A NOVEL BLIND IMAGE QUALITY ASSESSMENT METHOD BASED ON REFINED NATURAL SCENE STATISTICS

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Abstract

In this paper, a novel blind IQA method (NBIQA) based on refined NSS is proposed. The proposed NBIQA first investigates the performance of a large number of candidate features from both the spatial and transform domains. Based on the investigation, we construct a refined NSS model by selecting competitive features from existing NSS models and adding three new features. Then the refined NSS is fed into SVM tool to learn a simple regression model. Finally, the trained regression model is used to predict the scalar quality score of the image. Experimental results tested on both LIVE IQA and LIVE-C databases show that the proposed NBIQA performs better in terms of synthetic and authentic image distortion than current mainstream IQA methods.

Introduction

- Blind image quality assessment has been an increasing important and challenging issue in image communication engineering.
- Natural images have strong statistical regularities. Researchers set about designing natural scene statistics (NSS) model to capture those statistical.
- However, most existing methods construct the NSS model by extracting some distortion-specific features either from spatial domain or from transform domain.

The Proposed Method

The framework of the proposed method is shown in Fig. 1. We extract features from both spatial and transform domains to construct a refined NSS model.

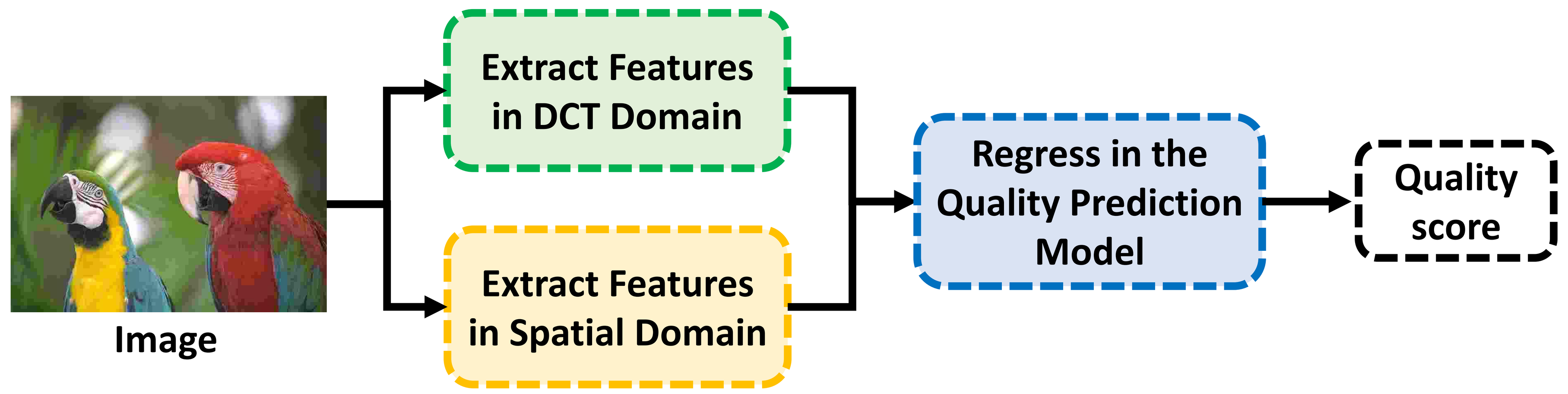


Fig. 1. Overview of the proposed NBIQA framework.

- **Feature Selection from Transform Domain**

(1). Based on Benford's law: Benford's law states that for a set of data from real life the distribution of leading digits satisfies.

$$p(n) = \log_m(1+\frac{1}{n}), n = 1, 2, ..., m-1,$$

where m is defined as a particular number in different bases. Take decimal number system as an example. The distribution is show in Table I. We find that the distribution of leading digits of full image DCT coefficients is in line with the ground truth quality score. Therefore, we introduce Euclidean distance to measure the deviation between two distributions, we take an instance and drawn in Fig. 2.

