# A new Tone-Mapped Image Quality Assessment Approach for High Dynamic Range Imaging System

*Yang Song, Gangyi Jiang*, Hao Jiang, Mei Yu, Feng Shao, Zongju Peng*

Faculty of Electrical Engineering and Computer Science, Ningbo University, China

*Email: jianggangyi@126.com

## ABSTRACT

Tone-mapping operators are designed to apply high dynamic range (HDR) images on widely-used low dynamic range (LDR) devices. Developing well-performed tone-mapped image quality assessment (IQA) method is highly desired because traditional IQA method cannot be adopted in cross dynamic range quality measuring. To this end, we proposed a quality assessment method based on image exposure property. Specifically, an image exposure property determination model is utilized to segment HDR image into different exposure region. Then, quality features are extracted according to the distortion characteristics of each exposure region. Finally, the quality of tone-mapped image can be acquired by a trained regression model. Validation experiments on public database show that the proposed method can accurately predict the quality of tone-mapped image.

***Index Terms***—Visual quality assessment, High Dynamic Range Imaging, Tone mapping operator, Image Segmentation

## 1. INTRODUCTION

The 256 levels of intensity in traditional low dynamic range (LDR) images inevitably leads to information losses as the visible range of human visual systems are much larger. To over come such limitation, high dynamic range (HDR) imaging techniques have already been rapidly developed in recent years. With a dynamic range up to 100000: 1[1] or higher, HDR images can reveal more details information and thus provide better watching experience for viewers. However, the existing HDR devices are expensive at current stage, and are still not available in most image processing systems [2]. In order to visualize HDR images in traditional LDR devices, several tone-mapping operators (TMO) have been proposed [3]. Naturally, how to precisely assess the quality of images obtained by different TMOs will be a challenging issue in the researching field of HDR imaging.

At the early stage of evaluating tone-mapped image, researchers mainly depended on subjective rating [4]. However, subjective experiments is time-consuming and limited in system integration. Therefore, objective assessment method, as a more practical alternative, becomes the focus of studying. By combining two traditional LDR image quality assessment (IQA) methods, MS-SSIM and natural scene statistics, Yageneh *et al*. firstly proposed the Tone-mapped image Quality Index (TMQI) [5]. Meanwhile, the tone-mapped image database (TMID) are established for performance validation of further studying. Similarly, Nafchi *et al*. also focused on modifying the well-performed LDR IQA method to support cross dynamic range comparison, and proposed Feature Similarity for Tone-mapped Image (FSITM) [6]. Recently, by considering information fidelity, image statistical characteristics and structural preservation, Gu *et al.* proposed Blind Tone-mapped Image Quality Index (BTMQI) [7].

All the above mentioned tone-mapped IQA methods can accurately predict the quality of tone-mapped image. However, they are still based on the assessment methods which are mainly designed for LDR images' quality evaluating. To this end, by fully considering the characteristics of distortion types appeared in tone-mapped image, we propose an tone-mapped IQA method. In this method based on the property of exposure in HDR image. Firstly, by using a image exposure property determination model, the HDR image is divided into two different parts, namely, easily-abnormal-exposure region (EAER), easily-normal-exposure region (ENER). Then, according to the characteristics of different exposure region, the corresponding quality features are extracted. Specifically, we designed abnormal ratio and extreme ratio to reflect the degree of abnormal exposure in EAER, while colorfulness index is computed as quality feature in ENER. Finally, a regression model is used to combine the aforementioned three respects of features to derive the overall quality score of a tone-mapped image.

The rest of this paper is organized as follows. Section 2 first describes the proposed tone-mapped IQA method in detail. In section 3, experimental results on publicly available TMID database and performance comparison with other methods are illustrated. We finally conclude this paper in Section 4.

