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Informal Complexity Analysis of Image Quality Based on Human Visual System

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Abstract: In this study, we propose NRDPF-IQA (No Reference Distortion Patch Features Image Quality Assessment) Model, aims to use to measure the image quality assessment for JPEG2000. The proposed method takes advantage over the other existing image quality assessment metrics of the contrast changes in the image quality. The proposed quality metric was tested by using LIVE image database and CSIQ image database. The experimental results show that the new index performance compared with the other NR-IQA Models that require training on LIVE databases, CSIQ database and TID database.

Key words: No reference, NRDPF-IQA, JPEG2000, live, CSIQ, TID

INTRODUCTION

The performance of any IQA Model is best gauged by its correlation with human subjective judgements of quality, since the human is the ultimate receiver of the visual signal, discussed by Li *et al.* (2011). Such, human opinions of visual quality are generally obtained by conducting large-scale human studies, referred to as subjective quality assessment where human observers rate a large number of distorted (and possibly reference) signals introduced by Mittal *et al.* (2012). When the individual opinions are averaged across the subjects, a Mean Opinion Score (MOS) or Differential Mean Opinion Score (DMOS) is obtained for each of the visual signals in the study (Sheikh *et al.*, 2005) where the MOS/DMOS is representative of the perceptual quality of the visual signal. The goal of an objective Quality Assessment (QA) algorithm is to predict quality scores for these signals such that the scores produced by the algorithm correlate well with human opinions of signal quality (MOS/DMOS) discussed by Sheikh and Bovik (2006). Practical application of QA algorithms requires that these algorithms compute perceptual quality efficiently. The Spearmans Rank Ordered Correlation Coefficient (SROCC) and pearsons (Linear) Correlation Coefficient (LCC) between the predicted score from the algorithm and DMOS are generally used to access QA performance, discussed by Mittal *et al.* (2012, 2013).

Typically, QoE algorithms are classified on the basis of the amount of information that is available to the algorithm. This study will focus on NRDPF-IQA (No Reference Distortion Patch Features-Image Quality Assessment) algorithm. Blind or No-Reference (NR) QA refers to automatic quality assessment of an image/video using an algorithm which only utilizes the distorted image/video whose quality is being assessed. NR QA approaches are further classified on the basis of whether the algorithm had access to subjective/human opinion prior to deployment discussed by Moorthy and Bovik (2010). Algorithms which use machine learning techniques along with human judgements of quality during the 'training' phase may be labelled 'opinion aware' algorithms (Moorthy and Bovik, 2010, 2011).

MATERIALS AND METHODS

Most existing blind IQA Models proposed in the past assume that the image whose quality is being assessed is afflicted by a particular kind of distortion (Saad *et al.*, 2010). These approaches extract distortion specific features that relate to loss of visual quality such as edge-strength at block-boundaries. However, a few

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general purpose approaches for NR IQA have been proposed recently. Li devised a set of heuristic measures to characterize visual quality in terms of edge sharpness, random noise and structural noise while Gabarda and Cristobal, modeled anisotropies in images using renyi entropy. Researchers use gabor filter based local appearance descriptors to form a visual codebook and learn DMOS score vector associating each word with a quality score. However, in the process of visual codebook formation each feature vector associated with an image patch is labeled by DMOS assigned to the entire image. This is questionable as each image patch can present a different level of quality depending on the distortion process the image is afflicted with (Saad *et al*., 2011). In particular, local distortions such as packet loss might afflict only a few image patches. Also, the approach is computationally expensive limiting its applicability in real time applications. Saad *et al*. (2012) proposed an approach which learns an ensemble of regressors trained on three different groups of features natural image statistics, distortion texture statistics and blur/noise statistics. Another approach is based on a hybrid of curvelet, wavelet and cosine transforms (Saad *et al*., 2011). Although, these approaches work on a variety of distortions, each set of features (in the first approach) and transforms (in the second) caters only to certain kinds of distortion processes. This limits the applicability of their framework in images and videos to new distortions discussed by Seshadrinathan and Bovik (2010).

