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RESEARCH ARTICLE

No Reference Image Sharpness Assessment Based on Global Color Difference Variation

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Abstract — Image quality assessment (IQA) model is designed to measure the image quality in consistent with subjective ratings by computational models. In this research, a valid no reference IQA (NR-IQA) model for color image sharpness assessment is proposed based on local color difference map in a color space. In the proposed model, the absolute color difference variation and relative color difference variation are combined to evaluate sharpness in YIQ color space (a color coordinate system for the development of the United States color television system). The difference between sharpest and blurriest spot of an image is represented by the absolute color difference variation, and relative color difference variation expresses the variation in the image content. Extensive experiments are performed on five publicly available benchmark synthetic blur databases and two real blur databases, and the results prove that the proposed model work better than the other state-of-the-art and latest NR-IQA models for the prediction accuracy on blurry images. Besides, the model maintains the lowest computational complexity.
Keywords — Image sharpness assessment, No reference, Color difference variation, Image quality.
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I. Introduction

Perceptual image quality assessment (IQA) has become a significant role in numerous visual data processing application [1]–[5]. Images are commonly analyzed based on pixels and structures in the image processing research. Color science researches mostly focus on visual function of large patches. Combining image processing with color science, the full quality experience can be modeled [6]. Sharpness assessment of digital images play an important role in modern image processing system [7]–[9]. IQA methods can be divided into two categories: human-based subjective assessment and algorithm-based objective assessment by mimicking subjective judgments [10]. There are three main frameworks well-established in IQA research according to the availability of a reference image: full reference (FR) [11], [12], reduced reference (RR) and no reference (NR) [13]–[15] or blind IQA.

Human visual system (HVS) is the ideal receiver of visual information and it is also the most reliable way to evaluate image quality with subjective judgement [16]. Whereas, subjective evaluation is infeasible under many conditions, i.e., psycho-visual experiments under standard protocols are laborious; subjective tests cannot be conducted for an automated system. Thus, the subjective opinion of human observers, for instance mean opinion score (MOS) and difference mean opinion score (DMOS), can be predicted by an objective model [17].

Sharpness is inversely related to blur, which is a critical factor in the perception of IQA [18]–[22]. In the literature, several state-of-the-art NR image sharpness assessment models have been proposed by using the lightness component or grayscale images and neglect color channels. Ferzli *et al.* proposed the just noticeable blur (JNB) model based on image local contrast to derive an edge-sharpness model [23]. Narvekar *et al.* introduced the cumulative probability of blur detection (CPBD) [24] to evaluate the edge information of image

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extended by JNB. The spectral and spatial sharpness (S_3) model [25] was proposed by Vu *et al.* to measure the slope of the magnitude spectrum and the total spatial variation. Vu and Chandler addressed a fast image sharpness (FISH) model in the wavelet domain [26]. Hassen *et al.* proposed a model utilizing local phase coherence (LPC) [27] and derived a flexible framework in arbitrary fractional scales. Bahrami and Kot [7] proposed a model based on the maximum local variation (MLV) and set weighted MLV distribution as a metric to measure sharpness. A NR sparse representation based image sharpness (SPARISH) model was proposed and this model employs overcomplete dictionary based sparse representation to achieve quality assessment [28]. A fast blind image sharpness/blurriness assessment model (BISHARP) was presented to deal with local contrast maps [29]. Qian *et al.* used difference quotients to construct an absolute difference quotient and a relative difference quotient to evaluate image sharpness [30]. Although many models for image sharpness assessment were proposed for grayscale images, the performance need to be improved. To improve performance, color channels had been utilized in image sharpness assessment models. The AR-based image sharpness metric (ARISM) was proposed to evaluate image sharpness by using the autoregressive parameter space [31]. Li *et al.* presented a blind image blur evaluation (BIBLE) algorithm using Tchebichef moments [32]. In our research, color channels' information will be taken into consideration.

Color information had been used in color science literature to extract the differences between color tones. The International Commission on Illumination (CIE) is responsible for the international coordination of lighting related technical standards including color difference. Color difference formulas are commonly utilized in tone matching for color reproduction. CIEDE2000 [33] color difference equation was developed by CIE technical committee and designed to quantify the perceptual image quality assessment [34]. In addition, the authors used the global mean color value difference of images in CMYK color space [35] and the other authors built a CID (color image difference) [36] and iCID (improved color image difference) [37] metrics to evaluate image quality in s-CIELAB color space. These three models are all FR-IQA. Inspired by these literatures, color difference index can be used as an effective component for NR-IQA.

