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A Reduced-Reference Image Quality Assessment Model Based on Joint-Distribution of Neighboring LOG Signals

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Abstract

Previous work have validated that the output of retinal ganglion cells in human visual pathway, which can be modeled as an LOG (Laplacian of Gaussian) filtration, can whiten the power spectrum of not only the natural images, but also the distorted images, hence the first-order (average luminance) and the second-order (contrast) redundancies have been removed when applying the LOG filtration. Considering the fact that human vision system (HVS) always ignores the first-order and the second-order information when sensing image local structures, the LOG signals should be efficient features in IQA (image quality assessment) task and a lot of LOG based IQA models have been proposed. In this paper, we focus on an interesting question that has not been investigated carefully yet: what is an efficient way to represent image structure features that is perceptual quality aware based on the LOG signals. We examine the relationship between neighboring LOG signals and propose to represent the relationship by computing the joint distribution of neighboring LOG signals, and thus propose a set of simple but efficient RR IQA feature and consequently yield an excellent RR IQA model. Experimental results on three large scale subjective IQA databases show that our proposed method works robustly across different databases and stay in the state-of-the-art RR IQA models.

Keywords: Image Quality Assessment, Laplacian of Gaussian, Whiten, Reduced-Reference, Joint Distribution

1. Introduction

Image Quality Assessment (IQA), which builds models to evaluate the image quality, has been developing rapidly in recent years. Aiming at estimating the subject quality of images, IQA algorithms are widely used in a variety of kinds of applications. Among different IQA metrics, full-reference (FR) IQA shows good performance when the reference image is provided, while the algorithms of no-reference (NR) and reduced-reference (RR) IQA are applied in situations when the source image is not available. However, in RR methods, partial information of the reference image is given according to the specific situation. FR method has been highly developed during recent years, however, it is always difficult to get all information from the referenced images in practical applications, while RR and NR methods are more convenient to achieve. In an RR IQA procedure, an accessory channel is given to transform the RR feature of the source information, in which there exists lower rate of error and requires smaller capacity compared with the whole information transformation in FR procedures, While the NR methods, with the lack of the reference information, always have higher deviation. Since RR IQA utilizes partial information directly from the source signal, it is more effective in practical situations and more significant to be researched. In order to evaluate the quality of the distorted images, the mainly used method of RR IQA is to extract certain features from distorted images and referenced images if available.

In sensing image local structures, human vision system (HVS) always ignores the first-order (average luminance) and the second-order (contrast) information in images. This can be explained as the whitening mechanism carried out by retinal ganglion receptive field [1], which response can be modeled as an LOG (Laplacian of Gaussian) filtration for natural images [2, 3]. In the context of IQA, it's common sense that perceptual distortion can be sensed by distinguishing the difference between image structures. Hence, the LOG signals, in which the first-order and the second-order redundancies that are unaware of image structures have been removed, should be efficient features to represent image structures for IQA model design. Some of our previous works have validated that the LOG signals serve all well for FR, RR, and blind IQA model developments [4, 5, 7-9, 11-13]. Furthermore, our previous work preliminarily suggests that the LOG filtration can also whiten distortion images [11]. And to further whiten the contrast variation in image of lager scale, we also proposed a normalization method to preprocess the LOG signals [8]. Given the LOG signals of the reference image and the distorted counterpart in which the structure-irrelevant information have been removed, the simplest L2-norm distance metric, i.e., the mean square error (MSE) can be applied to yield two simple but efficient FR IQA models [8, 11].

No matter how the LOG signals were used for IQA task before, what we are interested here lies in that with the LOG signals, is there a way to represent the property of image structures that is aware of image quality? Along this line, in this paper we first initiate an experiment to apply principle component analysis (PCA) and PCA whitening [2] on distorted images to extensively explore what property of the PCA whitening filter is for the distorted images. The experimental results show that the obtained filter can be modeled as LOG functions, which is consistent with the result of our previous preliminary investigation [11]. Then we examine the relationship between neighboring LOG signals to sense image structure features that is perceptual quality aware and propose to represent the relationship by computing the joint distribution of neighboring LOG signals, and based on the joint distribution computation, we propose a simple but efficient RR IQA model that performances well on three large scale subjective IQA databases and stay in the state-of-the-art RR IQA models.