We have also developed previous NR QA Models in the past, following the philosophy, first fully developed by Saad *et al*. (2010, 2012) that NSS models provide powerful tools for probing human judgements of visual distortions. NSS based FR QA algorithms, more recent RR Models and very recent research on NSS based NR QA (Mittal *et al*., 2012) have led us to the conclusion that visual features derived from NSS lead to particularly potent and simple QA Models (Mittal *et al*., 2012). Recently, proposed NSS based NR IQA Model, dubbed the Distortion Identification-based Image INtegrity and Verity Evaluation (DIIVINE) index and BRISQUE, deploys summary statistics derived from an NSS Wavelet Coefficient Model, using a two stage framework for QA: distortion-identification followed by distortion-specific QA. The BRISQUE index performs quite well on the LIVE IQA database, achieving statistical parity with the full-reference Structural Similarity (SSIM) index (Chen and Bovik, 2011). A complementary approach developed at the same time; named Blind Image Notator using DCT Statistics (BLIINDS-II index) is a pragmatic approach to NR IQA that operates in the DCT domain where a small number of features are computed from an NSS Model of block DCT coefficients (Soundararajan and Bovik, 2012). Efficient NSS features are calculated and fed to a regression function that delivers accurate QA predictions. BLIINDS-II is a single-stage algorithm that also delivers highly competitive QA prediction power. Although, BRISQUE index is multiscale, the small number of feature types 4 allows for efficient computation of visual quality and hence the index is attractive for practical applications. While, both DIIVINE and BRISQUE deliver top NR IQA performance (to date) each of them has certain limitations (Mittal *et al*., 2012). The large number of features that BRISQUE computes implies that it may be difficult to compute in real time. Although, BRISQUE is more efficient than BLIINDS, it requires nonlinear sorting of block based NSS features which slows it considerably. In the continued search for fast and efficient high performance NR-IQA indices, we have designed NRDPF-IQA algorithm to find the quality of the image without reference.

Complexity analysis of image: The approach for the NR IQA that we have developed can be summarized as follows. Given a (possibly distorted) image, first compute locally normalized luminance via local mean subtraction and divisive normalization. The following are the equations to applied to a given intensity image:

$$H : \nabla_x I(i,j) = I(i,j+1) - I(i,j) \quad (1)$$

$$V : \nabla_y I(i,j) = I(i+1,j) - I(i,j) \quad (2)$$

$$MD: \nabla_{xy} I(i,j) = I(i+1,j+1) - I(i,j) \quad (3)$$

$$SD: \nabla_{yx} I(i,j) = I(i+1,j-1) - I(i,j) \quad (4)$$

$$HV : \nabla_x \nabla_y I(i,j) = I(i-1,j) + I(i+1,j) - I(i,j-1) - I(i,j+1) \quad (5)$$

$$CD_1 : \nabla_{cx} \nabla_{cy} I(i,j)_1 = I(i,j) + I(i+1,j+1) - I(i,j+1) - I(i+1,j) \quad (6)$$

$$CD_2 : \nabla_{cx} \nabla_{cy} I(i,j)_2 = I(i-1,j-1) + I(i+1,j+1) - I(i-1,j+1) - I(i+1,j-1) \quad (7)$$

$$J(i,j) = \log[I(i,j) + K] \quad (8)$$

$$D_1 : \nabla_x J(i,j) = J(i,j+1) - J(i,j) \quad (9)$$

$$D_2 : \nabla_y J(i,j) = J(i+1,j) - J(i,j) \tag{10}$$

$$D_3 : \nabla_{xy} J(i,j) = J(i+1,j+1) - J(i,j) \tag{11}$$

$$D_4 : \nabla_{yx} J(i,j) = J(i+1,j-1) - J(i,j) \tag{12}$$

$$D_5 : \nabla_x \nabla_y = J(i-1,j) + J(i+1,j) - J(i,j-1) - J(i,j+1) \tag{13}$$

$$D_6 : \nabla_{cx} \nabla_{cy} J(i,j)_1 = J(i,j) + J(i+1,j+1) - J(i,j+1) - J(i+1,j) \tag{14}$$

$$D_7 : \nabla_{cx} \nabla_{cy} J(i,j)_2 = J(i-1,j-1) + J(i+1,j+1) - J(i-1,j+1) - J(i+1,j-1) \tag{15}$$

Equation 1-15 represent the features of the distortion patches. It also observed that the normalized luminance values strongly tend towards a unit normal Gaussian characteristic for images:

