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Blind Image Quality Assessment Based on Natural Scene Statistics

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no-reference image quality assessment, natural scene statistics, gradient image, key feature

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Blind Image Quality Assessment Based on Natural Scene Statistics

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Abstract: Nowadays blind/referenceless image spatial quality evaluator (BRISQUE) based on natural scene statistics is one of the state-of-the-art no-reference algorithms. But it only analyzes the original image and ignores the difference of the features constructed. *Here an improved algorithm BRISQUEs is proposed and implemented by three steps. First, we apply mean subtracted contrast normalized to the gradient images and construct a new feature vector to assess quality. Second, we weight some key features of BRISQUE to improve assessment. After the two assessments obtained, a further average is made to weaken the bias from different assessments.* Through the experiments on the LIVE IQA database, our approach has a remarkable performance than previous no-reference algorithms and is statistically superior to the popular multi-scale structural similarity index.

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基于自然场景统计的无参考图像质量评价

李海洋 [1,2]，曹伟国 [1,2]，李诗锐 [1,2]，陶克路 [1,2]，李华 [1,2]
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摘要：目前基于自然场景统计的无参考图像质量评价方法 BRISQUE 算法(Blind/Referenceless Image Spatial Quality Evaluator)是这类算法的典型代表；但它仅在原始图像基础上做统计分析，且忽略了各特征间的差异性。*由此提出了新的改进算法 BRISQUEs，并通过三个步骤实现：将被测图像的梯度图做去均值对比归一化处理，在此基础上构造新的特征向量来评价图像质量；将 BRISQUE 中的关键特征进行适当加权，并对图像再次评价；平均上述两次评价来进一步降低算法的偏差。*通过 LIVE 数据库上的实验，BRISQUEs 的统计评价性能明显好于之前的无参考评价算法，也要优于多尺度结构相似度指标。

关键词：无参考质量评估；自然场景统计；梯度图；关键特征
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Introduction

Image quality has a great impact on human visual perception. A good image is more easily understood and accepted by people. In the processes of image acquisition, transmission, compression and storage, there are various factors degrading the quality of the image. Establishing objective image quality assessment (IQA) consistent with the human visual system (HVS) is pretty important. IQA aims to use computational models to measure the image subjective quality as much as possible.

Generally objective quality assessment can be divided into three basic types according to the amount of information needed to the algorithm[1]:

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full-reference (FR), reduced-reference (RR) and no-reference (NR). In FR algorithms, the distortion free image with a "perfect" quality is given. Then algorithms evaluate the perceptual quality of each corresponding distorted image relative to the reference image. Peak signal-to-noise ratio (PSNR), structural similarity index (SSIM)[2], multi-scale structural similarity index (MS-SSIM)[3], visual information fidelity (VIF)[4] and most apparent distortion index (MAD)[5] are several common FR algorithms. RR algorithms need partial information from the original undistorted images[6-7]. What kind of information is required depends on the algorithms' schemes. They can be adopted to monitor image quality degradations or control the network streaming resources over wired or wireless networks. While NR algorithms only rely on the distorted images themselves.

NR is the most difficult IQA problem, but potentially the most useful. In the absence of a reference, NR-IQA algorithms need construct new models different from fidelity or similarity used by FR usually. Recently natural scene statistics (NSS) models provide powerful tools for probing human judgments of visual distortions[8]. Certain statistical properties can reflect "un-naturalness" in the image due to the presence of distortions. Based on NSS, many NR algorithms have been put forward[10-16]. Here we review several state-of-the-art algorithms. The Distortion Identification-based Image Integrity and Verity Evaluation (DIIVINE) index extracts statistical features derived from an NSS wavelet coefficient model, based on a 2-stage framework involving distortion identification followed by distortion-specific quality assessment[10]. It assesses the quality across a variety of distortion categories and is statistically equivalent to SSIM. At the same time, the Blind Image Notator using DCT Statistics (BLIINDS-II) index based on DCT coefficient model was presented[11]. Different from DIIVINE, BLIINDS-II adopts a lower dimensional feature space and a simpler single-stage framework operating in a more sparsely sampled DCT domain. While nonlinear sorting of block in BLIINDS-II slows the algorithms to some extent. Inspired by spatial natural scene model founded by Ruderman[9], Mittal et al. proposed a purely spatial algorithm, called blind/referenceless image spatial quality evaluator (BRISQUE)[12]. The algorithm is very simple, and has a fast and efficient performance, making it well suited for real time applications. Based on BRISQUE, the DErivative Statistics-based Quality Evaluator (DESIQUE), which extracted statistical features in both the spatial and frequency domains, was proposed by Zhang et al.[13] In DESIQUE, seven types of log-derivative statistics are used to model the relationship between neighboring pixel values, which are sensitive to distortion.