2. Methods

2.1 PCA Whitening

Principle component analysis (PCA), which can effectively imitate the mechanism of the whitening process in the human visual system, was used in the investigations of whitening natural images [1, 2]. Following our previous preliminary investigation [11], here we use the same technique for a large number of distorted images to extensively explore the property of whitening filter for distorted images. Let $\mathbf{x}$ denote the source data vector, which is formed by rearranging the image patch into a column wise manner. What we are interested in is to model the filter which could whiten the frequency spectrum of **x**, in the situation when **x** is a source data from distorted images.

We denote by **U** the matrix with the vectors defining the principles components as its columns, denote by **y** the coefficients of the principal components of **x**, denote by **z** the whitened version of **x** with zero phase, and denote by Λ a diagonal matrix with the inverse of the square root of the variance of **y** on its diagonal, as shown in Eq. (1):

$$\Lambda = \begin{bmatrix} \frac{1}{\sqrt{\mathrm{var}(y_1)}} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sqrt{\mathrm{var}(y_2)}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{\sqrt{\mathrm{var}(y_K)}} \end{bmatrix} \tag{1}$$

Then the zero-phase whitening equation is defined in Eq. (2) and Eq. (3):

$$\mathbf{y}=\mathbf{U}^{\mathrm{T}}\mathbf{x} \tag{2}$$

$$\mathbf{z}=\mathbf{U}\Lambda\mathbf{y}=\mathbf{U}\Lambda\mathbf{U}^{\mathrm{T}}\mathbf{x}=\mathbf{W}\mathbf{x} \tag{3}$$

In the whole PCA whitening process, $\mathbf{U}^{\mathrm{T}}$ transforms the original data **x** into the principle component space, denoted by **y**, Λ equalizes the spectrum power of **y**, and finally one more **U** make the representation go back from the principle space to the original coordinate. All of them can be completed in one matrix transformation which is denoted by **W**. The final step makes **W** a zero-phase filter. In the implementation of the process to image data, a low-pass filter is firstly applied to make sure that noise in image is not amplified.

2.2 Whitening filters for natural image and distorted image

We whiten the images from the LIVE database with the above mentioned PCA based whitening method, and examine the results of the procedure on natural images and distorted images separately. Fig. 1 shows the PCA-whitened results of two reference images and their distorted images from the LIVE database, which is one of the most commonly used databases in the field of computer vision.

Natural image statistics has revealed that the scatter plots of the pairs of neighboring pixels in natural images distribute near a straight line with a slope rate approximately equivalent to 1. And after whitening, the shape of the distribution of the scatter plots likes a circular plate. We check the whitening results of the distorted images and use scatter plots to show the relationship between the neighboring pixels in each whitened image, as shown in Fig. 2, where the semi-major axis and semi-minor axis of the ellipse are denoted by Ru and Rv separately. We use an ellipse to approximately fit the shape of the plot distribution, and compute the eccentricity of the fitted ellipse, which we suggest to be able to indicate the correlation between the neighboring pixels in the whitened images. According to the fitting, the eccentricity of the ellipse generated from natural images turns to be close to zero, while the eccentricity generated from distorted images varies in different types of distortion. By the experimental observation, it is shown that the whitened distorted images have different properties compared with the natural images. The relationship between the neighboring pixels reveals that not all the low-order correlation in the distorted images has been removed during the whitening process. Thus, we expect that the relationship between the neighboring pixels in a whitened image is useful to reflect the image quality.

Previous work [11] has revealed that the whitening filter for distorted image also looks like an LOG filter. Given the fact that LOG filter can whiten the power spectrum of the natural images, what we are interested in is that if it will still be appropriate to whiten the distorted images in the same way.

We generate the whitened images by PCA procedure with 17×17 sized window, and extract 10,000 samples from each source image and its corresponding whitened result, which are used to calculate the 17×17 whitening filter. We demonstrate the 1-D profile of the center row in the whiten matrix and use LOG filters of 3 different scales to fit the whiten matrix, as shown in Fig. 3. The parameters which indicates the variances of the fitted LOG filters are denoted as σ1, σ2, and σ3. According to the fitting of our LOG based filtering model, the whiten filter for natural images and distorted images can both be imitated by three LOG filters, in which the parameters σ1, σ2, and σ3 presents to be close to 0.5, 1 and 2 separately, among which the parameter σ1 of the first LOG filter is exactly 0.5 for different natural images and distorted images.