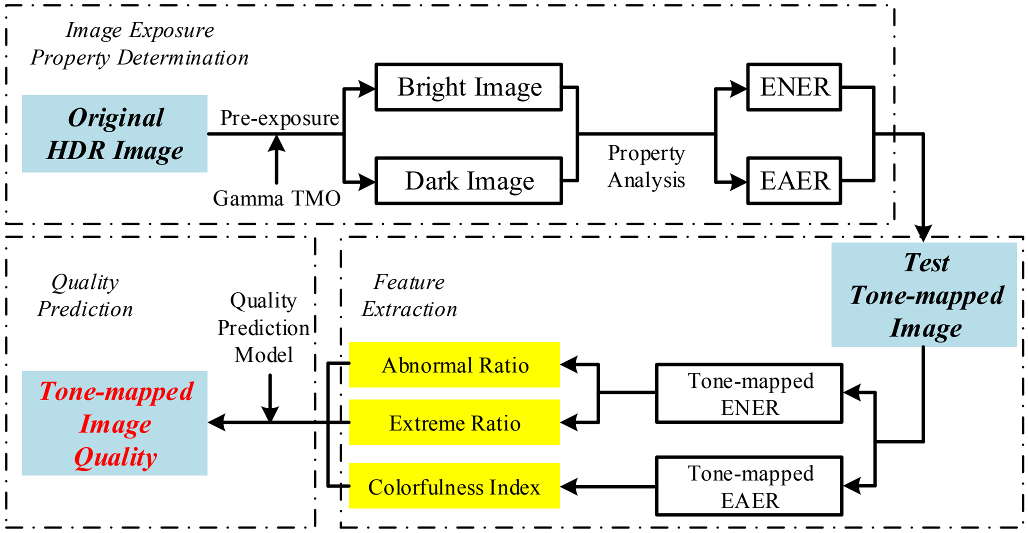


Fig. 1 Framework for the proposed Tone-mapped IQA method

## 2. PROPOSED TONE-MAPPED IMAGE QUALITY ASSESSMENT METHOD

It can be concluded that, in tone-mapped images with poor subjective qualities, the most common distortion types are the appearance of white and black region caused by abnormal exposure and unnatural color introduced by non-linear dynamic range reduction. Therefore, in this paper, we propose a tone-mapped image quality assessment method focused on these two distortion. The framework of proposed method is illustrated in Fig.1. This method is constructed by three parts, namely, image exposure property determination model, tone-mapped image quality feature extraction, and quality prediction model training, respectively.

### 2.1. HDR Image Exposure Segmentation

By reducing the dynamic range of original HDR image in tone-mapping, there are no sufficient intensity levels to represent the bright and dark scenes in tone-mapped image. As a result, the white and black regions are generate. It is reasonable to conclude that those regions that are easily abnormal exposed in tone-mapped image can be predicted according to the exposure property of original HDR image. Therefore, in this method, we designed an image exposure determination model (IEDM) to recognize the regions that could be abnormally exposed in tone-mapping.

In detail implementation of IEDM, the HDR image is pre-exposed by Gamma TMO [8], which is one the most simple TMOs and can be expressed as

$$I^{exposure} = (2^F \cdot I_{HDR})^{1/\gamma} \tag{1}$$

where, $\gamma$ is the Gamma correction parameter and $F$ is light amount parameter.

By alternating the value of $F$, we can obtain exposed images in different extreme exposure condition, which are extremely over-exposed image, $I_{over}^{exposure}$, and extremely under-exposed image, $I_{under}^{exposure}$. Since $I_{over}^{exposure}$ and $I_{under}^{exposure}$ are generated in extreme case, it is reasonable to deduce that the abnormal exposure region in practical tone-mapped image will not be fallen outside the abnormal exposure region in $I_{over}^{exposure}$ and $I_{under}^{exposure}$. Therefore, we firstly determined the abnormal exposure region in $I_{over}^{exposure}$ and $I_{under}^{exposure}$. As previously mentioned, abnormal exposure is characterized as white and black. Therefore, we attempt to set luminance thresholds and extract abnormal exposure region in $I_{over}^{exposure}$ and $I_{under}^{exposure}$ as

$$R_{over}^{exposure} = \left\{ I(x,y) > TH_{over} \,\middle|\, (x,y) \in I_{over}^{exposure} \right\} \tag{2}$$

$$R_{under}^{HDR} = \left\{ I(x,y) < TH_{under} \,\middle|\, (x,y) \in I_{under}^{exposure} \right\} \tag{3}$$

where $TH_{over}$ and $TH_{under}$are the luminance threshold.

Then, by combining the $R_{over}^{exposure}$ and $R_{over}^{exposure}$, the exposure condition region in an HDR image can be segmented into EAER and ENER as Eq. 4- Eq. 5.

$$R_{abnormal}^{HDR} = \left\{ I_{HDR}(x,y) \mid (x,y) \in R_{over}^{exposure} \cup (x,y) \in R_{under}^{exposure} \right\} \tag{4}$$

$$R_{normal}^{HDR} = \left\{ I_{HDR}(x,y) \mid (x,y) \notin R_{over}^{exposure} \cap (x,y) \notin R_{under}^{exposure} \right\} \tag{5}$$

Fig. 2 illustrated the result of exposure region segmentation by the proposed IEDM for an HDR images. It can be find that ENER mainly contains the scene with moderate luminance. While, in EAER, both outdoor scene with bright luminance and dark indoor scene are includes. Hence, the segmentation result is consistently with previous analysis.