In this paper, we propose an improved algorithm based on BRISQUE, called BRISQUEs. The algorithm further utilizes the operator, mean subtracted contrast normalized (MSCN), and features generated by BRISQUE. It's purely spatial and as simple as BRISQUE. The implementation is a three-step process. First, we apply MSCN to the gradient images generated from the distorted image and construct a new feature vector to assess quality. Second, we weight some key features of BRISQUE to improve assessment. After the two assessments obtained, a further average is made to weaken the bias. Through adequate experiments, our algorithm has a remarkable performance than previous NR algorithms and is statistically superior to MS-SSIM on the LIVE IQA database[17]. The paper is organized as follows. Section 1 describes two improved models based on gradient image and weighted features respectively. According to these theories, we make some experiments to evaluate the performance of our method in Section 2. In the last section, we make a summary of the whole improvement.

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1 NR-IQA Algorithm – BRISQUEs

1.1 The First Improvement Based on Gradient Image

The local non-linear operator MSCN (1) was first proposed by Ruderman and could normalize luminance[9]. For natural images, the normalized luminance tends towards a unit normal Gaussian distribution.

$$MSCN(I) = \hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \tag{1}$$

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} \cdot I_{k,l}(i,j) \tag{2}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} \cdot (I_{k,l}(i,j) - \mu(i,j))^2} \tag{3}$$

where $i \in 1,2,\cdots,M$; $j \in 1,2,\cdots,N$ are spatial indices, C is a small constant that ensures the denominator is non-zero, w is a 2D circularly-symmetric Gaussian weighting function, $\mu(i,j)$ is the local mean field, $\sigma(i,j)$ is the local variance field.

The MSCN field, while clearly not entirely decorrelated, exhibits a largely homogeneous appearance with a few low-energy residual object boundaries. Attracted by MSCN, we try to apply the model to the gradient maps, as (4)

$$GMSCN(I) = MSCN\left(\frac{\Delta I}{\Delta x}\right) + MSCN\left(\frac{\Delta I}{\Delta y}\right) \tag{4}$$

where $\Delta I/\Delta x$ and $\Delta I/\Delta y$ are the gradients of image in the horizontal direction and the vertical direction respectively.

Fig. 1 displays the differences between MSCN and GMSCN. We can clearly see that GMSCN has a better symmetry for five distortions in the LIVE IQA database. They both closely follow Gaussian-like distribution when the image distortion is not severe. But when the distortion becomes obvious, MSCN has a worse symmetry than GMSCN. So the properties of GMSCN can be modeled more easily and accurately. What's more, we can find some other interesting things intuitively. For JP2K, JPEG, BLUR and FF, the curves of GMSCN converge to the center with the intensification of image distortion. For WN, the situation is opposite. Different from JP2K, the coefficients of JPEG's GMSCN concentrate at zero with the bit rate (bpp) decreasing. Those properties have an important guiding significance for us. We can make use of the properties of different distortions to categorize images and retrieve images. However, those properties are utilized to design IQA models here. Unlike DIIVINE, we process the properties uniformly rather than use them to design a step of distortion classification.

BRISQUE applies the generalized Gaussian distribution (GGD)[18] to fit MSCN coefficients and the asymmetric generalized Gaussian distribution (AGGD)[19] to fit pairwise products of neighboring MSCN coefficients.

GGD is defined as

$$f(x;\alpha,\sigma^2) = \frac{\alpha}{2\beta\Gamma(1/\alpha)} \exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right) \tag{5}$$

where $\beta = \sigma\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$ (6)

The shape parameter α controls the 'shape' of the distribution while σ^2 controls the variance. Since MSCN coefficient distributions are symmetric, we can choose the zero mean distribution.