From our experiment, it is shown that the center-surround receptive field, which can whiten not only the pristine natural images, but also the distorted images, can be modeled with an LOG filter. This LOG-whiten filter of the distorted images is approximately the same with the natural images, which can generally normalize and decorrelate the distorted images.

For the reason that LOG signals only contain high order information of image structure and the fact that HVS is not sensitive to the first and second order correlation in image, the LOG signals have been widely utilized in IQA models.

2.3 LOG filter

Laplacian filters are derivative filters used to find areas of rapid change in images. Since derivative filters are very sensitive to noise, it is common to smooth the image (e.g., using a Gaussian filter) before applying the Laplacian. This two-step process is call the Laplacian of Gaussian operation. The LOG operator takes the second derivative of the given signals. Where the image is basically uniform, the LOG will give zero. Wherever a change occurs, the LOG will give a positive response on the darker side and a negative response on the lighter side.

The LOG filter we use to whiten images in this paper is defined as Eq.(4):

$$\nabla^2 G(x,y,\sigma) = -\frac{1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4}$$

where the variables x and y denote the coordinate of the input image, parameter σ represents the scale factor of the LOG filter. In this paper, multi-scale strategy is used in the whitening filtration, specifically, 3 scale factors are involved, indexed by i = 1, 2, and 3. When using the filter given above, the output can contain values that are quite large and may be negative, so it is important to use an image type that supports negatives and a large range, and then scale the output. Alternatively, a scaling factor can be used on the filter to restrict the range of values. In our experiment, we select the scale factors of the LOG operator for the whitening process as

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1, 2 and 4, which perform better in the evaluation process of our method.

2.4 Feature Extraction Using Joint Distribution

We use the LOG filters of three scales to generate the whitened reference and distortion images, and use divisive normalization method [8] to further remove contrast variation in the image of large scale, thus we generate a series of whitened images. The results are called as LOG images. Since much redundancy has been removed in the LOG signals, while the structural information has been left, we examine the relationship between the neighboring pixels in the LOG images to analyze what still remains, in order to evaluate the degree of the distortion.

For each 2×2 patch in the LOG image, we denote the pixels with number 1 to 4 as shown in Fig. 4.

