An Improved Image Quality Assessment in Gradient Domain

Yuling Ren, Wen Lu(✉), Lihuo He, and Tianjiao Xu

School of Electronic Engineering, Xidian University, Xi'an 710071, China
renyuling@stu.xidian.edu.cn, {luwen,lhhe}@mail.xidian.edu.cn

Abstract. The available image quality assessment (IQA) methods based on gradient calculation are mostly implemented without considering visual perception threshold (VPT) and color information. However, incorporating VPT with IQA model can reduce redundant information and human visual system (HVS) is extremely sensitive to color variation. An improved image quality assessment in gradient domain is proposed which utilizes minimum amount of gradient coefficients to capture the color and structure distortion of degraded image by applying a VPT to remove the unperceived gradient coefficients. The difference of perceived gradient coefficients between distorted and reference image is measured to acquire image quality score. Experimental results on two benchmarking databases (LIVEII and TID2008) indicate the rationality and validity of the proposed method.

Keywords: Image quality assessment · Human visual system · Gradient calculation · Visual perception threshold

1 Introduction

Objective image quality assessment is designed with the aim of interpreting the quality of distorted image automatically and responding consistently with the behavior of the HVS [1-2]. A huge number of IQA algorithms have been emerged with the evolution of image processing technology, which can be divided into two categories, namely HVS based paradigm and non-HVS based metrics. The traditional peak signal to noise ratio (PSNR) [3] just measure the pixel difference between degraded and reference image to obtain the image quality score, which doesn't accord with the way of human perceive information. The perfect IQA model is required to simulate the actual process of HVS perceive image. However, the HVS is extremely complex and the research on it is limited, which lead to the mainstream IQA methods are designed based on certain properties of HVS. The Multi-Scale structural similarity (MS-SSIM) [4] assumes that HVS is sensitive to structure information in an image when perceiving the image quality. Motivated by SSIM, the gradient SSIM (G-SSIM) [5] is built by Chen et al, which first compute the gradient of distorted image and reference image and then measure the luminance similarity, contrast similarity and structural similarity of gradient maps. Given the gradient magnitude maps, the gradient orientation

H. Zha et al. (Eds.): CCCV 2015, Part II, CCIS 547, pp. 293–301, 2015.
DOI: 10.1007/978-3-662-48570-5_29

maps and contrasts of reference and distorted image, the similarity among them is computed in geometric structure distortion (GSD) [6] method to acquire the image quality score. RR-VIF [7] constructs the IQA model by measuring the change of visual information fidelity in the distorted image. GMSD [8] explores the use of global variation of gradient based local quality map for overall image quality prediction.

The available IQA methods based on gradient calculation are mostly implemented ignoring VPT and color information. However, incorporating VPT with IQA model can reduce redundant information and HVS is extremely sensitive to color variation [9-10]. The human eyes cannot perceive image gradient with its magnitude under VPT. However, there is no consideration of this aspect for these models [4-8]. An improved image quality assessment in gradient domain is proposed in this paper. In the proposed framework, we first calculate the gradient of an image in RGB color space and grayscale domain to capture its color and structure distortion. And then the VPT is determined according to the properties of HVS, which is used to calculate the perceived visual feature. Finally, the difference of perceived visual feature between distorted and reference image is measured to acquire image quality score.

The remainder of this paper is organized as follows. Section 2 presents the comprehensive implementation of proposed algorithm. Section 3 illustrates the experimental result and a though analysis. Finally, conclusion is made in section 4.

2 Image Quality Assessment in Gradient Domain

Fig. 1. presents the structure of the proposed metric. In the first step, we calculate the gradient of distorted and reference image in RGB color space and grayscale domain. The greater of gradient magnitude imply the huger variation in the image and yet the tiny change in the image can't be perceived by human eyes. So the next step is to compute the VPT of reference image gradient magnitude. Afterwards, the proportion of perceived gradient magnitude of reference and distorted image is calculated according to the VPT. Finally, the objective image assessment is acquired by comparing the difference of the proportion of perceived gradient magnitude between reference and distorted image.