AGGD is defined as

$$f(x;v,\sigma_l^2,\sigma_r^2) = \begin{cases} \dfrac{v}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\dfrac{-x}{\beta_l}\right)^{v}\right) & x < 0 \\ \dfrac{v}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\dfrac{-x}{\beta_r}\right)^{v}\right) & x \geqslant 0 \end{cases} \tag{7}$$

where $\beta_l = \sigma_l\sqrt{\frac{\Gamma(1/v)}{\Gamma(3/v)}}, \quad \beta_l = \sigma_r\sqrt{\frac{\Gamma(1/v)}{\Gamma(3/v)}}$ (8)

The shape parameter v controls the 'shape' of the distribution while σ_l^2, σ_r^2 are scale parameters that control the spread on each side of the mode respectively. If $\sigma_l^2 = \sigma_r^2$, then the AGGD reduces to the GGD.

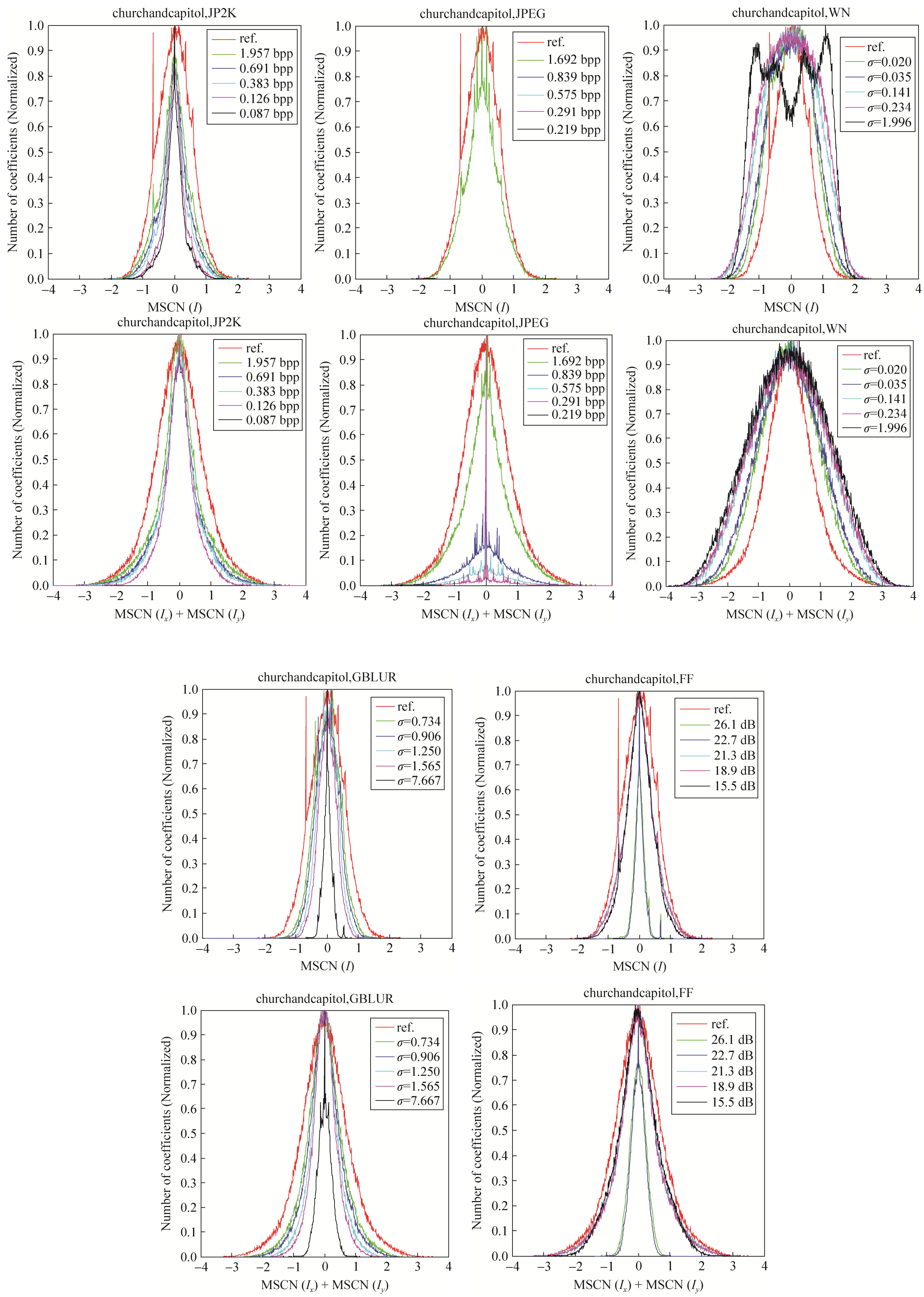

Fig. 1　Histograms of MSCN coefficients and GMSCN coefficients for a natural undistorted image and its five distorted versions from the LIVE IQA database

In the equations (5)~(8), $\Gamma(\cdot)$ is the gamma function:

$$\Gamma(a)=\int_0^{\infty} t^{a-1}e^{-t}dt \quad a>0 \tag{9}$$

Like BRISQUE, we extract a feature vector with 36 features from GMSCN, and construct a new feature vector by connecting the old feature vector in BRISQUE, written $[Feature_{MSCN}, Feature_{GMSCN}]$. Then we should map the vector to the corresponding difference mean opinion score (DMOS) of the image in the database. In the implementation, the support vector machine (SVM) and the support vector regressor (SVR) are used to map the feature space to quality scores[20]. After the model is established by enough training, any natural images can be predicted directly.

1.2 The Second Improvement Based on Weighted Features

Before training by SVM in BRISQUE, the features are normalized to the same interval as each feature has different magnitude. Intuitively, the importance of these features should be in different levels. Some features may be more important than other features. If we treat them in the same way, it's not fair to them. So we need to weight some key features. The simplest method is lengthening the feature vector by repeating the key features for several times like this.

$$V_{\text{new}}=\left[V_{\text{old}},\ R(F_{\text{key}},\ k)\right] \tag{10}$$

where V_{old} is the original feature vector; V_{new} is the new feature vector; F_{key} is a key feature in V_{old}; $R(F_{\text{key}},k)$ is an operator that can repeat F_{key} for k times.