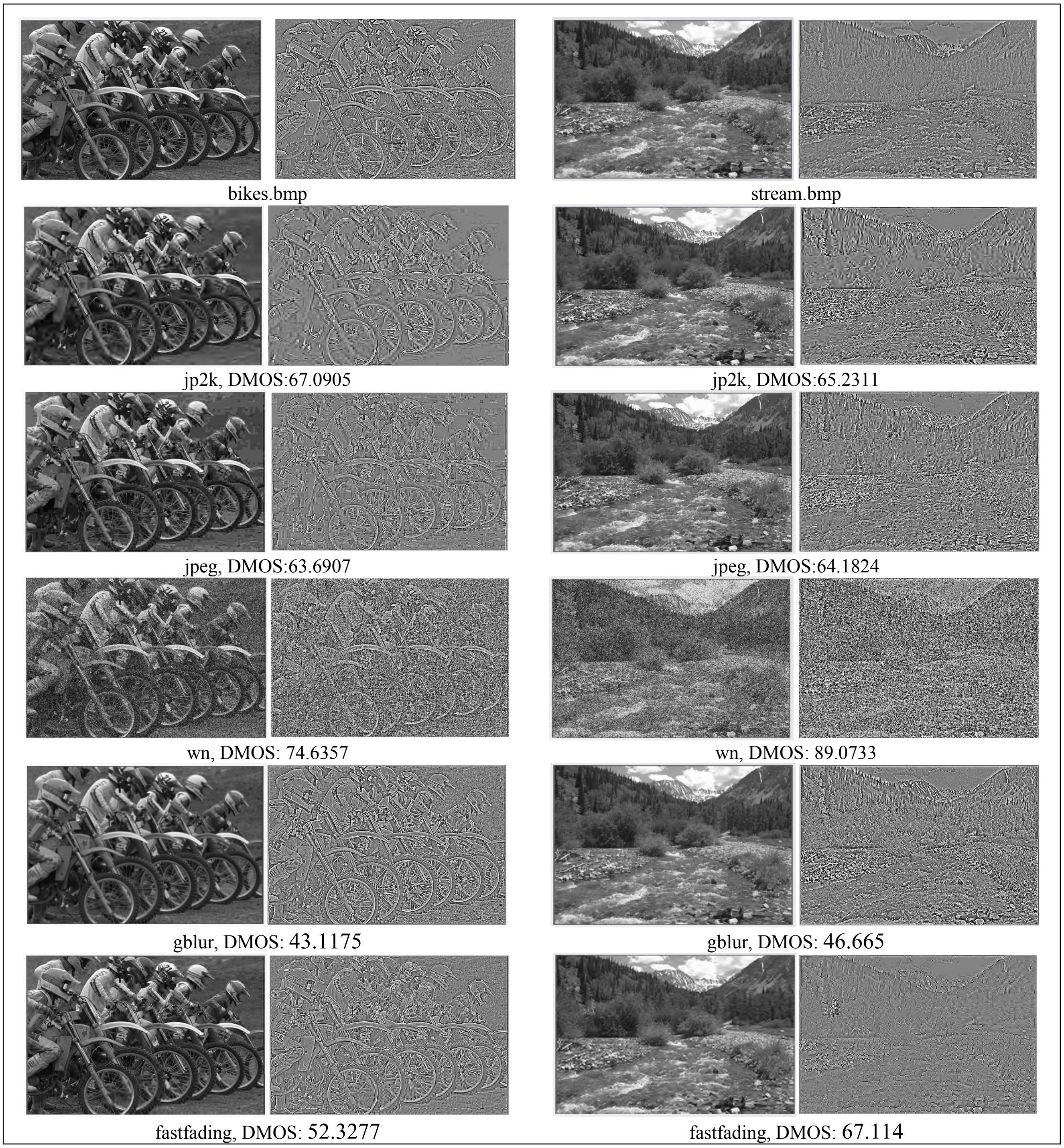

Figure 1. *whiten results for two reference images and their distorted images*

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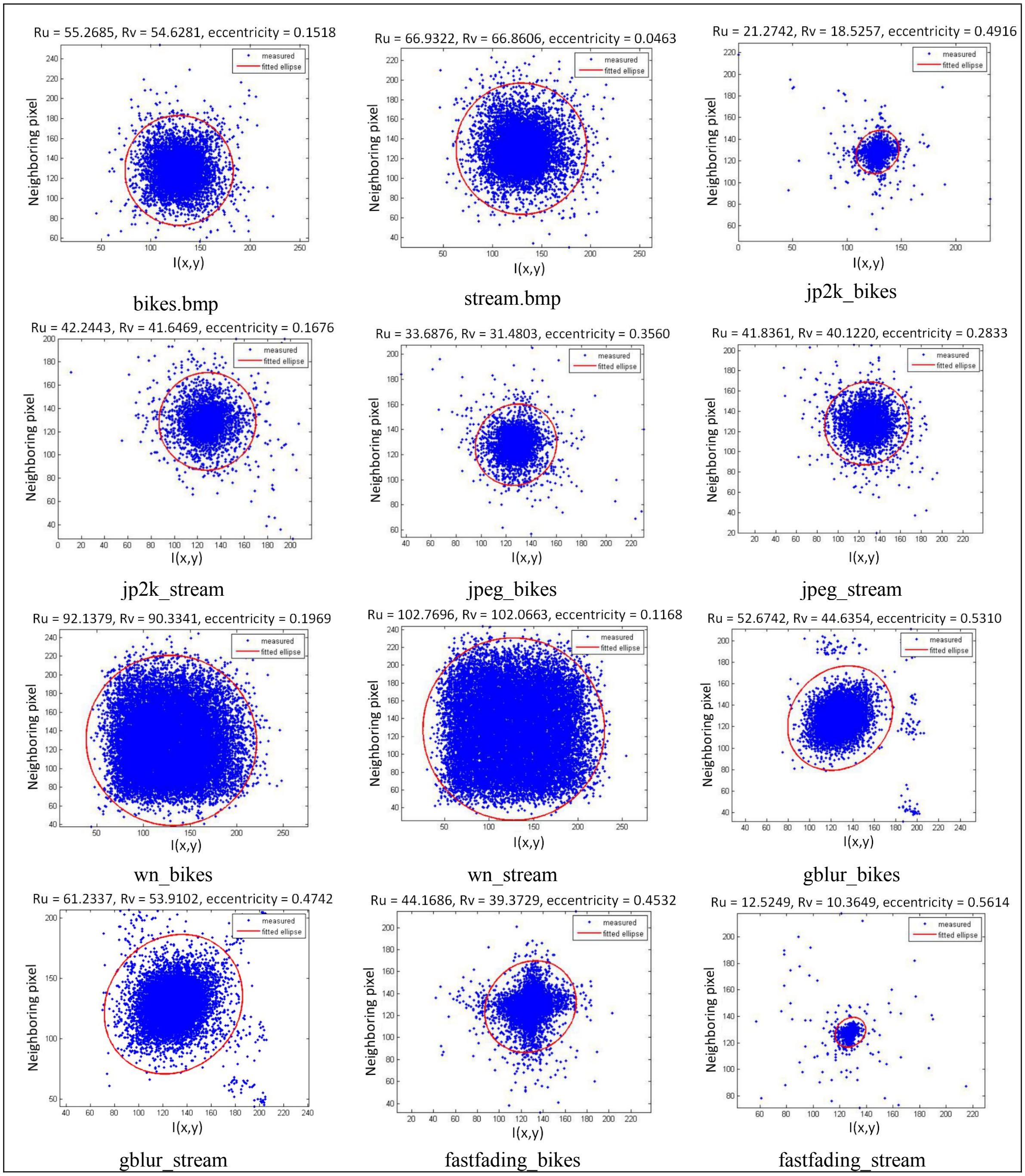