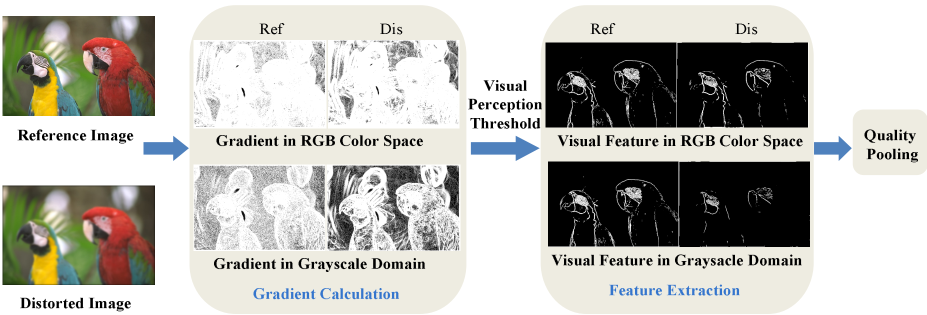

Fig. 1. The proposed image quality assessment algorithm framework

2.1 Gradient Calculation

It is well known that image gradient is sensitive to distortions, however, the mostly existing IQA methods just compute image gradient in grayscale domain, which ignores the fact that image gradient in RGB color space has a great influence on quality prediction. With g_x denotes the horizontal direction of the filter and g_y denotes the vertical direction, the calculation of gradient magnitude complies with the the following rules. Let I denote an image.

$$G_{gray} = \sqrt{(I \otimes g_x)^2 + (I \otimes g_y)^2} \ , \tag{1}$$

$$G_{rgb} = \sqrt{\begin{array}{l}(I_r \otimes g_x)^2 + (I_r \otimes g_y)^2 + (I_g \otimes g_x)^2 \\ + (I_g \otimes g_y)^2 + (I_b \otimes g_x)^2 + (I_b \otimes g_y)^2\end{array}} \ , \tag{2}$$

Where "$\otimes$" is the linear convolution operator and G_{gray} denotes the gradient in the grayscale domain, G_{rgb} denotes the gradient in RGB color space. I_r, I_g and I_b denote the R, G and B channel of image respectively. The gradient in the grayscale domain is compute at four scales to capture multiscale behavior, by low pass filtering. g_v is the Gaussian partial derivative filter applied along the horizontal (x) or vertical (y) direction:

$$g_v((x,y)\,|\,\alpha) = \frac{\partial}{\partial v} g((x,y)\,|\,\alpha) \tag{3}$$

$$= -\frac{1}{2\pi\alpha^2}\frac{v}{\alpha^2}\exp\left(-\frac{x^2+y^2}{2\alpha^2}\right), v \in \{x, y\} \ ,$$

Where α is the scale parameter. Fig. 2 shows the gradient map in RGB color space and grayscale domain of natural image and corresponding distorted image. What we can see from Fig. 2 is that the degradation of image will induce obvious change of image gradient in RGB color space and grayscale domain.

2.2 Visual Perception Threshold

The available IQA models based on gradient just compute the similarity of image gradient structure without considering the human visual perception threshold. However, the tiny change in the image can't be perceived by human and therefore the VPT is required to remove the diminutive gradient magnitude which doesn't arouse respond in HVS [11-12]. The VPT is defined by.

$$T = \omega\sqrt{\frac{C}{C-1}\sum_{k=1}^{C}(g(k)-\bar{g})^2} \ , \tag{4}$$

Where C is the amount of gradient coefficients, $g(k)$ is the kth gradient coefficients and $\overline{g}$ is the mean of all gradient coefficients, ω a tuning parameter. Based on the eq. (4), we can obtain the visual perception threshold in RGB color space and grayscale domain denoted by T_{rgb} and T_{gray}.