How to choose the key features is a problem. We could analyze the correlation of features with human judgments of quality (DMOS). It may be useful for the choice. After performing a large number of experiments, we choose the 1st, 2nd, 17th and 18th features in the BRISQUE's feature vector to repeat 20 times respectively. Of course, there are many other good combinations. At the last, another new feature vector is constructed like $[Feature_{MSCN}, R((F_1,F_2,F_3,F_4),20)]$ and used to predict image quality. Although the vector has been lengthened, the features are the same as BRISQUE. The implementation details are in the Section 2.

2 Performance Evaluations

In this section, we use the LIVE IQA database to test the two feature vectors constructed in the above section and combine them to further improve the performance.

The LIVE IQA database consists of 29 reference images with 779 distorted images spanning five types of representative realistic distortions: JPEG2000 (JP2K) compression, JPEG compression, additive white Gaussian noise (WN), Gaussian blur (Blur), and fast-fading channel distortions (FF), along with the associated human differential mean opinion scores (DMOS), which are representative of the subjective quality.

Like BRISQUE, we require a regressor module by training the database. We divide the LIVE database into two randomly non-overlapping sets: a training set and a testing set. The training set consists of 80% of the reference images and their associated distorted images, and the testing set consists of the remaining 20% of the reference images and their associated distortions. Then we repeat the random train-test procedure 1 000 times and use the LIBSVM package to implement the SVR with a radial basis function (RBF) kernel [21].

In the Table 1~4, we compute Spearman's rank ordered correlation coefficient (SROCC), Kendall's rank ordered correlation coefficient (KROCC), Person's (linear) correlation coefficient (LCC) and root mean square error (RMSE) between the predicted scores from different algorithms and DMOS respectively. Before computing LCC and RMSE, the algorithm scores need to pass through a logistic non-linearity (15) as described in [22].

SROCC is defined as

$$SROCC = 1 - \frac{6\sum_{i=1}^{N} d_i^2}{N(N^2-1)} \tag{11}$$

where d_i is the difference between the i-th image's ranks in subjective and objective evaluations. It's a non-parametric rank order based correlation metric and independent of any monotonic nonlinear mapping between subjective and objective scores.

