Blind Image Quality Assessment via Analysis of GLCM

Guanghui Yue(✉), Chunping Hou, Tongtong Ma, and Yang Yang

School of Electrical and Information Engineering, Tianjin University, Tianjin, China
{yueguanghui,hcp,matongtong,yang_yang}@tju.edu.cn

Abstract. Blind image quality assessment (BIQA) assesses the perceptual quality of the distorted image without any information about its original reference image. Features, in consistent with human visual system (HVS), have been proved effective for BIQA. Motivated by this, we propose a novel general purpose BIQA approach. Firstly, considering that HVS is sensitive to image texture and edge, the image gradient and wavelet decomposition is computed. Secondly, taking the direction sensitivity of HVS into account, the gray level co-occurrence matrixes (GLCMs) are calculated in two directions at four scales on the computed feature maps, i.e., gradient and wavelet decomposition maps, as well as the image itself. Then, four features are extracted for each of GLCM matrix. Finally, a regression model is established to map image features to subjective opinion scores. Extensive experiments are conducted on LIVE II, TID2013 and CSIQ databases, and show that the proposed method is superior to the state-of-the-art BIQA methods and comparable to SSIM and PSNR.

Keywords: Blind image quality assessment (BIQA)
Gray level co-occurrence matrix (GLCM) · Human visual system (HVS)
Image structure

1 Introduction

At present, digital images, as the carrier of massive information, have greatly enriched people's life as well as drastically facilitated the communication among people [1, 2]. Yet image distortion remains a stubborn problem in image transmission system. Therefore, it is indispensable to establish efficient methods for image quality assessment (IQA).

Generally, IQA method can be split into two major categories: subjective and objective assessment methods. Currently, objective IQA algorithm has been widely studied because it is easy to implement and portability. Given the available information of the pristine image, objective assessment method can be further classified into full-reference IQA (FR-IQA), reduced-reference IQA (RR-IQA) and no-reference IQA (NR-IQA). Since both FR-IQA and RR-IQA methods use information of the original reference image, so they are limited to special situations. In this paper, we mainly focus on the NR-IQA method.

At present, NR-IQA method can be broadly divided into two classes, i.e., training-based opinion-aware metric and opinion-unaware metric. The former one requires a training process to create a regression model for predicting image quality. For example,

Q. Zu and B. Hu (Eds.): HCC 2017, LNCS 10745, pp. 95–101, 2018.
https://doi.org/10.1007/978-3-319-74521-3_11

Moorthy and Bovik [3] proposed a two-step framework that called BIQI. Specifically, each distortion type was trained with a regression model. In such case, the distortion type of image can be obtained through these models. Subsequently, the image statistical properties are gradually applied into IQA and have been proved effectively. For instance, Saad *et al.* [4] provided a NR-IQA algorithm under the hypothesis that the statistics features of discrete cosine transform (DCT) coefficients change regularly along with image quality. Although these methods have achieved meaningful performance, they require training procedure. To tackle the problem, metrics, which don't require human opinion scores and any regression model, have been proposed. Xue *et al.* [5] used a set of cluster centroid with quality label as a codebook to predict image quality, called QAC. Natural image quality evaluator (NIQE) [6] established a completely blind BIQA metric by fitting the quality-aware features to a multivariate Gaussian (MVG) model. Although the training process is not required, their performances need to be further improved. In this paper, we propose a new blind image quality assessment method based on training.

It should be mentioned that the above methods mainly rely on mathematical statistics method but without full consideration of the HVS characteristics. GLCM can effectively describe image feature by measuring statistical characteristic of image in multi-direction and multi-scale. By considering characteristics of HVS and the variety of computing method for GLCM, this paper presents a simple yet effective BIQA metric. Figure 1 shows the pipeline of our method. It can be divided into the following three parts: calculation of GLCM, feature extraction and image quality prediction.