***Figure 2.** Scatter plots of the whiten results of two reference images and their distorted images*

In order to obtain the statistical data of the joint distribution histogram, all of the LOG signals have been quantified to 11 levels from -5 to 5.

To extract the correlation feature between the neighboring LOG signals, we compute the distributions of the reference image as shown in Eq. (5), where i indicates the scale of the LOG filter used in the whitening process.

$$J_{i,j}^{R}=\begin{cases}\text{marginal distribution of R1,} & \text{if } j=0\\ \text{joint distribution of R1, R2,} & \text{if } j=1\\ \text{joint distribution of R1, R3,} & \text{if } j=2\\ \text{joint distribution of R1, R4,} & \text{if } j=3\\ \text{joint distribution of R2, R3,} & \text{if } j=4\end{cases} \tag{5}$$

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The distributions of the distorted image can also be produced in the same way, as defined in Eq. (6).

$$J_{i,j}^{D} = \begin{cases} \text{marginal distribution of D1}, & \text{if } j=0 \\ \text{joint distribution of D1, D2}, & \text{if } j=1 \\ \text{joint distribution of D1, D3}, & \text{if } j=2 \\ \text{joint distribution of D1, D4}, & \text{if } j=3 \\ \text{joint distribution of D2, D3}, & \text{if } j=4 \end{cases} \quad (6)$$

2.5 RR feature

From the above process, we create five 11×11 joint distribution matrices for each image on every scale of LOG filtering. For an RR metric, we just need to transform partial information of the reference image, therefore, not all of elements in the joint distribution matrices are necessary to generate the RR feature. In order to extract effective information from the joint distribution results, we compute the mean value, deviation, and several other statistical data for every lines and columns of the