### 2.2. Tone-mapped Image Quality Feature Extraction

After exposure segmentation, in order to measure the quality of tone-mapped image more precisely, it is important to extract corresponding quality features in each exposure region. In our method, considering the distortion character in each region, we adopt abnormal ratio, extreme

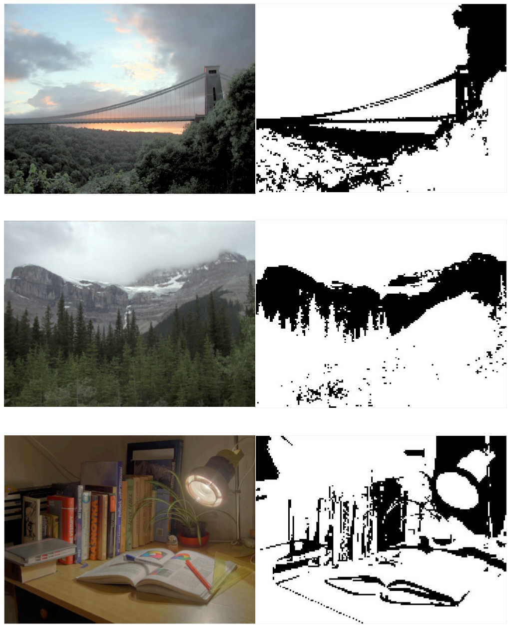

Fig. 2 Result of IEDM (Black region represents EAER, white region represents ENER)

ratio and colorfulness index as quality features. The detail implementations will be described below.

### *2.2.1 Abnormal Ratio*

It is clear that the area of abnormal exposure is highly correlated to image quality degradation Thus, the ability of normally exposing image scene in EAER is crucial to the TMO's performance. Therefore, firstly, we design abnormal ratio, which is ratio between the areas of abnormal exposure region and the whole image, as quality feature in EAER.

Before computing the abnormal ratio, it is necessary to make certain that whether the abnormal exposure occurred in EAER. As above mentioned, we have concluded that the abnormal exposure region can be characterized by two properties, abnormal bright or dark scene luminance and lack of detail information. Based on these two points, we attempted to distinguish abnormal exposure by mean value and variance value of luminance. That is to say, we define abnormal exposure blocks according to two basis: 1) the mean value is exceptional large or exceptional small, 2) the variance value approximates to 0.

After determination of abnormal exposure regions, the abnormal ratio can be calculated. Let $N\{B^{TM}_{abnormal}\}$ denote the numbers of blocks with abnormal exposure and $N\{B^{TM}\}$ denote the total block numbers in the tone-mapped image, hence, the abnormal ratio, denoted as $\eta_a$ can be expressed as

$$\eta_a = \frac{N\{B^{TM}_{abnormal}\}}{N\{B^{TM}\}} \tag{6}$$

where $N\{\ \}$ is the block numbers, which is used to represent the area of each region.

### *2.2.2 Extreme Ratio*

Previously, we introduce the abnormal ratio to reflect appearance frequency of abnormal exposure in a tone-mapped image. Meantime, the intensity of abnormal exposure is also the leading cause to quality degradation. Consequently, we attempt to design a feature to represent the intensity of abnormal exposure. Therefore, extreme ratio is designed to compete such task.

In detail implementation of extreme ratio, we first define those pixels with extreme luminance value as exceptional pixels. Specifically, extreme luminance value covers a luminance value range of [245, 255] or [0, 10]. Then, by observing Fig. 3, we can find that, with the image quality getting worse, the exceptional pixels become more. Specifically, for over-exposed image, the luminance values approximate to 255, while in under-exposed image, luminance values tend to be 0. Theoretically, if the TMO is not well-performed, more pixels will be extreme-abnormally exposed, and thus leading to quality degradation. Therefore, the ratio of exceptional pixels in abnormally exposed pixels can be used to represent the intensity of abnormal exposure.

