A No-reference IQA Metric Based on BEMD and Riesz Tansform

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ABSTRACT

In recent years, the research of the no-reference (NR) image quality assessment (IQA) has been very active. But the NR-IQA research for noise-distorted images hasn't been proposed yet. In this paper, we propose a NR-IQA metric for noise-distorted images based on bidimensional empirical mode decomposition (BEMD) and Riesz transform, namely BRIQ index. Firstly, the denoised image is obtained by using the BEMD, Riesz transform and the visual contrast sensitivity function (CSF) to denoise the distorted image. Then the similarity calculation is performed using five Riesz transform feature maps of the distorted image and the denoised image. Finally, we combine these five similarity indices to obtain the final quality score for the distorted image. Experimental results on pubic database show that the BRIQ index evaluates the noise-distorted images with good performance, as consistent as subjective quality ratings.

CCS CONCEPTS

•**Human-centered computing** → Visualization design and evaluation methods;

KEYWORDS

no-reference, image quality assessment, bidimensional empirical mode decomposition, Riesz transform, human visual system

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1 INTRODUCTION

With the booming development of digital technology and multimedia communication, image quality assessment (IQA) research has raised a lot of attention in the past 20 years[6]. IQA can be divided into subjective assessment and objective assessment. Considering that the subjective IQA is unadaptable to industrial practical applications [17], the objective IQA has become the main research content in this field. According to the presence or absence of the reference image, the IQA can be divided into full-reference (FR), reduced-reference (RR), and no-reference (NR) assessment[18].

As it's hard to obtain reference image in practical application, the study of NR-IQA has been very active in recent years. The NR-IQA can usually be divided into application-specific assessment and general purpose assessment. Considering that the general purpose NR-IQA is more difficult, most of the current studies focus on the application-specific assessment. Common types of distortion include JPEG compression distortion, blur distortion, noise distortion, and so on. Noise is an important factor in image distortion, but no studies investigated into this area previously, this paper is devoted to the study of NR-IQA for noise-distorted images with the human visual system (HVS) taken into consideration.

Empirical mode decomposition (EMD) is a signal processing method for non-stationary signal analysis proposed by Norden E. Huang *et al.*[5]. It can clearly distinguish the intrinsic mode functions (IMFs) of overlapping complex data without pre-setting the basis function as a wavelet decomposition. Nunes *et al.*[11] extended the one-dimensional EMD method to bidimensional application and proposed the bidimensional empirical mode decomposition (BEMD). As the research of the local feature analysis for IMF by Riesz transform[1], the function of Riesz transform has become more and more important in image processing. Considering the effect of BEMD on noise deduction when combined with Riesz transform[3], we propose a NR-IQA metric for noise-distorted images. We use this method to get denoised images from distorted images, and then compute feature maps corresponding to distorted and denoised images. Five similarity indices are obtained after the similarity caculation of feature maps. Finally, similarity indices are weighted and summed to obtain the final IQA score.

This paper is organized as follows: Section 2 first introduces the structural block diagram of the proposed NR-IQA metric, then introduces the BEMD. A brief introduction on Riesz transform and visual contrast sensitivity function (CSF) will also be included in this section. Finally the calculation formula of the proposed BRIQ index based on BEMD and Riesz Transform is obtained. Section 3 contains experimental analysis. Section 4 concludes this paper.

2 THE PROPOSED ALGORITHM

In this paper, the block diagram of the proposed BRIQ index based on BEMD and Riesz transform is shown in Figure 1. The distorted image f is firstly decomposed by BEMD to obtain four image components $IMF1$, $IMF2$, $IMF3$, and $RESIDUE$. Then, Log-Gabor filter[10], first-order and second-order Riesz transform[8] are used on each component, and five groups of feature maps (each group of feature maps contains 4 image components) are obtained. The four image components in one group are weighted by CSF to get the feature maps $R_x\{g\}$, $R_y\{g\}$, $R_{xx}\{g\}$, $R_{xy}\{g\}$, and $R_{yy}\{g\}$ of denoised image g, which can be denoted as g_1, g_2, g_3, g_4, and g_5. At the same time, we obtain the five feature maps $R_x\{f\}$, $R_y\{f\}$, $R_{xx}\{f\}$, $R_{xy}\{f\}$, and $R_{yy}\{f\}$ by using Log-Gabor filter, first-order and second-order Riesz transform on the distorted image f, which can be denoted as f_1, f_2, f_3, f_4 and f_5. We calculate similarity on feature maps to acquire five similarity maps and use the average method to obtain five similarity indices $S_i(i = 1, 2, ..., 5)$. The five similarity indices are weighted and summed to obtain the final IQA score.