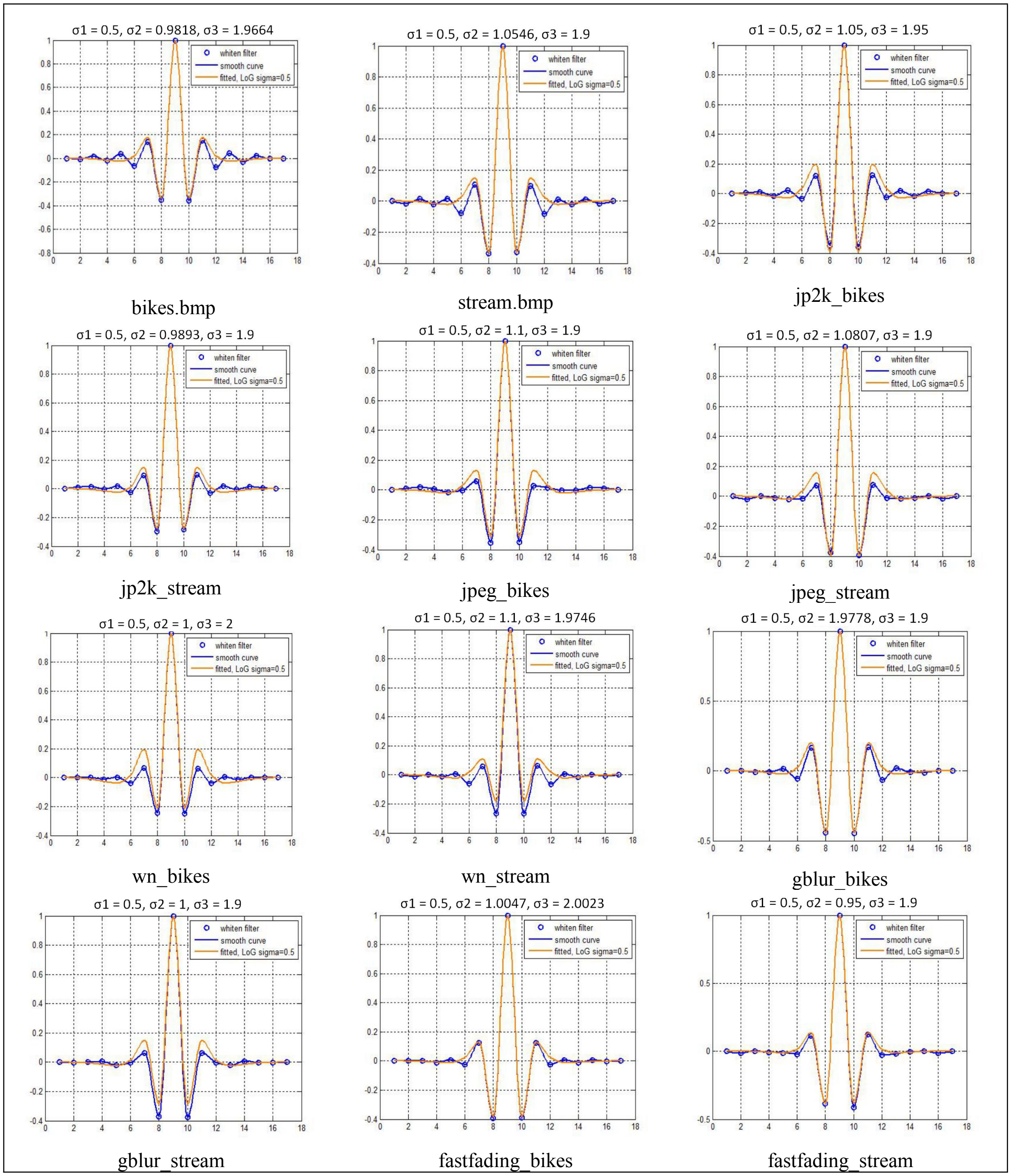

Figure 3. *Whiten filters of two reference images and their distorted images.*

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matrices separately, and then find that the main diagonal data and the counter-diagonal data are more sensitive to the correlation between the neighboring pixels from the LOG images, among which the central point has much more effect on the statistical results.

(a) Patch from reference image *(b) Patch from distorted image*
Figure 4. direction number in a 2×2 patch from the LOG images

Therefore, for each 11×11 distribution of a reference image, we define the central point of $J_{i,j}^{R}$ as $P_{i,j,0}^{R}$, and use $P_{i,j,1}^{R}$, $P_{i,j,2}^{R}$ to represent the mean value of the main diagonal data and counter-diagonal data except $P_{i,j,0}^{R}$ separately. $P_{i,j,0}^{D}$, $P_{i,j,1}^{D}$, $P_{i,j,2}^{D}$ can be produced in the same way from distorted images.

In this part, we generate these three RR features from each joint distribution matrix, that is, we create 3×5×3 = 45 RR features in total for each image.

2.6 RR-IQA model

Since the distorted information changes along with the quality of the image, we use $P_{i,j,k}^{R}$ and $P_{i,j,k}^{D}$ (k=0,1,2) as the RR IQA features, and calculate perceptual distortion with the ratio of every pair of RR features, separately, as shown in Eq. (7), where each ratio might be larger or smaller than 1, hence we create a non-linear function F(x) to calculate the distortion separately.

$$L_{i,j} = F\left(\frac{P_{i,j,1}^{D}+\alpha_1}{P_{i,j,1}^{R}+\alpha_1}\right) + F\left(\frac{P_{i,j,2}^{D}+\alpha_2}{P_{i,j,2}^{R}+\alpha_2}\right) + \beta F\left(\frac{P_{i,j,0}^{D}}{P_{i,j,0}^{R}}\right) \tag{7}$$