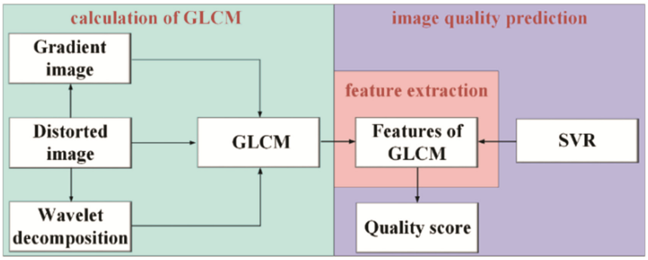

Fig. 1. The pipeline of the proposed method

2 The Proposed Method

2.1 Feature Map Extraction

(1) Gradient map and wavelet transform

Given a color image, firstly, it is transformed into grayscale, which is denoted by $I(x, y)$. The direction templates in the horizontal and vertical directions are denoted by T_x and T_y

$$T_x = [-1 \;\; 0 \;\; 1] \tag{1}$$

$$T_y = T'_x \tag{2}$$

where '$\prime$' denotes transpose.

Then, the gradient components in the horizontal and vertical directions, denoted by G_x and G_y, are computed as:

$$G_x = T_x * I \tag{3}$$

$$G_y = T_y * I \tag{4}$$

where '*' denotes convolution. Finally, the gradient map G is calculated as:

$$G = \frac{|G_x| + |G_y|}{2} \tag{5}$$

Wavelet transform decomposes image into multi-scale and multi-direction. The image is usually transformed along horizontal, vertical and diagonal directions. And then the decomposition sub-graphs in those three directions are usually denoted by HL, LH and HH, respectively [15]. In this paper, the wavelet decomposition scale is set to 1, which gets good results.

As image distortion always induces the structural degradation, we desire to evaluate image quality by utilizing image structure information. Image gradient and decomposition sub-graphs are complementary to each other in representing rich image structure. On the one hand, image gradient describes the global image structure while misses orientation information. On the other hand, wavelet decomposition reflects image features in different orientation, while ignores global structure. Hence, their combination ensures integrity of the image structure information.

(2) **GLCM matrix calculation**

Usually, image distortion brings about a significant change of image statistic characteristics. GLCM can provide image statistic characteristics in different directions and at different scales in spatial domain, so it can describe image characteristics from various aspects. Based on this, in this paper, the GLCM matrixes of the above image structure maps are calculated.

The GLCM is composed of the joint probability density between image gray tones. There are three important parameters in GLCM: angle (θ), quantized gray tones (L) and distance (d). Firstly, the image is quantized to L gray tones. Then, the probability of occurrences of the pair of gray tones i and j in original image is expressed in $\mathrm{P}(i, j, d, \theta)$ ($i = 1, 2, \ldots, L, j = 1, 2, \ldots, L$). Each entry (i, j) is depart at a distance d in angle θ. Finally, the GLCM can be denoted as $[\mathrm{P}(i, j, d, \theta)]_{L \times L}$, where $\mathrm{P}(i, j, d, \theta)$ is the element of $[\mathrm{P}(i, j, d, \theta)]_{L \times L}$ in the i-th row and j-th column.

2.2 Feature Extraction

In [7], fourteen features were extracted from GLCM to represent image properties from multiple perspectives. Currently, researchers usually used part of them in view of the redundancy among them [8]. In this paper, we employ four commonly used features, namely contrast, energy, correlation, and homogeneity, to extract quality sensitive features for IQA. Those four selected features involve local and global image characteristics. Among them, contrast and energy describe the overall characteristics of the image. Specifically, contrast describes image definition. Energy reflects the image distribution as well as roughness. On the contrary, correlation and homogeneity are local image descriptors. Concretely, correlation illustrates the local correlation of image grayscale. Homogeneity measures local change of image grayscale. Overall, the selected features can reflect both local and global features of image, to a certain extent. Therefore, they can be applied into IQA problem.

Although we have demonstrated the feasibility of GLCM in IQA problem, how to choose the parameters, i.e., θ, L, d, is still a thorny problem. Research shows that HVS is more sensitive to the horizontal and vertical image information than the oblique direction [9]. Moreover, different viewing distances produce various perception for HVS. HVS focuses on outline of image at large viewing distance, while at small distance, it will pay attention to image details [10]. And for GLCM, small scale in GLCM can describe characteristics of fine image structure, while large scale obtains characteristics of rough image structure. Inspired by these, we extract GLCM in multi-direction and multi-scale. Specifically, θ is set as 0° and 90° to highlight the sensitive direction of HVS, the distance d is set as 1, 2, 4, and 8 for simulating the variation of viewing distance, and L is set as 8. Since distortion also corrupts the brightness information, to avoid its loss, we also extract the above features on distorted image. Overall, the GLCM for gradient image, decomposed high-frequency sub-images (HL, LH and HH after one scale wavelet decomposition) and distorted image is calculated in two directions (0° and 90°) at 4 scales, resulting in eight GLCM matrices for each calculated image. A total of 40 GLCM matrices are attained, followed by four features extraction for each GLCM matrices.