2.1 Bidimensional Empirical Mode Decomposition (BEMD)

For bidimensional $M \times N$ image signal $f(x, y)$, $x = 1, ..., M$, $y = 1, ..., N$, BEMD implementation process[12] is shown as follows:

(1) Use 8 neighborhood pixels to find the local extreme point (maximum and minimum) of the image surface.
(2) Use the cubic spline interpolation metric to obtain the upper envelope $\mu_{max}(x, y)$ and the lower envelope $\mu_{min}(x, y)$ of the image surface.
(3) Determine the mean of the upper and lower envelopes $m(x, y)$.
(4) Subtract the mean envelope $m(x, y)$ from the image $f(x, y)$:

$$h(x, y) = f(x, y) - m(x, y) \tag{1}$$

(5) Determine whether $h(x, y)$ satisfies the IMF screening termination condition:

$$SD = \sum_{x=0}^{M}\sum_{y=0}^{N} \frac{|h_j(x, y) - h_{j-1}(x, y)|^2}{{h_{j-1}}^2(x, y)} \tag{2}$$

Here we set $SD = 0.2$.

Repeat from step 1 to step 5 until the criterion is satisfied, so we can obtain the first layer of the bidimensional IMF $IMF1$ $c_1(x, y)$. The first layer residue $r_1(x, y)$ is obtained by subtracting $IMF1$ from the original image. The IMF $c_j(x, y)(j = 2, ..., K)$ and the K layer residua $r_K(x, y)$ are obtained successively when repeating step 1 to step 5 on the residue.

The final BEMD result is:

$$f(x, y) = \sum_{j=1}^{K} c_j(x, y) + r_K(x, y) \tag{3}$$

As the fact that the feature scale parameter is the actual measured data, the components obtained by the above method have obvious physical meaning, which characterizes the fluctuation and the frequency range of the signal on a certain feature scale parameter[16]. The image is decomposed, in the scale from small to large, into a series of detailed information in the order of "fine to coarse" and the large-scale trend information[7].

2.2 Riesz Transform

For the image $f(x, y)$, the first order Riesz transform can be expressed as:

$$f_R(x, y) = \begin{pmatrix} f_x(x, y) \\ f_y(x, y) \end{pmatrix} = \begin{pmatrix} R_x * f(x, y) \\ R_y * f(x, y) \end{pmatrix} = \begin{pmatrix} R_x\{f\}(x, y) \\ R_y\{f\}(x, y) \end{pmatrix} \tag{4}$$

where (R_x, R_y) represents the Riesz nucleus in the spatial domain.

Using the first-order Riesz transform, we can extract the local linear features of the image, but we can not express the corner points and intersection points in the image[19]. In order to characterize the various low-level features existing in the image, it is necessary to use higher order Riesz transform. In this paper, we use the second-order Riesz transform to express more complex features:

$$\begin{cases} R_{xx}\{f\}(x, y) = R_x\{R_x\{f\}\}(x, y) \\ R_{xy}\{f\}(x, y) = R_x\{R_y\{f\}\}(x, y) \\ R_{yy}\{f\}(x, y) = R_y\{R_y\{f\}\}(x, y) \end{cases} \tag{5}$$

Feature maps $f_i(i = 1, 2, ..., 5)$ are obtained by Log-Gabor filter, first-order and second-order Riesz transform of the distorted image respectively. Feature maps $g_{ij}(i = 1, 2, ..., 5; j = 1, 2, 3, 4)$ are obtained by using the same method on four image components $IMF1, IMF2, IMF3$ and $RESIDUE$.

2.3 Visual Contrast Sensitivity Function (CSF)

At present, physiology and psychology has established a variety of HVS models to simulate the significant features of visual perception. Since CSF can reflect the subjective visual