Considering of the non-linear properties of the variance of the distortion, the nonlinear adjusting function F(x) is defined as Eq. (8):

$$F(x) = \begin{cases} c1\times\left(1-\dfrac{1}{\exp(c2\times(1-x))}\right), & x \le 1 \\ 1-\dfrac{1}{\exp(c3\times(x-1))}, & x > 1 \end{cases} \tag{8}$$

Here we set $\alpha_1 = 5\times10^{-4}, \alpha_2 = 2.7\times10^{-4}$, $\beta = 4.5$, c1=1.07, c2=1.88, and c3=7.83.

Finally, the estimated score of the proposed RR IQA model is defined as Eq.(9):

$$Ms = \sum_{i=1}^{3}\sum_{j=0}^{4} L_{i,j} \tag{9}$$

Thus, we get an evaluation score of every specific image from the databases. In most NR and RR metrics, the computation needs to process high dimensional data, which occupies much time and capacity. However, in our computation, for each image, we have only created a 45-dimensional RR feature, which is requires less space in the storage device and transformation unit compared with a large amount of other RR and NR IQA metrics.

3. Experimental Results

3.1 Test database

We tested the performance of the proposed RR model on three benchmark IQA databases: LIVE, CSIQ and TID2008, as well as the competitors. The three databases were selected for their large scale.

LIVE database contains 982 subject-rated images created from 29 referenced images with 5 types of distortions: JPEG compression, JPEG2000 compression, white noise, Gaussian blur and fast fading, while CSIQ database consists of 900 subject-rated images created from 30 referenced images with 6 types of distortions. TID2008 database contains 1700 images of 17 different distorted types, which is the largest database of the commonly used databases.

The reference images existed in the three databases are with various content, ranging from indoor scene to outdoor scene, from people to animal and from wildlife to urban building. Besides, the distortion procedures exposed to these images include JPEG compression, JPEG2000 compression, Gaussian blur, and kinds of noise contamination.

3.2 IQA performance

The involved RR IQA competitors were selected based on:

1) There is the evaluation results on the three IQA databases reported in the original literature, or

2) The source code of the model is publically available.

In our experiment, the scale factors of the LOG operator for the whitening process in the proposed metric were selected as 1, 2 and 4. Taking advantages of existing databases on IQA which include both pristine images and distorted images, we investigate the results of the model scores for each image from the three databases to compare with the value of DMOS or MOS given from the databases, and the spearman rank-order correlation coefficients (SROCC) regarding to the model scores versus the human subjective opinion scores on the different databases were given in tables 1, 2 and 3. The results of the competitors on LIVE and CSIQ were obtained from references [4, 6, 10, 14], while the results on TID2008 were calculated by using the source code provided by their authors.

Among the metrics showed in the tables, the overall performance of the proposed metric ranks 3rd on LIVE database, 2nd on CSIQ, and 1st on TID2008. Since the TID2008 is the largest database among the three databases, model working well on such database is more significant, which indicates that the proposed metric has stable performance on different types of distorted images. Fig. 5 shows the scatter plots of the human subjective opinion scores versus the modeling predicted objective scores on the LIVE, CSIQ and TID2008 databases. In order to show the comparison of the results on the common types of distortions, we only select 5 specific distorted types in TID2008 to show the scatter plots.

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Table 1 Performance of IQA metrics in terms of SROCC on LIVE database

SROCC	JP2K	JPEG	AWGN	GB	FF	overall
Proposed	0.9400	0.9001	**0.9683**	0.9163	0.9060	0.8801
Zhang *et.a*l. [4]	0.9444	0.9260	0.9578	0.9371	0.9258	0.8366
Li *et.a*l. [6]	**0.9509**	0.9226	0.9559	**0.9584**	**0.9443**	**0.9287**
Xue *et.a*l. [10]	0.9288	**0.9466**	0.8610	0.9378	0.9376	0.8827
Wang *et.a*l. [14]	0.9330	0.9204	0.8639	0.9145	0.9162	0.8437