It is valuable to preserve visually sensitive gradient coefficients by VPT and the amount of visual sensitive gradient coefficients reflects the visual quality of the images, which reduce the amount of feature and decrease the complexity of algorithm.

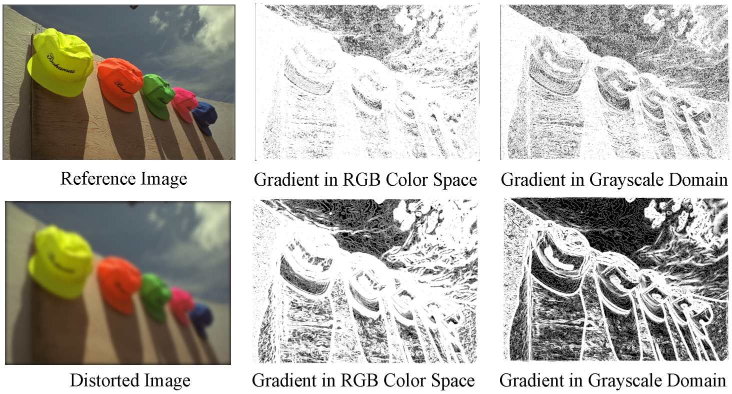

Fig. 2. Gradient map in RGB color space and grayscale domain

2.3 Visual Perception Feature Extraction

By using VPT obtained by eq. (4), we can count the number of visually sensitive gradient coefficients in RGB color space and grayscale domain. Therefore, for a given image, we can obtain the proportion of perceived gradient coefficients N based on eq. (6).

$$C_T = \{C > T\}, \tag{5}$$

$$N = \frac{C_T}{C}, \tag{6}$$

Where C is total number of gradient coefficients and C_T is the visual perceived gradient coefficients which are greater than VPT. With eq. (5), (6) the proportion of visual perceived gradient coefficients in RGB color space and grayscale domain are got and denoted by N_{rgb}, N_{gray} , which are defined as the visual perception feature.

2.4 Quality Pooling

In the proposed framework final quality index is defined by weighted strategy of Q_{rgb} and Q_{gray}.

$$Q_{rgb} = \frac{1}{1+\log_2(1+\frac{D_{rgb}}{\lambda})}, \tag{7}$$

$$Q_{gray} = \frac{1}{1+\log_2(1+\frac{D_{gray}}{\lambda})}, \tag{8}$$

$$Q = \alpha Q_{rgb} + \beta Q_{gray}, \tag{9}$$

Where λ , α , β are the tuning parameters, D_{rgb} and D_{gray} are the difference of visual feature in the RGB color space and grayscale domain, which are obtained by the following equations.

$$D_{rgb} = |N_{rgb\_r} - N_{rgb\_d}|, \tag{10}$$

$$D_{gray} = \sum_{i=1}^{S} |N_{gray\_r}(i) - N_{gray\_d}(i)|, \tag{11}$$

Where N_{rgb_r}, $N_{rgb\_r}(i)$ and N_{rgb_d} , $N_{rgb\_d}(i)$ are the visual perception feature of reference and distorted image in RGB color space and grayscale domain. S is the number of image scale in grayscale domain obtained by low pass filtering and i is the scale index.

3 Experimental Results

Experiments are done on the LIVE database II [13] and the TID2008 database [14] to verify the rationality and validity of proposed. LIVE database II contains 29 high-resolution 24 bits/pixel RGB color images and 175 corresponding JPEG and 169 JPEG2K compressed images, as well as 145 white noisy (WN), 145 Gaussian blur (GB), and 145 fast-fading (FF) Rayleigh channel noisy images at a range of quality levels. We select five types of distortion in the TID2008 database to complete the experiment, i.e., Gaussian blur (GB), Image denoising (DEN), JPEG compression (JPEG), JPEG2K compression (JPEG2K) and JPEG transmission errors (JGTE). The assessment indexes considered in the experiment is spearmans rank ordered correlation coefficient (SROCC). The value of SROCC closer to 1 implies superior consistency with human perception.