Let $P_e$ denote the exceptional pixels, hence, the extreme value can be expressed as

$$\eta_e = \frac{N\{P_E\}}{N\{B^{TM}_{abnormal}\} \times k^2} \tag{7}$$

where $N\{P_E\}$ is the number of the exceptional pixels, and $N\{B^{TM}_{abnormal}\}$ is the number of abnormally exposed blocks in tone-mapped image, and $k$ is the size of image block.

### *2.2.3 Colorfulness Index*

While dynamic range reduction, those regions can be normally exposed will also be affected by quality normally exposed will also be affected by quality degradation. Differently, the detail information can usually be preserved in normal exposure region. However, the color

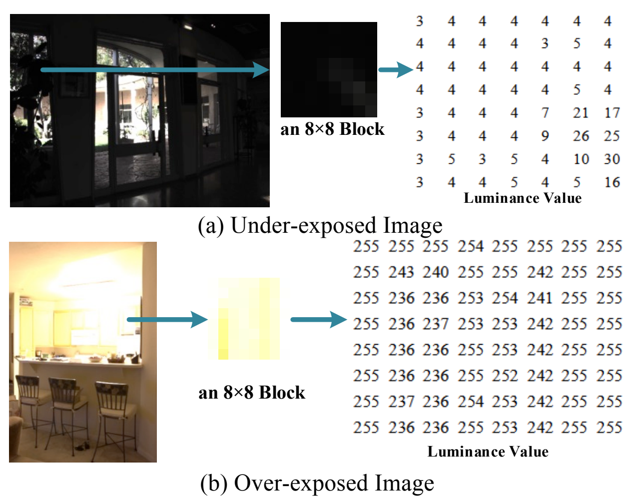


Fig. 3 Luminance value in tone-mapped image with different exposure condition

information may be distorted due to the non-linearity mapping in TMOs. Therefore, we computed colorfulness index as quality feature in normal exposure region.

Here, we adopted the colorfulness metric proposed in [9] to obtain colorfulness index. This metric is mainly based on variance and mean, which have tremendous advantages in calculation complexity. The colorfulness index, denoted by $C_n$ can be acquired as

$$C_n = \sigma_{rgyb} + \omega_c \cdot \mu_{rgyb} \tag{8}$$

where, $\sigma_{rgyb} = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2}$, $\mu_{rgyb} = \sqrt{\mu_{rg}^2 + \mu_{yb}^2}$, $\mu_{rg}$, $\mu_{yb}$, $\gamma_{rg}$ and $\gamma_{yb}$ are the mean and variance of *rg* chanel and *yb* channel in opponent color space respectively.

### 2.3. Quality Prediction Model

As above mentioned, three image quality features have already been extracted in a tone-mapped HDR image. Thereafter, we need to establish a mapping function from quality feature to subjective quality score with a regression model, and then use the regression model to predict the quality score of tone-mapped images. Considering the wide application of support vector regression (SVR) in image processing field [10], we also utilize it following the method applied in [11]. The final quality score of a tone-mapped image can be expressed as

$$Q_{TM}(i) = f[\eta_a(i), \eta_e(i), C_n(i)] \tag{9}$$

where $f[\ ]$ is the quality prediction model trained by SVR.

## 3. RESULTS AND DISCUSSION

In experiments, the TMID database is used to verify the evaluation performance of the proposed method. The details about TMID database can be referred in [5]. As suggested by Video Quality Expert Group (VQEG) [11], three performance indicators are adopted to validate the performance : the Pearson Linear Correlation Coefficient (PLCC), Spearman Rank Order Correlation Coefficient (SROCC) and Rooted Mean Square Error (RMSE). For an ideal tone-mapped IQA method, PLCC and SROCC approximate to 1, and RMSE is close to 0.

Because proposed method requires a regression training procedure to establish the prediction model, a 5 fold cross-validation test is utilized to ensure the efficiency. In cross-validation test, all 120 tone-mapped images in TMID database are randomly divided into two non-overlapping sets. The training set contains 96 images, and the rest 24 images are chosen as test set. To eliminate the performance bias, train-test procedure repeats for 500 times, and the median values of performance indicators are chosen for verification.

To specifically illustrate the performance of our proposed method, Table 1 lists the performance indicators derived from TMID database by proposed tone-mapped IQA method and several other IQA methods. These comparative methods include traditional LDR IQA method (SSIM, FSIM) and leading tone-mapped IQA method (TMQI, FSITM, BTMQI). By comparison of the performance indicators in Table 1, we can draw two conclusions. Firstly, traditional LDR IQA method aims to process reference and test images with same dynamic range. Therefore, such methods cannot be competent for quality assessment for HDR images and tone-mapped image. Secondly, different with existing tone-mapped IQA methods, the proposed method takes exposure condition into consideration and mainly focus on the typical distortion in tone-mapped image, thus it can be more sensitive to quality degradation, and can predict their qualities more accurately.