2.3 Image Quality Assessment

After the feature extraction, the realization of image quality assessment is based on a regression model. Specifically, the train samples is denoted as $T = \{(F_1, D_1), (F_2, D_2), \ldots, (F_i, D_i), \ldots, (F_m, D_m)\}$, where i is the index of the train images, $F_i \in R^n$ represents image feature vectors and D_i denotes image opinion scores. The array T is trained to learn a model. Then, the obtained regression model can be used to predict image quality. Its mapping function can be abbreviated as $D_t = model\,(F_t)$, where F_t is the feature vector of the test image and D_t is the predicted quality score. In our metric, we employ support vector regression (SVR) to evaluate image quality. The LIBSVM toolbox is utilized to implement Epsilon-SVR with kernel of radial basis function [11].

3 Experiment Results and Analysis

3.1 Experiment Setup

The proposed method is tested on three public databases: LIVE II [12], TID2013 [13] and CSIQ [14] database. In LIVE II database, we test the proposed algorithm on all of the five distortion types, i.e., JPEG2000 compression (JP2K), JPEG compression (JPEG), white noise (WN), Gaussian blur (Gblur) and transmission errors in the JP2K using Fast-fading Rayleigh channel model (FF). In TID2013 and CSIQ databases, four distortion types are tested, namely JP2K, JPEG, WN and Gblur. Three general IQA criteria, i.e., Spearman rank order correlation coefficient (SROCC), Pearson linear correlation coefficient (PLCC) and root-mean-squared error (RMSE), are employed for performance evaluation. A better performance means a value close to 1 for PLCC and SROCC while a value close to 0 for RMSE.

In order to verify the effectiveness of the proposed method, we select two public FR algorithms (SSIM [15] and PSNR) and several mainstream NR methods (QAC [5], BIQI [3], ILNIQE [14], GM-LOG [16] and YCLTYCbCr [17]) for comparison. For ROI-BRISQUE, because the source code is not obtained, we directly use the experiment results on LIVE II database provided in the original paper for comparison. Since the proposed method is based on training, we divide the image set into two non-overlapping image sets: training set and testing set. The training set contains 80% of the reference images and corresponding distortion versions of them, and the testing set is comprised by the residual images. After the random train-test split is repeated 1000 times, the median performance is taken as the final results.

3.2 Experiment Results

Table 1 shows the performance tested on the entire database. For better observation, the top three performed algorithms are highlighted in bold. As we can see, the performance of the proposed method always lies in top three. In fact, compared with those IQA methods in Table 1, our method achieves the best performance in all three databases.

Table 1. SROCC, PLCC and RMSE (median value across 1000 train-test trials) of SSIM, PSNR, QAC, BIQI, NIQE, ILNIQE, GM-LOG and YCLT-YCbCr on the overall database of LIVE II, TID2013 and CSIQ respectively.

Database	Metric	SSIM	PSNR	QAC	BIQI	IL-NIQE	GM-LOG	YCLT-YCbCr	Pro.
LIVE II	PLCC	**0.9397**	0.9122	0.8755	0.8909	0. 9011	**0.9539**	0.9354	**0.9581**
	SROCC	0.9244	0.8000	0.8803	0.8899	0. 8996	**0.9503**	**0.9348**	**0.9524**
	RMSE	**7.9001**	14.0604	11.1677	10.5236	12.1186	8.1723	**5.9386**	**6.6445**
CSIQ	PLCC	**0.9294**	0. 9281	0.8645	0.9101	0.8991	**0.9408**	0.8980	**0.9482**
	SROCC	**0.9274**	0. 8550	0.8338	0.8925	0.8854	**0.9228**	0.8869	**0.9432**
	RMSE	**0.1040**	0.1483	0.1411	0.1198	0.1491	**0.0950**	0.1295	**0.0890**
TID2013	PLCC	0.8591	**0.9149**	0.8273	0.8048	0.9001	**0.9439**	0.8789	**0.9512**
	SROCC	0.8291	**0.9058**	0.8188	0.7846	0.8714	**0.9282**	0.8690	**0.9377**
	RMSE	0.7232	**0.5908**	0.7670	0.8254	0.6728	**0.4629**	0.9017	**0.4293**

4 Conclusion

In this paper, we propose a simple yet efficient blind IQA metric based on GLCM statistic model of image structure. To verify the performance of our proposed method, we conducted a set of experiments on LIVE II, CSIQ and TID2013 databases. We apply it on the entire database, and the experimental results demonstrate that our predicted scores is more accuracy than two public FR-IQA algorithms and the mainstream NR-IQA methods. In summary, we can draw the conclusion that the proposed method obtains excellent performance in BIQA.