KROCC is defined as

$$KROCC = \frac{N_c - N_d}{N(N-1)/2} \tag{12}$$

where N_c and N_d are the numbers of concordant and discordant pairs in the data set respectively.

LCC is defined as

$$LCC = \frac{\sum_{i=1}^{N}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\overline{x})^2\sum_{i=1}^{N}(y_i-\overline{y})^2}} \tag{13}$$

It's computed after a nonlinear mapping between the subjective and objective scores by (15). Where x_i is the objective mapped score, y_i is the subjective score. $\overline{x}$ and $\overline{y}$ are the mean objective score and mean subjective score respectively.

RMSE can be computed as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-y_i)^2} \tag{14}$$

where x_i and y_i have the same as above.

Nonlinear mapping function is given by

$$f(x) = \frac{\beta_1-\beta_2}{1+e^{-(x-\beta_2)/|\beta_4|}} + \beta_5 \tag{15}$$

where the parameters β_1, β_2, β_3, β_4, β_5, are chosen to minimize the RMSE between the set of DMOS/MOS values $\{x_i\}$ and the corresponding set of transformed predicted values $\{f(x_i)\}$. The minimization is conducted under the constraint that $f(x)$ must be a monotonic function of x over the range of predicted values.

In the tables, there are four full-reference indices: PSNR, SSIM, MS-SSIM and VIF. PSNR is very simple and defined via the mean squared error (MSE). Although it's often used in literatures, its ability is limited during describing human perception and can't reflect the structure information of one image. The other three algorithms all make use of geometric structure.

The SSIM metric for the whole image can be computed as the mean of the local values calculated by using the sliding window approach. Its simplified formula can be described as

$$SSIM = \frac{(2\overline{xy}+C_1)(2\sigma_{xy}+C_2)}{(\sigma_x^2+\sigma_y^2+C_1)(\overline{x}^2+\overline{y}^2+C_2)} \tag{16}$$

where C_1 and C_2 are two small constants preventing the possible division by zero; $\overline{x}$ and $\overline{y}$ denote the mean values of the original and distorted image respectively; σ_x^2, σ_y^2 and σ_{xy} stand for the respective variances and the covariance for the currently analyzed fragments of both images.

MS-SSIM is a famous extension of SSIM. It's a multi-scale version using the dyadic pyramid. The luminance (l), contrast (c) and structure (s) factors are calculated for different scales and weighted using the specified exponents values. The final result of the MS-SSIM metric can be calculated as

$$MS\_SSIM = (l_M(x,y))^{\alpha_M} \cdot \prod_{j=1}^{M}((c_j(x,y))^{\beta_j}(s_j(x,y))^{\gamma_j}) \tag{17}$$

where M stands for the highest scale obtained after M–1 iterations of low-pass filtration and down-sampling by a factor of two. SSIM and MS-SSIM are two classical methods based on the image structure.

Based on NSS, the VIF metric utilizes the wavelet decomposition or the simplified one operates in the pixel domain. Both of them are correlated well with subjective perception of some typical image distortions. We can define the simplify metric as

$$VIF = \sum_{j=0}^{S}\sum_{i=1}^{M_j} I(c_{i,j}; f_{i,j}) / \sum_{j=0}^{S}\sum_{i=1}^{M_j} I(c_{i,j}; e_{i,j}) \quad (18)$$

where S is the number of sub-bands (or scales), M_j is the number of blocks at *j-th* sub-band (scale in the pixel domain) and $I(x;y)$ denotes the mutual information between x and y. The numerator and denominator are interpreted as the information that vision extracts from the distorted and reference images respectively. It is assumed that c denotes a block vector at a specified location in the reference image, e is the perception of block c by a human observer with additive noise n, and f is the perception of distorted block c.

Others in the table are no-reference algorithms indicated by Italics. DIIVINE and BRISQUE are two state-of-the-art algorithms. BRISQUE is statistically better than DIIVINE. STEP1 denotes the first step in IQA according to Section 1.1, and Step2 denotes the second step in IQA according to Section 1.2. In MIN, quality score is the minimum between Step 1 and Step 2, as min($score_{\text{Step 1}}$, $score_{\text{Step 2}}$). In BRISQUEs, quality score is the average between Step 1 and Step 2, as mean($score_{\text{Step 1}}$, $score_{\text{Step 2}}$).