Table I. The distribution (%) in Benford's law for decimal number system.

n	1	2	3	4	5	6	7	8	9
$p(n)$	30.1	17.6	12.5	9.7	7.9	6.7	5.8	5.1	4.6

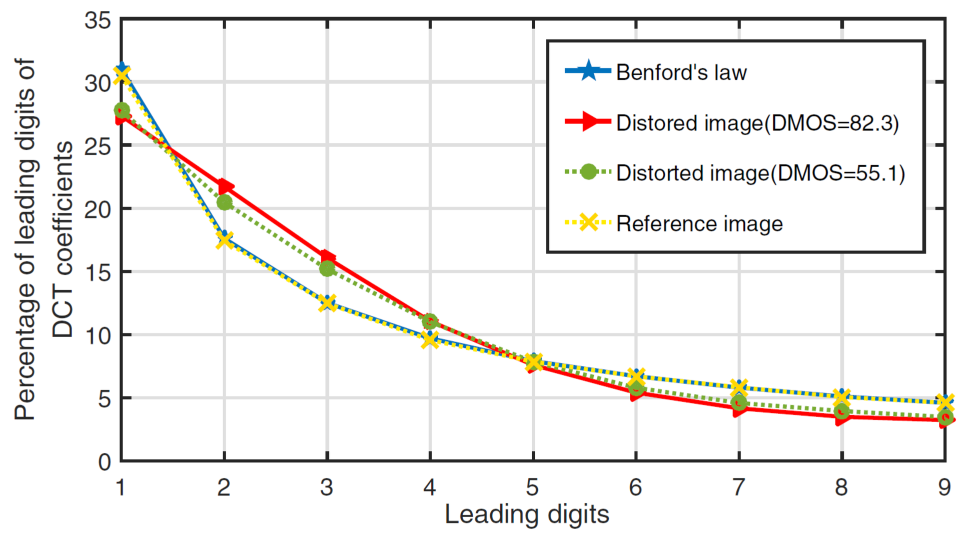


Fig. 2. Histograms of leading digits of DCT coefficients

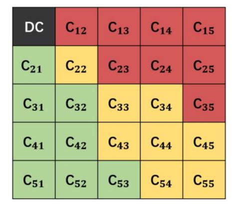
(2). Based on DCT energy: The DCT coefficients of each 5 x 5 block can be divided into 3 energy subbands.

(a). The energy subband ratio of each block is calculated by

$$R_n = \frac{|\sigma_n^2 - \frac{1}{n-1}\sum_{j<n}\sigma_j^2|}{\sigma_n^2 + \frac{1}{n-1}\sum_{j<n}\sigma_j^2},$$

(b). The frequency variation of each block is calculated by

$$\zeta_j = \frac{\sigma_j}{\mu_j},$$



where $n = 2, 3$; $j = 1, 2, 3$; $\sigma_{n/j}$ denotes the energy of the n/j-th subband; μ_j is the mean of the j-th DCT coefficient magnitudes.

- **Feature Selection from Spatial Domain**

(1). Based on generalized Gaussian distribution (GGD): For a color image I, we first compute a locally normalized luminance image: $L(i,j) = \frac{I(i,j) - u(i,j)}{\sigma(i,j)+1}$, where, $u(i,j) = \sum_{l=-3}^{3}\sum_{k=-3}^{3} w_{k,l} I(i-k, j-l)$, and $\sigma^2(i,j) = \sum_{l=-3}^{3}\sum_{k=-3}^{3} w_{k,l}[I_{k,l}(i,j) - u(i,j)]^2$, $w_{k,l}$ is a 2-D Gaussian lowpass weighting filter. And L can be strongly fitted by generalized Gaussian distribution (GGD): $f(x;\alpha,\sigma^2) = \frac{\alpha}{2\beta\Gamma(1/\alpha)}\exp(-(\frac{|x|}{\beta})^\alpha)$, where, $\beta = \sigma\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$, and $\Gamma(\cdot)$ denotes a Gamma function. The GGD shape parameter α and similar variance σ^2 are calculated as features.

(2). Based on asymmetrical GGD: we compute the pairwise product of neighboring L (PPON-L), they can be fitted by asymmetrical GGD (AGGD):

$$f(x;v,\sigma_l^2,\sigma_r^2) = \begin{cases} \frac{v}{(\beta_l+\beta_r)\Gamma(1/v)}\exp(-(\frac{-x}{\beta_l})^v) & x<0 \\ \frac{v}{(\beta_l+\beta_r)\Gamma(1/v)}\exp(-(\frac{-x}{\beta_l})^v) & x \geq 0 \end{cases},$$

where $\beta_l = \sigma_l\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$, $\beta_r = \sigma_r\sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$ compute $\eta = (\beta_r - \beta_l)\Gamma(1/v)/\Gamma(3/v)$

(3). Based on image entropy: The entropy e of I can be computed by $e = -\sum p_j(I)\log_2 p_j(I)$, where p_j is probability of intensity value j in I. Then we can compute the probability $p(e) = \frac{1}{\sqrt{2\pi}\sigma}\exp(\frac{-(e-\mu)^2}{2\sigma^2})$.