Recently, learning-based models had been another way to solve image sharpness evaluation problem, i.e., Yu's CNN [38], RISE [8] and SFA [39]. Besides, several IQA models without learning training also had been proposed, including Maxpol [40], Qian's model [30] and DFT-based model [41].

In this research, a NR-IQA model is introduced to evaluate sharpness based on global color difference variation in a color space. A simple color difference index [42] was selected as the operators for dealing with blur distortion. By using this color difference index, the color difference value in horizontal and vertical direction will be calculated as color difference map in pixel level. An absolute color difference variation (CDV_a) and a relative color difference variation (CDV_r) can be obtained to assess sharpness. In the proposed model, CDV_a and CDV_r are combined to evaluate sharpness. Experimental results prove that our model performs better than most of the state-of-the-art and latest NR-IQA models on blurry image in seven public databases: CSIQ [43], LIVE [44], TID2008 [45], TID2013 [46] and VCL [47], CID2013 [48] and BID [49].

II. Global Color Difference Variation Model

In this section, a novel NR-IQA model is introduced for sharpness assessment based on color difference variation (CDV). The input to the model is one RGB image with identical spatial resolution, $\boldsymbol{X}$, signifying the distorted images. To better approximate the color perception of vision system, original RGB images need to transform to a color space that is more compatible with human's intuition. Among various perceptual color models, CIELAB [50], LMN [51] and YIQ [52] color spaces are normally utilized to deal with IQA problems. Gaussian blur distortion is measured by color difference index in pixel level, which is the difference between two pixels' color channels in color space. In a test RGB image, the difference between two neighbor pixels can be well expressed by color difference, which is more compatible with human intuition. After RGB to a color space transformation, each pixel of $\boldsymbol{X}$ contains three color components: lightness ${C_1}^*$, color channels ${C_2}^*$ and ${C_3}^*$. The color difference index (ΔE) is calculated via (1) [42].

$$\Delta E=\sqrt{({C_{11}}^*-{C_{12}}^*)^2+({C_{21}}^*-{C_{22}}^*)^2+({C_{31}}^*-{C_{32}}^*)^2} \tag{1}$$

where ${C_{11}}^*$ and ${C_{12}}^*$ are the lightness channels of two neighbor pixels, ${C_{21}}^*$ and ${C_{22}}^*$ are a color channels of two neighbor pixels, ${C_{31}}^*$ and ${C_{32}}^*$ are another color channels of two neighbor pixels.

1. Local color difference operator

Two local color difference operators in horizontal and vertical direction with ${C_n}^*$ channels can be defined as:

$$\Delta E_h\left(i,j\right)=\sqrt{\sum_{n=1}^{c}\left({C_n}^*\left(i,j\right)-{C_n}^*\left(i,j+1\right)\right)^2} \tag{2}$$

$$\Delta E_v\left(i,j\right)=\sqrt{\sum_{n=1}^{c}\left({C_n}^*\left(i,j\right)-{C_n}^*\left(i+1,j\right)\right)^2} \tag{3}$$

where ${C_n}^*\left(i,j\right)$ represent the intensity at pixel location (i,j) for each color channel. The color channel number is represented by c. In an image, the difference between two neighbor pixels value can be calculated by (1). By combining the two local color difference operators in a color space, a new index is introduced and named local color difference (ΔE_l) for pixel (i, j), which can be formulated as (4).

$$\Delta E_l\left(i, j\right) = \left(\Delta E_h\left(i, j\right) + \Delta E_v\left(i, j\right)\right)/2 \tag{4}$$

Although the calculation way of (4) is similar to gradient feature extraction, the meaning of (4) is different from normal gradient computing. Color difference is a color science index and it represent the difference between two colors with three channels. It can be utilized to test the difference between two neighbor pixels in an image. In a blurry image, the neighbor pixels value become the same. Therefore, color difference can used as basic index to solve image sharpness evaluation problem.

To solve the NR-IQA problem for gaussian blur distortion, the new model predicts image sharpness consisting of two global components: absolute color difference variation (CDV_a) and relative color difference variation (CDV_a). Typical images from CSIQ with different blur level and local color difference map in CIELAB color space are shown in Figure 1. From Figure 1, it can be observed that the color difference values in pixel level are from discrete to continuous in block with blur level increasing in flat region. The discrete color difference region represents the difference among pixels is larger than the continuous one. Furthermore, in a color difference map, the darker point means a lower color difference value. Similar, the whiter region with high color difference value represents more edge and structure information in texture region. Therefore, the color difference map is a suitable way to represent the blur level changes.

Figure 1 (a1)–(a5) Typical images extracted from CSIQ with difference blur level; (b1)–(b2) Local color difference map for the first-row images.