From the four tables and Fig. 2, Step 1 and Step 2 both have made different level improvements. MIN and BRISQUEs are two different fused approaches based on Step 1 and Step 2, while BRISQUEs shows better performance. Compared with four FR algorithms, BRISQUEs is statistically superior to MS-SSIM on the LIVE IQA database. In addition, our method is better than some current NR algorithms, such as DIIVINE and BRISQUE. In [23-27], there are some available codes supplied by relevant authors.

Table 1 Median Spearman Rank Ordered Correlation Coefficient (SROCC) Across 1 000 Train-Test Combination on the LIVE IQA Database. Italics Indicate No-Reference Algorithms

	JP2K	JPEG	WN	BLUR	FF	ALL
PSNR	0.8954	0.8809	0.9854	0.7823	0.8907	0.8756
SSIM	0.9614	0.9764	0.9694	0.9517	0.9556	0.9479
MS-SSIM	0.9627	0.9815	0.9733	0.9542	0.9471	0.9513
VIF	0.9696	0.9846	0.9858	0.9728	0.9650	0.9636
DIIVINE	0.9018	0.9206	0.9822	0.9380	0.8813	0.9247
BRISQUE	0.9000	0.9642	0.9795	0.9453	0.8898	0.9391
Step 1	0.9272	0.9555	0.9762	0.9522	0.8936	0.9446
Step 2	0.9228	0.9690	0.9822	0.9466	0.8928	0.9480
MIN	0.9318	0.9689	0.9813	0.9586	0.8974	0.9510
BRISQUEs	0.9350	0.9678	0.9811	0.9554	0.9052	0.9536

Table 2 Median Kendal Rank Ordered Correlation Coefficient (KROCC) Across 1000 Train-Test Combination on the LIVE IQA Database. Italics Indicate No-Reference Algorithms

	JP2K	JPEG	WN	BLUR	FF	ALL
PSNR	0.7106	0.6912	0.8939	0.5847	0.7069	0.6865
SSIM	0.8239	0.8650	0.8523	0.8010	0.8207	0.7963
MS-SSIM	0.8252	0.8820	0.8649	0.8094	0.8102	0.8045
VIF	0.8473	0.8944	0.8981	0.8594	0.8395	0.8282
DIIVINE	0.7055	0.8148	0.8815	0.7813	0.7002	0.7790
BRISQUE	0.7012	0.8324	0.8709	0.7996	0.7086	0.7879
Step 1	0.7478	0.8081	0.8661	0.8174	0.7192	0.7979
Step 2	0.7399	0.8417	0.8841	0.8042	0.7123	0.8059
MIN	0.7536	0.8421	0.8795	0.8261	0.7249	0.8125
BRISQUEs	0.7597	0.8407	0.8803	0.8216	0.7330	0.8156

Table 3 Median Linear Correlation Coefficient (LCC) Across 1000 Train-Test Combination on the LIVE IQA Database. Italics Indicate No-Reference Algorithms

	JP2K	JPEG	WN	BLUR	FF	ALL
PSNR	0.8928	0.8867	0.9578	0.7721	0.8847	0.8723
SSIM	0.9665	0.9773	0.9591	0.9433	0.9542	0.9449
MS-SSIM	0.9683	0.9812	0.9688	0.9529	0.9454	0.9489
VIF	0.9720	0.9849	0.9866	0.9740	0.9618	0.9604
DIIVINE	0.9016	0.9322	0.9785	0.9189	0.8912	0.9243
BRISQUE	0.9032	0.9689	0.9800	0.9390	0.8977	0.9405
Step 1	0.9309	0.9625	0.9759	0.9510	0.8961	0.9447
Step 2	0.9247	0.9745	0.9815	0.9392	0.9064	0.9488
MIN	0.9377	0.9735	0.9846	0.9601	0.8987	0.9519
BRISQUEs	0.9407	0.9732	0.9846	0.9546	0.9144	0.9552

Table 4 Median Root Mean Square Error (RMSE) Across 1000 Train-Test Combination on the LIVE IQA Database. Italics Indicate No-Reference Algorithms