Experiment Result

Five mainstream NSS-based NR-IQA methods are used for comparison, and we adopt SROCC and LCC to measure the performance of methods. The experiments result on the LIVE are shown in Table II and Fig. 3. Moreover, the performance on LIVE-C are shown in Table III and Fig. 4.

Table II. Mean SROCC over 1000 trials on LIVE database.

Method	JP2K	JP	WN	GB	FF	All
DIIVINE [2]	0.913	0.910	0.984	0.921	0.863	0.916
CORNIA [5]	0.927	0.944	0.961	0.955	0.910	0.942
BLIINDS-II [4]	0.934	0.942	0.953	0.898	0.879	0.917
BRISQUE [3]	0.931	0.921	0.961	0.962	0.889	0.941
NIQE [6]	0.917	0.938	0.966	0.934	0.859	0.914
Proposed NBIQA	0.951	0.940	0.977	0.964	0.921	**0.959**

Table III. Mean SROCC and LCC on LIVE-C database.

Method	SROCC	PLCC
DIIVINE [2]	0.58±0.04	0.60±0.03
CORNIA [5]	0.61±0.03	0.62±0.04
BLIINDS-II [4]	0.45±0.06	0.46±0.06
BRISQUE [3]	0.59±0.04	0.61±0.04
NIQE [6]	0.43±0.04	0.45±0.05
Proposed NBIQA	**0.63±0.03**	**0.64±0.03**

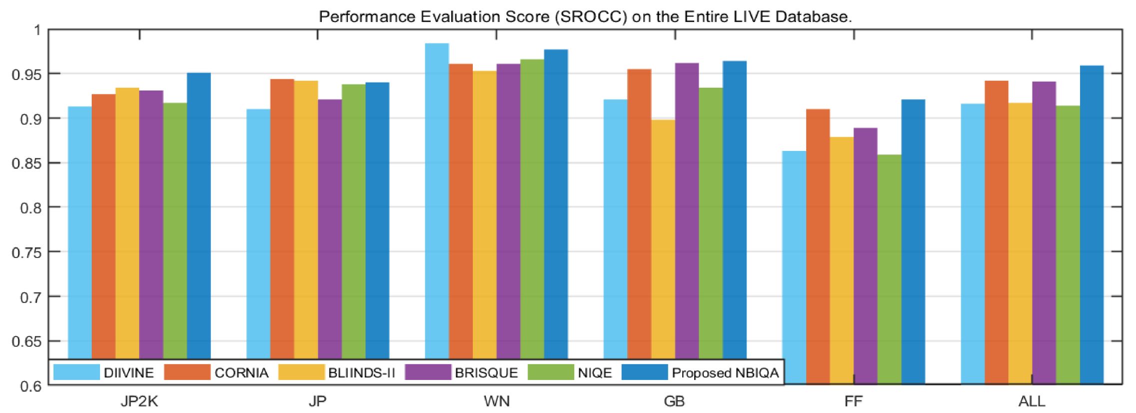


Fig. 3. Histogram of SROCC over 1000 trials on LIVE database.

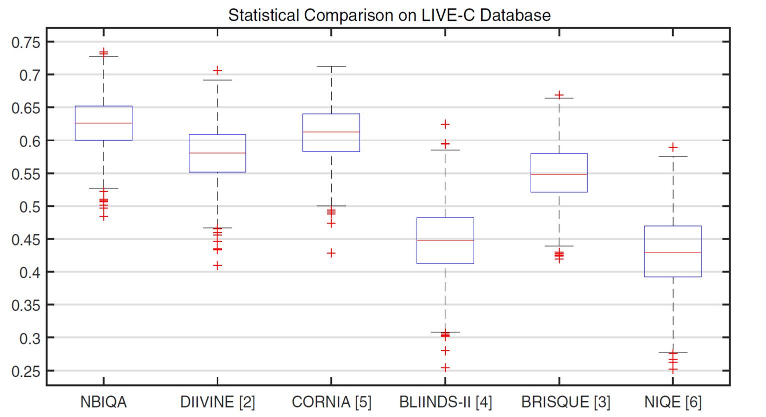


Fig. 4. Box plot of SROCC distributions.

Conclusion

In this paper, we have proposed a novel blind image quality assessment method (NBIQA). The experimental results show the proposed NBIQA method not only obtains the stable performance in evaluating the synthetically distorted images, but also has a significant improvement in evaluating authentically distorted images compared with the five current mainstream NR-IQA methods. In future work, we would like to apply the proposed NBIQA method to evaluate the quality of natural images generated by adversarial learning.