2. Absolute color difference variation

The first part of proposed model takes the color difference changes of a blurry image into account by HVS. The component $(\max\left(\Delta E_l\right))$ is utilized to calculate the sharpest location of a blurry image, and $\min\left(\Delta E_l\right)$ is determined by the blurriest location. The global absolute color difference variation can be defined via (5).

$$CDV_a = \max\left(\Delta E_l\right) - \min\left(\Delta E_l\right) \tag{5}$$

where ΔE_l represents the local color difference map of a given image.

According to the above equation, CDV_a value is the differences between the maximum and minimum value of a color difference map. It is difference from the maximum local variation model [7], [25], which only takes the maximum of local variation. The CDV_a is more sensitive to the sharpness than the maximum global variation because the difference between the maximum and minimum local color difference are all considered into CDV_a. Some representable images are selected to demonstrate the relationship between CDV_a and blur level. After calculating, the CDV_a values of Figures 1(a1)–1(a5) are 43.5226, 26.9270, 13.3638, 5.3847 and 1.9877, respectively. These values have monotonicity with respect of the blur level. The sharpest Figure 1(a1) has the largest CDV_a value, and the blurriest Figure 1(a5) has the smallest CDV_a value. More examples are used to check the monotonicity of CDV_a value with blur level in the following subsection. However, the difference between sharpest and blurriest points cannot express all features included in a blurry image under quality evaluation procedure. For example, the DMOSs of Figures 2(a) and 2(b) are similarity, but the CDV_a values of these two blurry images have a considerable difference (69.2982 and 39.3435). Thus, some potential useful contents for IQA should be considered to enhance the statistical performance.

3. Relative color difference variation

The second part of proposed model takes the overall content relative variation of a blurry image into consideration. The relative variations of neighbor pixels for

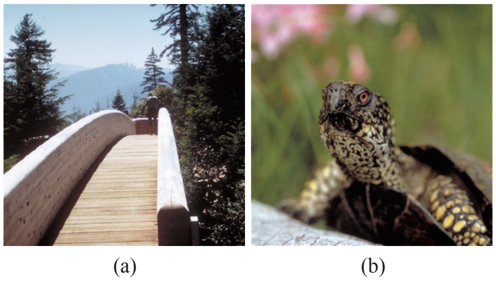

Figure 2 Two typical images extracted from CSIQ. The DMOSs of (a) and (b) are 0.061 and 0.060.

sharp image are large, and the relative variations are small for the blurry image. It meant that the ratio of color changes among pixels also have an effect on the overall sharpness assessment for HVS perceptual image. CDV_r is introduced to achieve a convincing image sharpness evaluation by considering the relative variations in image content [30], [53]. CDV_r is a simple and effectively indicator to describes image sharpness, and is defined as:

$$CDV_r = \frac{\max(\Delta E_l) - \min(\Delta E_l)}{average(\Delta E_l)} \tag{6}$$

By the definition of CDV_r, it will approach to 0 when the difference between maximum and minimum local color difference reduces. On the contrary, CDV_r value will approach to a large value when minimum local color difference is much less than the maximum one. From Figure 1, higher CDV_r value indicate lower blur level (after calculating, the CDV_r values of Figures 1(a1)–1(a5) are respectively 16.1677, 12.5937, 8.8279, 5.7002 and 3.7747). The CDV_r values of Figures 2(a) and 2(b) are respectively 12.7107 and 12.2439. The CDV_r value has a better correlation for Figures 2(a) and 2(b). Therefore, it is reasonable to use CDV_r as the second part to evaluate the image blurriness.

4. NR-IQA model

With the extracted CDV_a and CDV_r, a novel model is defined in IQA task for sharpness evaluation, and a simple pooling method is utilized and shown as:

$$S = CDV_a^{\alpha} \cdot CDV_r^{1-\alpha} \tag{7}$$

where α is the parameter to adjust the relative importance of the two components [53], [54]. The flowchart of the proposed method is shown in Figure 3. In next section, the value of α will be determined for the best correlation on a publicly available benchmark database.

To prove the monotonicity of CDV_a and CDV_r with respect to the blur level, six typical images from CSIQ database are selected, i.e., boston, bridge, couple, lake, shroom and swarm. The results are shown in Figure 4, in which the performance of CDV_a and CDV_r are presented. From Figure 4, for the six given images, the two proposed color difference indices decrease monotonically with blur level increasing. It suggests that the CDV_a and CDV_r are able to correctly reflect the reduction in sharpness. It is worthy to note that the ranges of CDV_a and CDV_r are different as shown in Figure 4. It is necessary to give different weight when the two components are combined together into an overall sharpness index.