	JP2K	JPEG	WN	BLUR	FF	ALL
PSNR	11.8818	17.0090	9.2210	13.4298	13.4081	13.3597
SSIM	7.2157	10.7690	10.1938	7.2436	8.5370	8.9455
MS-SSIM	6.9748	9.8160	9.4530	7.1089	9.2840	8.6188
VIF	8.6417	8.0601	6.4238	6.0312	8.2670	7.6137
DIIVINE	10.3851	11.2369	5.9893	8.3216	13.5172	9.9859
BRISQUE	10.8688	8.1652	6.0175	7.6011	13.2162	9.5178
Step 1	9.2514	8.7126	6.3729	6.8691	13.2477	9.1995
Step 2	9.6146	7.4268	5.5626	7.4342	12.6173	8.8388
MIN	9.0740	7.3414	4.9335	5.5791	12.6430	8.3694
BRISQUEs	8.8456	7.3511	4.9001	5.9916	11.6169	8.0861

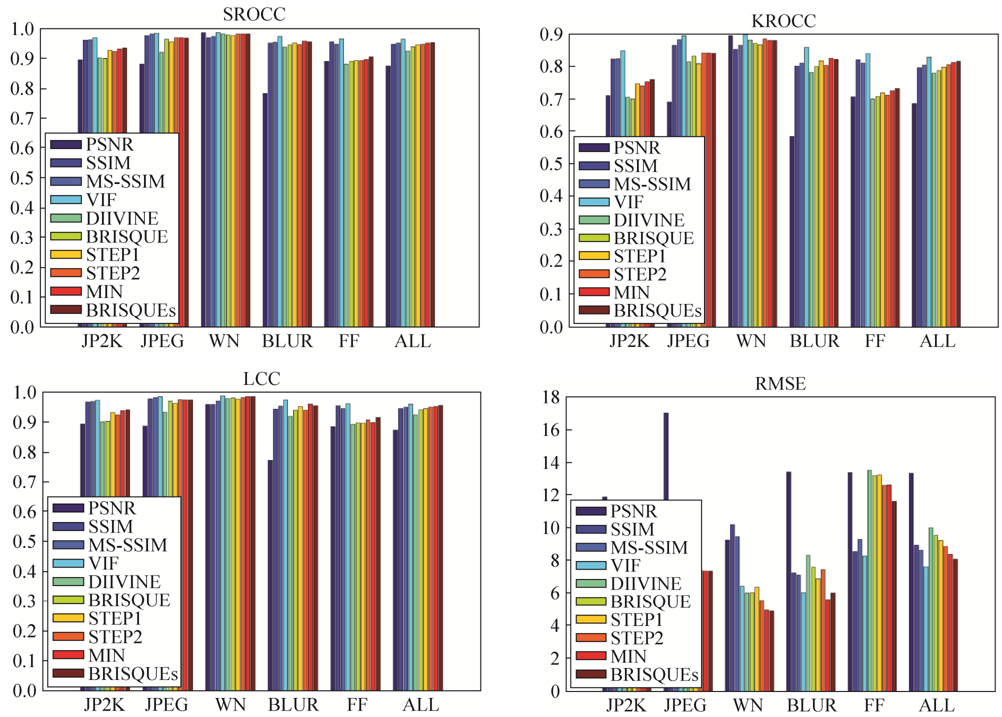

Fig. 2 The four subfigures correspond to the above four tables respectively

3 Conclusions

In the paper, we propose an improved NR-IQA algorithm BRISQUEs based on the state-of-the-art BRISQUE. The principle is that natural images possess certain regular statistics properties which are measurably modified by the present of distortions. The algorithm is purely spatial and a three-step framework. We apply MSCN to the gradient maps and weight some key features in the BRISQUE. BRISQUE is statistically better than PSNR and SSIM, but remains slightly inferior to MS-SSIM. While the statistical results show that our BRISQUEs is superior to MS-SSIM on the LIVE IQA database. Similarly to BRISQUE, BRISQUEs has very low computational complexity, making it well suited for real time applications. From the experiments, the method is not limited by the type of distortions that afflict the image. Its features may be used for distortion identification as well. We can apply the method not only to image quality assessment, but also to blind image denoising/ deblurring. It's an important tool in image processing. Up to now, NR-IQA is developing and becoming more comparable with FR-IQA, while there are a lot of difficulties still waiting for us to research.

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