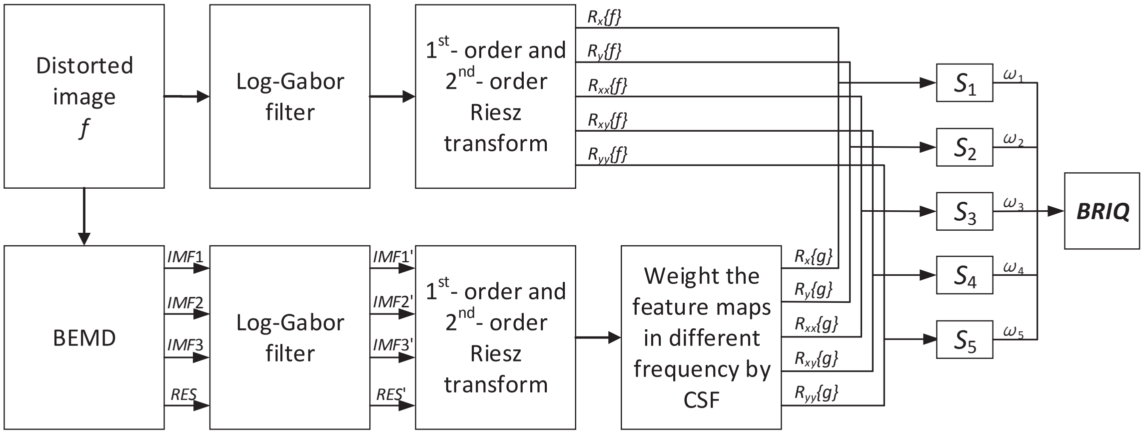

Figure 1: Illustration of the Proposed BRIQ Index.

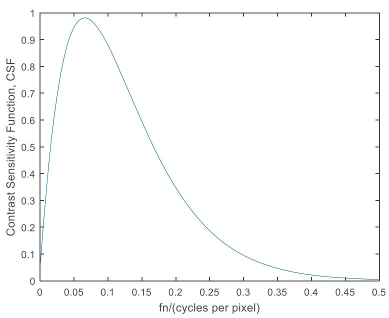

Figure 2: Curve of contrast sensitivity function.

experience, it has been applied to many IQA metrics [4]. In this paper, we use the CSF model proposed by Mannos *et al.* [9]:

$$A(f_r) \approx 2.6(0.0192 + 0.114 f_r) \exp^{-(0.114 f_r)^{1.1}} \tag{6}$$

where f_r is the spatial frequency, in units of cycle per degree. As the spatial frequency f_r is the function of the image size and distance, we normalize it as $f_n \in [0, 0.5]$. The feature curve of normalized CSF is shown in Fig. 2.

It can be seen from the CSF curve in Fig. 2 that the contrast sensitivity of the CSF curve is larger at the intermediate frequency region than that at the low frequency and high frequency regions. The decomposed distorted image by BEMD have four components: $IMF1$, $IMF2$, $IMF3$ and $RESIDUE$, the main information of which are in different frequency. It is obvious that the contrast sensitivity of HVS among them is different too. In order to make the final assessment result more close to the subjective perception, we can use CSF to weight the different image components.

Assuming that the contrast sensitivity of corresponding image components, $IMF1$, $IMF2$, $IMF3$, and $RESIDUE$, are $CSF_j(j = 1, 2, 3, 4)$, respectively. Then:

$$g_i = \sum_{j=1}^{4} g_{ij} \cdot CSF_j \tag{7}$$

among them, $g_i(i = 1, 2, ..., 5)$ are five feature maps of the denoised image g. In this paper, $CSF_j(j = 1, 2, 3, 4)$ are determined as: $CSF_1 = 0.12$, $CSF_2 = 0.98$, $CSF_3 = 0.13$, $CSF_4 = 0.01$.

2.4 BRIQ Index

The similarity map calculation formula is defined as[18]:

$$s_i(x, y) = \frac{2 f_i(x, y) g_i(x, y) + C_i}{{f_i}^2(x, y) + {g_i}^2(x, y) + C_i} \tag{8}$$

where $s_i(x, y)$ is the similarity map of f_i and $g_i(i = 1, 2, ..., 5)$. $f_i(x, y)$ and $g_i(x, y)$ are the pixel values of the feature maps f_i and g_i at (x, y), respectively. $C_i(i = 1, 2, ..., 5)$ are very small positive values to avoid the instability caused by the denominator being zero or close to zero. In this paper, we take $C_i = 0.01(i = 1, 2, ..., 5)$.

After obtaining the five similarity maps, we use the following average formula to obtain five similarity indices:

$$S_i = \frac{\sum_{x=1}^{M} \sum_{y=1}^{N} s_i(x, y)}{M \times N} \tag{9}$$

among which $S_i(i = 1, 2, ..., 5)$ are taken as the similarity indices of feature maps f_i and g_i.