3.1 Consistency Experiment

In this section, we compare the performance of the proposed framework with standard IQA methods, i.e., PSNR [3], MS-SSIM [4], G-SSIM [5], GSD [6] and RR-VIF [7]. The values for SROCC of all the IQA metrics mentioned above are given in tables 1, 2. Fig. 3 presents the nonlinear fitting of the objective quality score obtained by proposed versus mean opinion score (MOS) on LIVE database II. In implement the IQA task, methods [3-6] require full information of reference image while the proposed just utilize a fraction of information, which reduce the redundant information and complexity of algorithm. RR-VIF [7] build IQA model based on the additive noise model, while the mostly of distortions on LIVE II database are induced by additive noise and hence the performance of RR-VIF [7] on LIVE II database is superior to the proposed. However, the distortions on TID2008 are generated by additive noise and multiplicative noise and therefore the performance of RR-VIF [7] declined. Mostly of the SROCC values on TID2008 for the proposed are higher than that for algorithms [3-7]. In general, consistency experiment shows that the proposed owns a preferable result.

Table 1. SROCC of different metrics on LIVE II database

Metric	JPEG2K	JPEG	WN	GB	FF
PSNR	0.895	0.881	0.985	0.782	0.891
MS-SSIM	0.963	0.981	0.973	0.954	0.947
G-SSIM	0.935	0.944	0.926	0.968	0.948
GSD	0.911	0.931	0.879	0.964	0.953
RR-VIF	0.950	0.885	0.946	0.961	0.941
Proposed	0.927	0.827	0.919	0.956	0.937

Table 2. SROCC of different metrics on TID2008 database

Metric	GB	DEN	JPEG	JPEG2K	JGTE
PSNR	0.870	0.942	0.872	0.813	0.752
MS-SSIM	0.691	0.859	0.956	0.958	0.932
G-SSIM	0.924	0.880	0.859	0.944	0.855
GSD	0.911	0.878	0.839	0.923	0.880
RR-VIF	0.942	0.948	0.599	0.928	0.891
Proposed	0.937	0.946	0.796	0.951	0.787

3.2 Rationality Experiment

To verify the rationality of the proposed metric, we choose four sets of images with different distortions, which are Gaussian blur, spares sampling and reconstruction, chromatic aberrations and Image denoising. Fig. 4 illustrates the prediction trend of the four sets images with different quality. It can be observed that the proposed method prediction trend rises with the increasing of MOS on different types of distortions. It proves the rationality of the proposed framework.

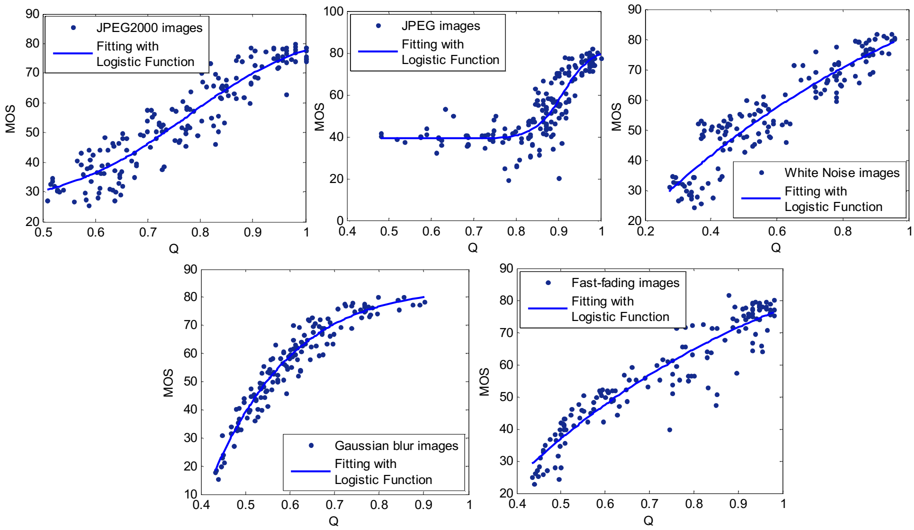

Fig. 3. Nonlinear scatter plots of MOS versus the proposed metric.

