundararajan, A.C. Bovik and L.K. Cormack, 2010. Study of subjective and objective quality assessment of video. IEEE Trans. Image Process., 19: 1427-1441.

Sheikh, H.R. and A.C. Bovik, 2006. Image information and visual quality. IEEE Trans. Image Proc., 15: 430-444.

Sheikh, H.R., Z. Wang, L. Cormack and A.C. Bovik, 2005. LIVE image quality assessment database release 2. Laboratory for Image and Video Engineering. http://live.ece.utexas.edu/research/quality/subjective.htm

Shnayderman, A., A. Gusev and A.M. Eskicioglu, 2006. An SVD-based grayscale image quality measure for local and global assessment. IEEE Trans. Image Process., 15: 422-429.

Soundararajan, R. and A.C. Bovik, 2012. RRED Indices: Reduced reference entropic differencing for image quality assessment. IEEE Trans. Image Process., 21: 517-526.

Toufik, B. and N. Mokhtar, 2012. The Wavelet Transform for Image Processing Applications. In: Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology, Baleanu, D. (Ed.). Chapter 17, InTech, USA., pp: 395-422.

Wang, Z. and A.C. Bovik, 2006. Modern Image Quality Assessment (Synthesis Lecture on image Video and Multimedia Processing). Morgan and Claypool Publishers, New York, ISBN-13: 9781598290226, Pages: 146.

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

Wu, J., W. Lin and G. Shi, 2013. Reduced-reference image quality assessment with visual information fidelity. IEEE Trans. Multimedia, 15: 1700-1705.

Yu, Z., H.R. Wu, S. Winkler and T. Chen, 2002. Vision-model-based impairment metric to evaluate blocking artifacts in digital video. IEEE Proc., 90: 154-169.

Zhai, G., J. Cai, W. Lin, X. Yang, W. Zhang and M. Etoh, 2008. Cross-dimensional perceptual quality assessment for low bit-rate videos. IEEE Trans. Multimedia, 10: 1316-1324.

Zhang, J., T.M. Le, S.H. Ong and T.Q. Nguyenc, 2011. No-reference image quality assessment using structural activity. Signal Process., 91: 2575-2588.