Table 1 Performance Comparison in TMID Database

| | Method | PLCC | SROCC | RMSE |
|---|---|---|---|---|
| Traditional IQA Algorithm | SSIM | 0.3568 | 0.3143 | 1.6529 |
| | FSIM | 0.5652 | 0.5184 | 1.4652 |
| Leading TM IQA Algorithm | TMQI | 0.7716 | 0.7394 | 1.2236 |
| | FSITM | 0.7525 | 0.7028 | 1.2669 |
| | BTMQI | 0.8541 | 0.8282 | ------ |
| **Proposed Method** | | **0.8566** | **0.8295** | **0.9628** |

## 4. CONCLUSION

In this paper, we proposed a tone-mapped image quality assessment by analyzing exposure property. The main idea underlying this method is to divide tone-mapped image into different exposure region and then extract corresponding quality features in each region. Specifically, we first designed an image exposure determination model to partition the tone-mapped image into two exposure region. Then, two novel features, abnormal ratio and extreme ratio, are extracted. Meantime, colorfulness index is also calculated as quality feature. Eventually, support vector regression is utilized to establish the quality prediction model. Experiments on the TMID database showed that the proposed method performed satisfactorily in predicting tone-mapped image quality. In future work, some outstanding issues need to be considered, such as a better exposure feature design and more accurate segmentation model.

## 5. ACKNOLEDGEMENTS

This work was supported by the Natural Science Foundation of China under Grant Nos. U1301257, 61671258, and 61620106012, the National High-tech R&D Program of China under Grant No. 2015AA015901, and the Natural Science Foundation of Zhejiang Province under Grant Nos. LY15F010005 and LY16F010002.

## 6. REFERENCES


[1] E. Reinhard, W. Heidrich, P. Debevec, *et al*. High dynamic range imaging: acquisition, display, and image-based lighting. Morgan Kaufmann, 2010.

[2] K. Ma, H. Yeganeh, K. Zeng, *et al*. High dynamic range image compression by optimizing tone mapped image quality index. IEEE Transactions on Image Processing, 2015, 24(10): 3086-3097.

[3] Q. Shan, J. Jia, M. S. Brown. Globally optimized linear windowed tone mapping. IEEE transactions on visualization and computer graphics, 2010, 16(4): 663-675.

[4] P. Ledda, A. Chalmers, T. Troscianko, *et al*. Evaluation of tone mapping operators using a high dynamic range display. ACM Transactions on Graphics (TOG), 2005, 24(3): 640-648

[5] H. Yeganeh, Z. Wang. Objective quality assessment of tone-mapped images. IEEE Transactions on Image Processing, 2013, 22(2): 657-667.

[6] H.Z. Nafchi, A. Shahkolaei, R.F. Moghaddam, *et al*. FSITM: A Feature Similarity Index For Tone-Mapped Images. IEEE Signal Processing Letters, 2015, 22(8): 1026-1029.

[7] K. Gu, S. Wang, G. Zhai, *et al*. Blind Quality Assessment of Tone-Mapped Images Via Analysis of Information, Naturalness, and Structure. IEEE Transactions on Multimedia, 2016, 18(3): 432-443.

[8] M. Slavković-Ilić, A. Gavrovska, M. Milivojević, *et al*. Potential applications of HDR in echocardiography, 2014 12th IEEE Symposium on Neural Network Applications in Electrical Engineering (NEUREL), 2014: 29-32.

[9] D.Hasler, S.E. Suesstrunk. Measuring colorfulness in natural images. International Society for Optics and Photonics, Electronic Imaging 2003, 2003: 87-95.

[10] B. Schokopf, A.J. Smola, R.C. Williamson, *et al*, “New support vector algorithms,” Neural Computing., 2000, 12(5): 1207–1245, 2000

[11] A.K. Moorthy, A.C. Bovik. Blind image quality assessment: From natural scene statistics to perceptual quality. IEEE Transactions on Image Processing, 2011, 20(12): 3350-3364.

[12] VQEG, Final report from the video quality experts group on the validation of objective quality metrics for video quality assessment, http://www.its.bldrdoc.gov/vqeg/projects/frtv_phaseI