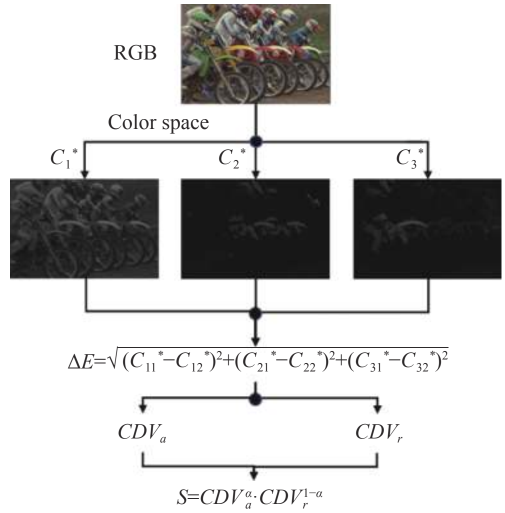

Figure 3 Flowchart of the proposed model.

III. Experimental Results and Discussion

1. Assessment criteria and databases

In our research, seven publicly available databases are used for model validation and comparison, i.e., CSIQ,

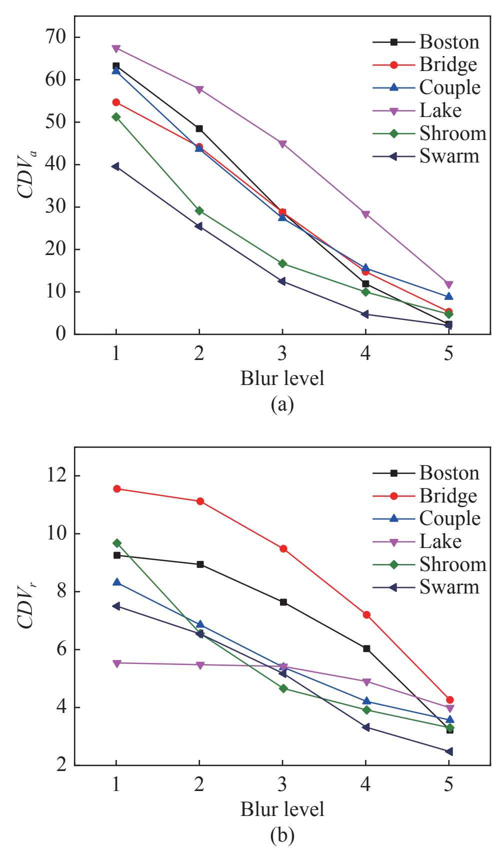

Figure 4 The monotonicity of (a) CDV_a and (b) CDV_r with respect to the blur level.

LIVE, TID2008, TID2013, VCL, CID2013 and BID. CSIQ, LIVE, TID2008, TID2013 and VCL are all synthetic blur image databases. CID2013 and BID are all public realistic blur image databases. The information of each database is introduced in Table 1. These seven databases are the most commonly utilized collections in IQA research covering a wide range of ordinarily encountered distortions in real world application.

Table 1 Benchmark test databases for IQA

Databases	Non-blurry images	Gaussian blur images	Subjective scores	Typical size
CSIQ	30	150	DMOS	512×512
LIVE	29	145	DMOS	768×512
TID2008	25	100	MOS	512×384
TID2013	25	125	MOS	512×384
VCL	23	138	MOS	768×512
CID2013	–	473	MOS	1600×1200
BID	–	586	MOS	1280×960

In order to evaluate whether a model is statistically consistent with human vision sense, validation is calculated by comparing model scored with provided subjective ratings. Three commonly evaluation criteria for IQA model are employed: Spearman rank-order correlation coefficient (SROCC), Pearson linear correlation coefficient (PLCC), and root mean squared error (RMSE) [11], [55]. For the RMSE, a smaller value indicates better performance. To compute the PLCC and RMSE indices, a logistic regression is adopted to get the same scale values with subjective judgments by using:

$$p\left(x\right) = (\beta_1 - \beta_2)/\left[1 + \exp\left((x - \beta_3)/\beta_4\right)\right] - \beta_2 \qquad (8)$$

where $\beta_1, \beta_2, \ldots, \beta_4$ are the parameters to be fitted, x represents the original IQA scores, and $p(x)$ is the IQA score after the regression [44].

2. Parameter setting and discussion

To determine the color space, some experiments are conducted and the results are shown in Table 2. The best results are highlighted in boldface for the three indices in Table 2. The performance in YIQ color space is better than the others, i.e., CIELAB and LMN. After comparison, YIQ is selected to build our model. The parameter α needs to be optimized for the proposed model. An alternative strategy was adopted to fit the parameter by determining the performance on a database based on [56].