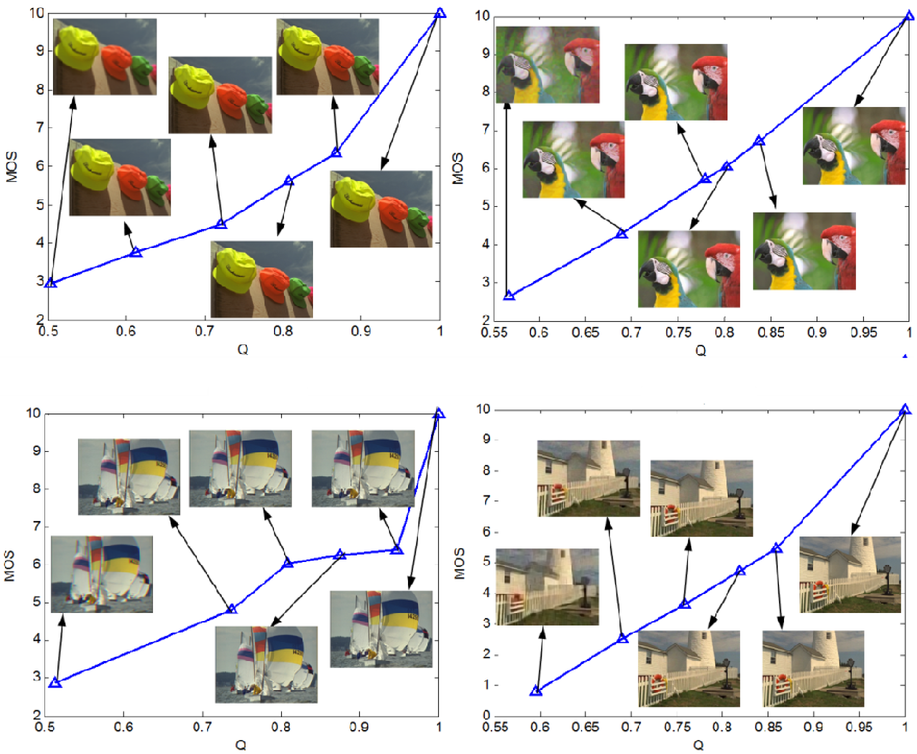

Fig. 4. Results of rationality experiment

3.3 The Performance of Gradient in RGB Color Space

The available IQA metrics based on image gradient just calculate the gradient in grayscale domain, which fails to consider the case that HVS is sensitive to color change. Therefore, we compute the gradient both in the grayscale domain and RGB color space to capture the structure and color feature. The first strategy map gradient in grayscale domain to the quality score and denote as G_{gray}. Both the gradient in grayscale domain and RGB color space is used to obtain the quality score denote as $G_{gray+rgb}$, which is defined as the second strategy. Tables 3, 4 show the performance of the two different strategies. The values for SROCC of $G_{gray+rgb}$ are higher than that of G_{gray}, which verifies the rationality and validity of gradient in RGB color space in the proposed IQA model.