Table 2 Performance of IQA metrics in terms of SROCC on CSIQ database

SROCC	AWGN	JPEG	JP2K	AGPN	GB	contrast	overall
Proposed	**0.9034**	0.8761	0.9106	0.8842	0.9495	0.7172	0.8385
Zhang *et.al*. [4]	0.8548	0.9094	0.9456	0.8400	**0.9722**	0.9257	0.6470
Li *et.al*. [6]	0.8916	0.9301	**0.9510**	0.8703	0.9690	**0.9534**	0.6979
Xue *et.al*. [10]	0.8751	**0.9369**	0.9215	**0.8963**	0.9174	0.8877	**0.8534**

Table 3 Performance of IQA metrics in terms of SROCC on TID2008 database

SROCC	Zhang *et.al*. [4]	Li *et.al*. [6]	Xue *et.al*. [10]	Proposed
AWGN	0.6839	0.7192	0.7491	**0.7556**
ANC	0.7081	0.6538	0.6517	**0.7489**
SCN	0.5561	0.7999	0.7688	**0.8269**
MN	0.6126	**0.6944**	0.5495	0.6400
HFN	0.8094	0.8517	0.8783	**0.8924**
IN	0.5183	0.6521	**0.8340**	0.7600
QN	0.4353	0.6535	**0.7656**	0.6595
GB	0.8680	**0.9501**	0.9473	0.8427
DEN	0.8575	**0.9694**	0.9230	0.8141
JPEG	**0.8707**	0.8207	0.8372	0.8357
JP2K	0.9497	**0.9555**	0.9392	0.9058
JGTE	0.7627	**0.8501**	0.7048	0.8221
J2TE	0.7279	0.7890	0.7670	**0.8288**
NEPN	**0.6742**	0.6650	0.6684	0.3130
Block	**0.8153**	0.7133	0.4876	0.5841
MS	**0.5167**	0.4390	0.4130	0.4342
CTC	0.5798	**0.6995**	0.6216	0.4921
Overall	0.5888	0.5714	0.5417	**0.6520**

Though the feature of joint distribution of neighboring LOG signals exhibits promising property being perceptual quality aware, there is still much space to improve the proposed method. In this paper, the joint distributions were computed on the whole image, which indeed ignores local information of textures with different content. In future, we will take the feature of texture into account by applying local statistics, which would improve the model performance further.

4. Conclusion

Being validated the fact that the LOG filtration can remove the first-order and the second-order information that are unaware of image structures both of the reference and distortion images, the LOG signal is promising for the purpose of sensing perceptual change in image structures. In this paper, we proposed to compute the joint distribution of neighboring LOG signals for building perceptual quality aware features in IQA task, and proposed an RR IQA model based on the joint distribution features, which works stably on different databases. Experimental results have validated that the proposed metric performs well and stably on the LIVE, CSIQ and TID2008 databases and stay in the state-of-the-art RR IQA models. This fact exhibits that the proposed joint distribution feature is high perceptual quality aware and very promising in IQA model design.

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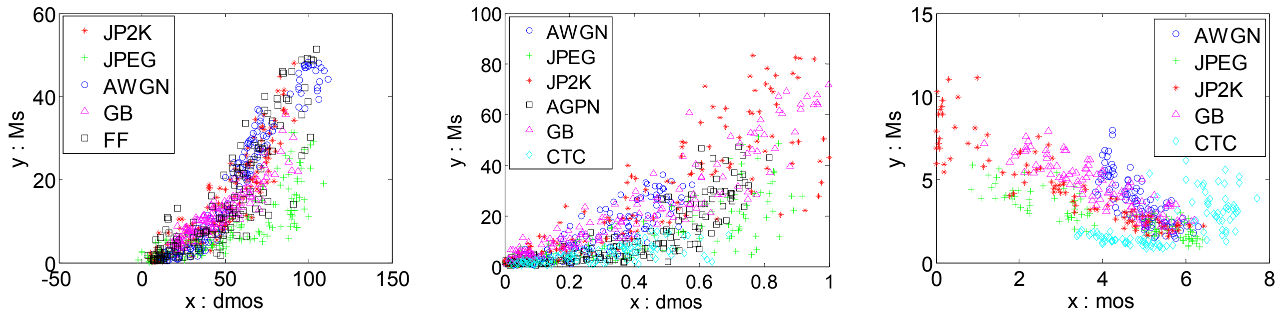

(a) Proposed metric on LIVE database *(b) Proposed metric on CSIQ database* *(c) Proposed metric on TID2008 database*

Figure. 5 *Scatter plots of the proposed metric on LIVE, CSIQ and TID2008 database*

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