Figure 5 shows the influence of α with the plots of SROCC and PLCC as functions of CSIQ database. From the figure, there is a satisfactory performance under $\alpha = 1$, namely CDV_a individually used condition. Nevertheless, the final results have increased by connecting CDV_r, which means that considering the relative variations of image is an essential solution. In addition, an optimal value of α which leads the high-level performance under [0.5, 0.7] condition and α is set as 0.65. Moreover, this value would be utilized throughout the rest parts of this research.

Table 2 Performance comparison of proposed model in three color space

Databases criteria		CIELAB	LMN	YIQ
CSIQ	SROCC	0.9528	**0.9533**	0.9487
	PLCC	0.9683	**0.9696**	0.9662
	RMSE	0.0716	**0.0701**	0.0739
LIVE	SROCC	0.9292	0.9399	**0.9407**
	PLCC	0.9365	0.9469	**0.9489**
	RMSE	5.5151	5.0552	**4.9595**
TID2008	SROCC	0.9177	0.9386	**0.9403**
	PLCC	0.9118	0.9312	**0.9335**
	RMSE	0.4818	0.4278	**0.4207**
TID2013	SROCC	0.9403	0.9479	**0.9521**
	PLCC	0.9368	0.9425	**0.9457**
	RMSE	0.4366	0.4171	**0.4054**
VLC	SROCC	0.8998	0.9168	**0.9207**
	PLCC	0.9049	0.9259	**0.9284**
	RMSE	10.3663	9.1986	**9.0524**

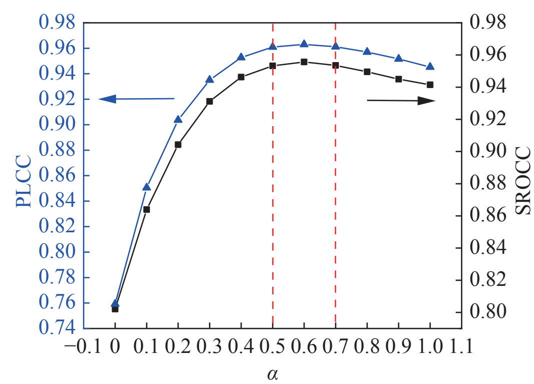

Figure 5 Plots of SROCC and PLCC as functions of α in the proposed model for CSIQ database.

Table 3 lists the results of three measures on the five blurry databases. SROCC and PLCC were utilized as evaluation measurement. The best results are highlighted in boldface for the two indices in Table 3. CDV_a and CDV_r indicate the measures that individually use the absolute color difference variation and relative color difference variation as the image quality evaluator for blurry images. The performance of CDV_a has a higher correlation with subjective results than CDV_r. However, the proposed model with combining CDV_r in content performs better than CDV_a individually used condition in most conditions.

3. Performance comparison on different models

An ideal IQA model should yield good performance overall and should also predict consistently well. In this

Table 3 SROCC and PLCC for proposed model on five databases

Databases	CDV_a		CDV_r		Proposed	
	SROCC	PLCC	SROCC	PLCC	SROCC	PLCC
CSIQ	0.9313	0.9525	0.7553	0.8052	**0.9487**	**0.9662**
LIVE	**0.9412**	**0.9499**	0.4676	0.5258	0.9407	0.9489
TID2008	0.8740	0.7489	0.7584	0.7811	**0.9403**	**0.9335**
TID2013	0.8945	0.8982	0.7714	0.7821	**0.9521**	**0.9457**
VCL	0.9081	0.9143	0.6856	0.6923	**0.9207**	**0.9284**
W. A.	0.9129	0.9027	0.6808	0.7119	**0.9404**	**0.9456**

section, the proposed model was compared with state-of-the-art models, including CPBD [24], LPC-SI [27], MLV [7], ARISM [31], BIBLE [32], SPARISH [28], BISHARP [29]. Especially, SPARISH is designing by learning-based method. Moreover, three general-purpose NR-IQA models, i.e., BRISQUE [57], NIQE [58] and ILNIQE [59], were selected to be compared. The best three results are highlighted in boldface for the three indices in Table 4. Besides, according to Wang and Li's work [60], the weighted and direct average (W. A. and D. A.) values of the three indices results over five databases were also presented in Table 4 to evaluate the overall performance. The weight of each database is linearly based on the number of the distortion images the database contained.