Table 3. SROCC of different quality pooling on LIVE database II

	JPEG2K	JPEG	WN	Gblur	FF
G_{gray}	0.910	0.812	0.850	0.946	0.924
$G_{gray+rgb}$	0.927	0.827	0.919	0.956	0.937

Table 4. SROCC of different quality pooling on TID2008 database

	GB	DEN	JPEG	JP2K	JGTE
G_{gray}	0.871	0.915	0.745	0.933	0.760
$G_{gray+rgb}$	0.937	0.946	0.796	0.951	0.787

4 Conclusion

A novel image quality assessment metric in gradient domain is proposed. In the proposed framework, the gradient is first calculated in RGB color space and grayscale domain to obtain the change in the color and structure of a distorted image. VPT which determined from the reference image is utilized to produce a noticeable variation in sensory experience. Finally, the objective image quality assessment is acquired by measuring the difference of the proportion of visual sensitive gradient coefficients between reference and distorted image. Although the proposed achieves a desirable performance, it is essential to develop blind image quality metrics that estimate the quality of images without any prior information of nature image.

Acknowledgements. This research was supported partially by the National Natural Science Foundation of China (No. 61125204, 61372130, 61432014), the Fundamental Research Funds for the Central Universities (No. BDY081426, JB140214, XJS14042), the Program for New Scientific and Technological Star of Shaanxi Province (No. 2014KJXX-47), the Project Funded by China Postdoctoral Science Foundation (No. 2014M562378).

References

1. Wang, Z., Bovik, A.C.: Modern image quality assessment. Synthesis Lectures on Image, Video, and Multimedia Processing **2**(1), 1–156 (2006)
2. Park, H., Har, D.H.: Subjective image quality assessment based on objective image quality measurement factors. IEEE Transactions on Consumer Electronics **57**(3), 1176–1184 (2011)
3. Hore, A., Ziou, D.: Image quality metrics: PSNR vs. SSIM. In: 20th International Conference on Pattern Recognition, pp. 2366–2369. IEEE, Istanbul (2010)
4. Wang, Z., Simoncelli, E.P., Bovik, A.C.: Multiscale structural similarity for image quality assessment. In: Conference Record of the Thirty-Seventh Asilomar Conference on Signals, Systems and Computers 2004, pp. 1398–1402 (2003)
5. Chen, G.H., Yang, C.L., Xie, S.L.: Gradient-based structural similarity for image quality assessment. In: 2006 IEEE International Conference on Image Processing, pp. 2929–2932. IEEE (2006)
6. Cheng, G., Huang, J.C., Zhu, C., et al.: Perceptual image quality assessment using a geometric structural distortion model. In: International Conference on Image Processing, pp. 325–328. IEEE (2010)
7. Wu, J., Lin, W., Shi, G., Liu, A.: Reduced-reference image quality assessment with visual information fidelity. IEEE Transactions on Multimedia **15**(7), 1700–1705 (2013)
8. Xue, W., Zhang, L., Mou, X., et al.: Gradient magnitude similarity deviation: A highly efficient perceptual image quality index. IEEE Transactions on Image Processing **23**(2), 684–695 (2014)
9. McCollough, C.: Color adaptation of edge-detectors in the human visual system. Science **149**(3688), 1115–1116 (1965)
10. Gerhard, H.E., Wichmann, F.A., Bethge, M.: How sensitive is the human visual system to the local statistics of natural images. PLoS Computational Biology **9**(1), e1002873 (2013)
11. Blakemore, C., Muncey, J.P.J., Ridley, R.M.: Stimulus specificity in the human visual system. Vision Research **13**(10), 1915–1931 (1973)
12. Chitprasert, B., Rao, K.R.: Human visual weighted progressive image transmission. IEEE Transactions on Communications **38**(7), 1040–1044 (1990)
13. Sheikh, H.R., Wang, Z., Cormack, L., Bovik, A.C.: Live image quality assessment database, release 2. http://live.ece.utexas.edu/research/quality
14. Ponomarenko, N., Lukin, V., Zelensky, A., Egiazarian, K., Carli, M., Battisti, F.: Tid 2008 - a database for evaluation of full-reference visual quality assessment metrics. Advances of Modern Radioelectron **10**(4), 30–45 (2009)