Finally, we use $SROCC_i(i = 1, 2, ..., 5)$ as the weight of the five similarity indices $S_i(i = 1, 2, ..., 5)$ which is obtained by fitting the similarity indices $S_i(i = 1, 2, ..., 5)$ of each feature map with DMOS respectively, and the final IQA score can be defined as:

$$BRIQ = \frac{\sum_{i=1}^{5} SROCC_i \cdot S_i}{\sum_{i=1}^{5} SROCC_i} \tag{10}$$

where $SROCC_i(i = 1, 2, 3, 4, 5)$ are determined as: $SROCC_1 = 0.9569$, $SROCC_2 = 0.9530$, $SROCC_3 = 0.9686$, $SROCC_4 = 0.9536$, $SROCC_5 = 0.9560$.

3 EXPERIMENTAL ANALYSIS

In order to verify the performance of BRIQ index, we ran tests on LIVE database[15]. The LIVE database contains 29 reference images and 779 distorted images, whose distortion

Table 1: Performance Comparison of SROCC/KROCC/PLCC/RMSE on Live Database

Model	FR/NR	LIVE			
		SROCC	KROCC	PLCC	RMSE
PSNR	FR	0.985	0.894	0.980	5.551
SSIM	FR	0.964	0.852	0.983	5.135
FSIM	FR	0.965	0.839	0.972	6.590
FRIQUEE	NR	0.982	0.886	0.898	12.287
BLIINDSII	NR	0.960	0.826	0.969	6.896
BRIQ	NR	0.967	0.847	0.976	6.059

types include JPEG2000, JPEG compression, white noise, Gaussian blur and Rayleigh fading. The database provides the Differential Mean Opinion Scores (DMOS) for each image, and smaller DMOS value represents higher image quality.

In this paper, 5-parameter nonlinear logistic regression function is used to fit the data[14]. The performance of the metric is evaluated by four assessment indices[2]: Spearman rank-order correlation coefficient (SROCC), Kendall rank-order correlation coefficient (KROCC), Pearson linear correlation coefficient (PLCC), and root mean squared error (RMSE).

$$f(x) = \beta_1[\frac{1}{2} - \frac{1}{1+\exp(\beta_2(x-\beta_3))}] + \beta_4 x + \beta_5 \qquad (11)$$

where x is the objective IQA score, $f(x)$ is the IQA regression fitting score, β_1, β_2, β_3, β_4 and β_5 are regressing function parameters.

Table 1 lists out the different IQA metrics for LIVE database. As can be seen from Table 1, BRIQ index has great performance on LIVE database.

Figure 3 shows the scatter plots of four different metrics for noise-distorted images in the LIVE database, where SSIM[18] and FSIM[20] are classical FR-IQA metrics, and BLIINDSII[13] and BRIQ proposed in this paper are NR-IQA metrics. It can be seen from Figure 3 that the scatter plot of the algorithm BRIQ is evenly distributed in the whole coordinate system and has a strong linear relationship with DMOS, which proves the robust performance of BRIQ index.

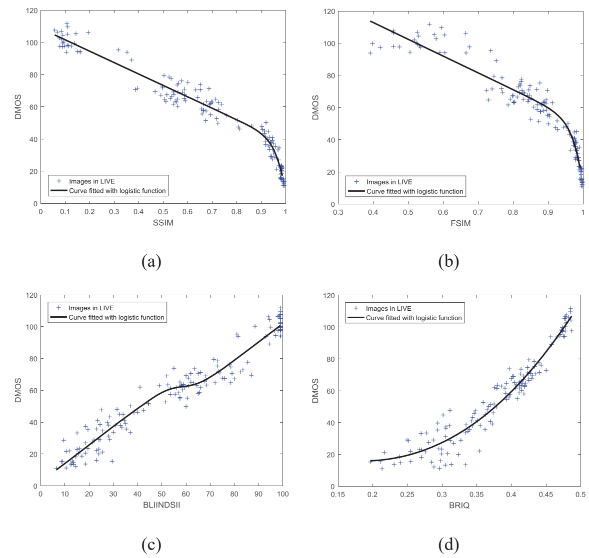

Figure 3: Scatter plots of predicted quality scores on LIVE database. From left to right, top to bottom are respectively the (a) SSIM, (b) FSIM, (c) BLIINDSII and (d) BRIQ.

4 CONCLUSIONS

In this paper, an effective NR-IQA metric for noise-distorted images named BRIQ index is proposed by combining BEMD and Riesz transform with appropriate application of CSF curve. The metric is tested on LIVE database, and the scatter plots experiment is carried out on LIVE database. The experimental results show that the BRIQ index has a good performance in evaluating the noise-distorted images.

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