Table 4 Performance comparison of state-of-the-art IQA models on five databases

Databases	criteria	CPBD	LPC-SI	MLV	ARISM	BIBLE	SPARISH	BISHARP	BRISQUE	NIQE	ILNIQE	Proposed
CSIQ	SROCC	0.8847	0.9071	**0.9247**	**0.9255**	0.9132	0.9141	0.9125	0.9033	0.8945	0.8576	**0.9487**
	PLCC	0.8818	0.9159	**0.9488**	**0.9456**	0.9404	0.9380	0.9186	0.9279	0.9260	0.7986	**0.9662**
	RMSE	0.1370	0.1166	**0.0805**	**0.0945**	0.0988	0.1007	0.1132	0.1068	0.1082	0.2865	**0.0739**
LIVE	SROCC	0.9182	0.9389	0.9312	0.9511	**0.9607**	0.9593	**0.9611**	**0.9745**	0.9329	0.9162	0.9407
	PLCC	0.8955	0.9181	0.9429	0.9560	**0.9622**	0.9595	**0.9614**	**0.9719**	0.9434	0.9002	0.9489
	RMSE	8.3361	7.4246	6.1522	5.4939	**5.1022**	5.2750	5.9818	**3.7009**	6.1278	6.8482	**4.9595**
TID2008	SROCC	0.8412	0.8561	0.8548	0.8548	**0.8915**	**0.8896**	0.8850	0.7990	0.8165	0.8099	**0.9403**
	PLCC	0.8236	0.8574	0.8584	0.8428	**0.8929**	0.8891	**0.8911**	0.8047	0.8315	0.8277	**0.9335**
	RMSE	0.6794	0.6165	0.6019	0.6447	**0.5393**	0.5483	**0.5326**	0.6967	0.6518	0.6586	**0.4207**
TID2013	SROCC	0.8518	0.8888	0.8787	0.8980	**0.8988**	0.8927	**0.9088**	0.8134	0.7968	0.8155	**0.9521**
	PLCC	0.8553	0.8918	0.8827	0.8953	**0.9051**	0.9004	**0.9089**	0.8239	0.8165	0.8238	**0.9457**
	RMSE	0.6573	0.5740	0.5885	0.5651	**0.5392**	0.5519	**0.5203**	0.7072	0.7204	1.2479	**0.4054**
VLC	SROCC	0.8627	**0.9268**	0.5268	**0.9228**	0.8594	0.8016	0.8976	0.9006	0.9038	0.8410	**0.9207**
	PLCC	0.8954	**0.9247**	0.7684	**0.9396**	0.8889	0.8555	0.9066	0.9039	0.8998	0.7079	**0.9284**
	RMSE	11.0061	**9.4123**	15.8199	**8.4622**	11.3236	12.7982	10.2797	10.4174	10.6288	17.2033	**9.0524**
W. A.	SROCC	0.8746	0.9070	0.8233	**0.9146**	0.9064	0.8927	**0.9152**	0.8855	0.8745	0.8518	**0.9404**
	PLCC	0.8738	0.9048	0.8834	**0.9215**	**0.9205**	0.9109	0.9195	0.8941	0.8892	0.8112	**0.9456**
D. A.	SROCC	0.8717	0.9035	0.8232	**0.9104**	0.9047	0.8915	**0.9130**	0.8782	0.8689	0.8480	**0.9405**
	PLCC	0.8703	0.9016	0.8802	0.9159	**0.9179**	0.9085	**0.9173**	0.8865	0.8834	0.8116	**0.9445**

From the Table 4, it can be seen that the proposed model performs consistently well on all the standard databases compared with other image sharpness assessment models. Particularly, the proposed model almost yields all the best performance on the CSIQ, TID2008 and TID2013 databases. For LIVE and VCL, the proposed model performs only slightly worse than the best rank. In addition, the proposed model also yields top three rank in the weighted and direct average value of three indices. Compared with general-purpose models, the proposed model performs better, except LIVE database. It should be noted that BRISQUE is trained based on the images in LIVE database. So BRISQUE can perform the best rank for LIVE database tests. BIBLE and BISHARP also play better performance than proposed model for LIVE database. It can be found that BIBLE is consist of three features, i.e., block variances, gradient and saliency. Although BIBLE yields better than proposed model on LIVE database, BIBLE is more complex than proposed model. It can be noted that BISHARP is based on contrast feature. The main reason for the better performance of BIBLE and BISHARP on

LIVE database is the difference basic image features selection. IQA model based on different features can yield different performance on different databases. We can also find that there is no one model can perform best on all databases. However, proposed model performs better than BIBLE and BISHARP on other four databases. Furthermore, the proposed model outperforms the other state-of-the-art model for top three rank number (17 times). The second and third ranks for models are BIBLE (11 times) and BISHARP(10 times). It can be concluded that the proposed model yields the best overall performance.