Acknowledgement. This work was supported by the National Natural Science Foundation of China under Grant 61471262, the International (Regional) Cooperation and Exchange under Grant 61520106002.

References

1. Gu, K., Lin, W.S., Zhai, G.T., Yang, X.K.: No reference quality metric of contrast-distorted images based on information maximization. IEEE Trans. Cybern. **47**, 4559–4565 (2016)
2. Gu, K., Zhai, G.T., Yang, X.K., Zhang, W.J.: Using free energy principle for blind image quality assessment. IEEE Trans. Multimed. **17**(1), 50–63 (2015)
3. Moorthy, A.K., Bovik, A.C.: A two-step framework for constructing blind image quality indices. IEEE Signal Process. Lett. **17**(5), 513–516 (2010)
4. Saad, M.A., Bovik, A.C., Charrier, C.: Blind image quality assessment: a natural scene statistics approach in the DCT domain. IEEE Trans. Image Process. **21**(8), 3339–3352 (2012)
5. Xue, W.F., Zhang, L., Mou, X.Q.: Learning without human scores for blind image quality assessment. In: Computer Vision and Pattern Recognition, pp. 995–1002 (2013)
6. Mittal, A., Soundararajan, R., Bovik, A.C.: Making a completely blind image quality analyzer. IEEE Signal Process. Lett. **20**(3), 209–212 (2013)
7. Haralick, R.M., Shanmugam, K., Dinstein, I.: Textural features for image classification. IEEE Trans. Syst. Man Cybern. **smc-3**(6), 610–621 (1973)
8. Gadelmawla, E.S.: A vision system for surface roughness characterization using the gray level co-occurrence matrix. NDT E Int. **37**(7), 577–588 (2004)
9. Lambrecht, C.J.V.D.B., Verscheure, O.: Perceptual quality measure using a spatiotemporal model of the human visual system. In: Electronic Imaging: Science & Technology, pp. 450–461. International Society for Optics and Photonics (1996)
10. Gu, K., Wang, S.Q., Yang, H., Lin, W.S.: Saliency guided quality assessment of screen content images. IEEE Trans. Multimed. **18**(6), 1 (2016)
11. Chang, C.C., Lin, C.J.: LIBSVM: a library for support vector machines. ACM Trans. Intell. Syst. Technol. **2**(3), 389–396 (2007). Article 27
12. Sheikh, H.R., Sabir, M.F., Bovik, A.C.: A statistical evaluation of recent full reference image quality assessment algorithms. IEEE Trans. Image Process. **15**(11), 3440–3451 (2006)
13. Ponomarenko, N., Lukin, V., Zelensky, A., Egiazarian, K., Carli, M., Battisti, F.: TID2008-a database for evaluation of full-reference visual quality assessment metrics. Adv. Mod. Radioelectron. **10**(4), 30–45 (2009)
14. Larson, E.C., Chandler, D.M.: Categorical image quality (CSIQ) database (2010). http://vision.okstate.edu/csiq

15. Wang, Z., Bovik, A.C., Sheikh, H.R., Simoncelli, E.P.: Image quality assessment: from error visibility to structural similarity. IEEE Trans. Image Process. **13**(4), 600–612 (2004)
16. Xue, W., Mou, X., Zhang, L., Bovik, A.C., Feng, X.: Blind image quality assessment using joint statistics of gradient magnitude and Laplacian features. IEEE Trans. Image Process. **23**(11), 4850–4862 (2014)
17. Wu, Q.B., Li, H.L., Meng, F.M., Ngan, K.N., Luo, B., Huang, C., Zeng, B.: Blind image quality assessment based on multichannel feature fusion and label transfer. IEEE Trans. Circuits Syst. Video Technol. **26**(3), 425–440 (2016)