Furthermore, the results of statistical significance tests to evaluate the performances of the competing models are presented and illustrated in Table 5, which is achieved by performing a series of hypothesis tests based on the prediction residuals of each model after nonlinear regression [11], [61], [62]. Specifically, the left-tailed F-test is employed to compare every two competing models. A value of $H = 1$ for the left-tailed F-test at a significance level of 0.05 represents that the first model (proposed model) is superior in IQA performance to the second model (model in raw) with a confidence greater than 95%. A value of $H = 0$ shows that these two competing models have no significance difference in IQA performance.

Table 5 Statistical significance comparison of different IQA models

Databases	CPBD	LPC-SI	MLV	ARISM	BIBLE	SPARISH	BISHARP	BRISQUE	NIQE	ILNIQE
CSIQ	1	1	1	1	1	1	1	1	1	1
LIVE	1	1	0	0	0	0	0	0	0	1
TID2008	1	1	1	1	1	1	1	1	1	1
TID2013	1	1	1	1	1	1	1	1	1	1
VCL	1	0	1	0	1	1	1	1	1	1

Based on the results in Table 5, it can be observed that the statistical significance tests of IQA performance are consistent with the results shown in Table 4. In the Table 5, the number of total statistical comparisons for two models is 50, and the number of comparisons in which proposed model surpasses the other models statistically is 41. Therefore, the proposed model yields significant improvement in 82% of the cases. In all, the proposed model obtains very promising statistical performance when compared with the most of other models.

The efficiency of an IQA model is also the crucial factor for model evaluation. Some experiments were conducted of running time on a PC with a 2.5 GHz Intel Core i5 CPU and an 8G RAM. The software platform was MATLAB R2013b. The time cost of each model for comparison measured 512 × 384 resolution color images in TID2008 database and the results were listed in the Table 6. From Table 6, it can be observed that our model is the fastest among the representable chosen models, which means proposed model performs well with relatively low complexity.

Figure 6 shows the scatter plots and fitted curves of the results from the proposed method versus the subjective scores on the five databases. It can be seen that the objective scores predicted by the proposed method correlate consistently with the subjective evaluations.

Table 6 Runtime comparison between partial state-of-the-art models

IQA models	CPBD	LPC-SI	MLV	ARISM	BIBLE	SPARISH	BISHARP	BRISQUE	NIQE	ILNIQE	Proposed
Time (s)	1.1045	1.1100	0.1490	17.3800	1.6620	7.3020	0.3630	0.3169	0.2794	11.7984	**0.0315**

Compared with state-of-the-art models, proposed model yields better performance in five synthetic blur databases. In the real-world image application, sharpness assessment of realistic condition is also significant. In the following part, two real blur databases, i.e., CID2013 and BID, are selected to measure sharpness evaluation performance. Table 7 lists the SROCC and PLCC performances of proposed model and six latest models on five synthetic blur databases and two real blur databases. Because of the lack of source code of the latest models, some data are replaced by "–". The best two performances are highlight in boldface. To reach better performance on real blur databases, the α value of proposed model is set as 1 after some parameter tests. From the Table 7, the proposed model also yields better performance than the latest models on five synthetic blur databases. For the two real blur databases, all the models yield similar performance, including the proposed model. Furthermore, performances of these models are all lower than the prediction accuracy in synthetic blur databases. This indicates that good sharpness evaluation models, which can effectively measure real blur situation, are still lacking.

IV. Conclusions

In this research, a novel and good performance NR-IQA model for sharpness evaluation was proposed. The proposed model consists of the absolute color difference

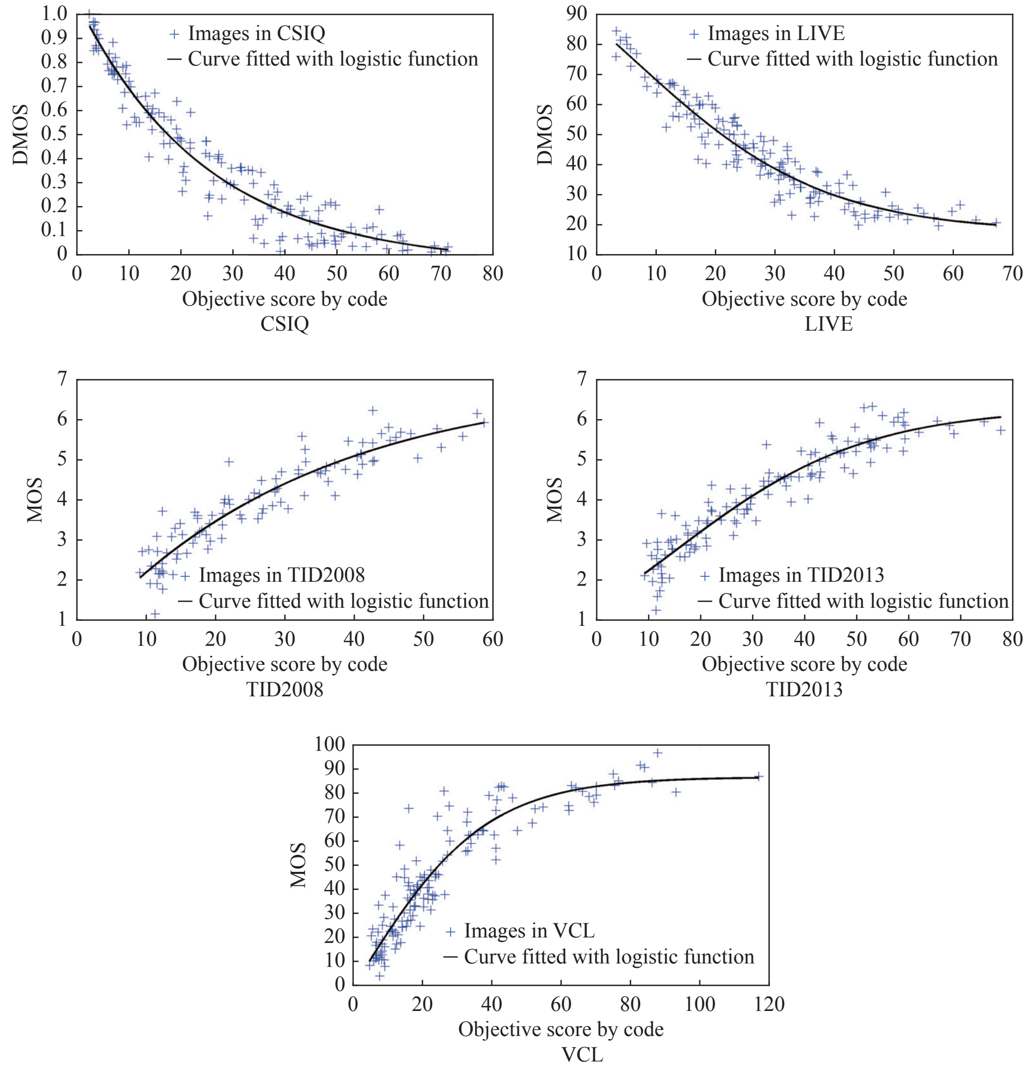

Figure 6 Scatter plots of subjective scores against scores calculated by proposed models' prediction for five databases.

variation and relative color difference variation of an image with gaussian blur distortion. Local color difference map is comprised of YIQ color difference operators in horizontal and vertical direction, which is an effective

Table 7 Performance comparison of newly IQA models on seven databases

Databases criteria		Yu's CNN	RISE	Maxpol	Qian's model	SFA	DFT-based model	Proposed
CSIQ	SROCC	0.9235	0.9279	0.9208	0.9103	**0.9405**	0.8890	**0.9487**
	PLCC	0.9416	**0.9463**	0.9381	0.9445	0.9450	–	**0.9662**
LIVE	SROCC	**0.9646**	0.9493	0.9596	0.9342	**0.9722**	0.9590	0.9407
	PLCC	**0.9735**	0.9620	0.9569	0.9452	**0.9631**	–	0.9489
TID2008	SROCC	0.9189	0.9218	0.8507	0.8639	**0.9313**	0.8230	**0.9403**
	PLCC	**0.9374**	0.9289	0.8533	0.8617	0.9217	–	**0.9335**
TID2013	SROCC	0.9135	0.9338	0.8746	0.8634	**0.9429**	0.8500	**0.9521**
	PLCC	0.9221	0.9419	0.8774	0.8643	0.9429	–	**0.9457**
VLC	SROCC	–	–	0.3471	–	–	**0.9040**	**0.9207**
	PLCC	–	–	**0.5247**	–	–	–	**0.9284**
CID2013	SROCC	0.5087	0.2178	0.5310	–	**0.5818**	–	**0.5959**
	PLCC	0.4511	0.3839	**0.6582**	–	0.6432	–	**0.6807**
BID	SROCC	**0.4501**	0.2099	0.2717	–	**0.3566**	–	0.2936
	PLCC	**0.4437**	0.1927	0.3237	–	**0.3738**	–	0.3379

way to represent color feature. To prove the outstanding performance of the proposed model, the other 16 state-of-the-art and latest image sharpness assessment and normal-purpose IQA models on seven large-scale IQA databases were selected as the comparison one. The commonly evaluation criteria results prove that the proposed model yields statistically better performance of prediction accuracy than other competing models with a lower computational complexity. Moreover, the proposed model is an open source algorithm [63], and it will update with research area development direction, especially for real-world application.

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