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \tag{16}$$

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l} I_{k,l} I(i,j) \tag{17}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l} (l_{k,l} I(i,j) - \mu(i,j))^2} \tag{18}$$

$$f(x;\alpha,\sigma^2) = \frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)} \exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right) \tag{19}$$

$$\beta = \alpha \sqrt{\frac{\Gamma\left(\frac{1}{\alpha}\right)}{\Gamma\left(\frac{3}{\alpha}\right)}} \tag{20}$$

$$\Gamma(a) = \int_0^1 t^{a-1} e^{-t} dt \qquad a > 0 \tag{21}$$

$$H(i,j) = \hat{I}(i,j)\hat{I}(i,j+1) \tag{22}$$

$$V(i,j) = \hat{I}(i,j)\hat{I}(i+1,j) \tag{23}$$

$$D_1(i,j) = \hat{I}(i,j)\hat{I}(i+1,j+1) \tag{24}$$

$$D_2(i,j) = \hat{I}(i,j)\hat{I}(i+1,j-1), \quad i \in \{1, 2, \ldots, M\},\ j \in \{1, 2, \ldots, N\} \tag{25}$$

$$f(x,\rho) = \frac{\exp\left(\frac{|x|\rho}{1-\rho^2}\right) k_0 \left(\frac{|x|}{1-\rho^2}\right)}{\Pi\sqrt{1-\rho^2}} \qquad x < 0 \tag{26}$$

$$f(x,\nu,\sigma_l^2 \sigma_r^2) = \begin{cases} \dfrac{\nu}{\beta_l + \beta_r \Gamma\left(\frac{1}{\nu}\right)} \exp\left(-\left(\dfrac{x}{\beta_r}\right)^{\nu}\right) \\ \dfrac{\nu}{\beta_l + \beta_r \Gamma\left(\frac{1}{\nu}\right)} \exp\left(-\left(\dfrac{x}{\beta_r}\right)^{\nu}\right) \end{cases} \tag{27}$$

For $x \geq 0$

$$\beta_l = \sigma_l \sqrt{\frac{\Gamma\left(\frac{1}{\nu}\right)}{\Gamma\left(\frac{3}{\nu}\right)}} \tag{28}$$

$$\beta_r = \sigma_r \sqrt{\frac{\Gamma\left(\frac{1}{\nu}\right)}{\Gamma\left(\frac{3}{\nu}\right)}} \tag{29}$$

$$\eta = \frac{(\beta_r - \beta_l)\left(\Gamma\left(\frac{2}{\nu}\right)\right)}{\Gamma\left(\frac{1}{\nu}\right)} \tag{30}$$

$$b_0 = \frac{\sum_{i=1}^{N} x_{(i)}}{N} \tag{31}$$

$$b_r = \frac{\sum_{i=r+1}^{N} \frac{(i-1)(i-2)\ldots(i-r)}{(n-1)(n-2)\ldots(n-r)} X_{(i)}}{N} \tag{32}$$

$$l_1 = b_0 \tag{33}$$

$$l_2 = 2b_1 - b_0 \tag{34}$$

$$l_3 = 6b_2 - 6b_1 + b_0 \tag{35}$$

$$l_4 = 20b_3 - 30b_2 + 12b_1 - b_0 \tag{36}$$

Thus for each paired product, 36 parameters (6 parameters/orientation x 6 orientations) are computed, yielding the next set of features.

RESULTS AND DISCUSSION

We used LIVE IQA database, TID database and CSIQ database to test the performance of NRDPF-IQA algorithm, LIVE IQA database which consisting of 982 images in different categories like JPEG2000, JPEG, White Gaussian Noise (WN), Gaussian Blur, a Rayleigh fast fading channel simulation. Each of the distortion images has an associated Difference Mean Opinion Score (DMOS) which represents the subjective quality of the image.

Since, NRDPF-IQA approach requires a training procedure to calibrate the regressor module, we divide the LIVE database into two randomly chosen subsets 80% training and 20% testing such that no overlap between train and test content occurs. We do this to ensure that the reported results do not depend on features extracted from known content which can artificially improve performance. Further, we repeat this random test procedure 1000 times and report the median of the performance across these 1000 iterations, in order to eliminate performance bias.

Statistical significance evaluation is done as shown in Table 1. The results of one-sided t-test with 97% confidence level between SROCC values generated by NRDPF-IQA algorithm across 1000 train test trials. The results are shown in Table 1 in which "0", "1", "-1" indicates that the mean correlation of the NRDPF-IQA algorithm in row is statistically equivalent, superior or inferior to the mean correlation of the algorithm in column. Also, included PSNR, SSIM, MS-SSIM, CBIQ, LBIQ, BLIINDS-II, DIIVINE, BRISQUE for comparison.

To describe that NRDPF-IQA features can be used for different distortion identification, mean and median classification accuracy of the classifier in the two-stage framework for each of the distortions in the LIVE database as shown in Table 2 as well as across all distortions. Median SROCC across 1000 train-test combinations on the LIVE database for NRDPF-IQA algorithm as shown in Table 3 which shows the better results compared with other algorithms. The approach is compared with FR-IQA Methods in LIVE and TID2008 databases, the corresponding SROCC values are shown in Table 4.

The performance of NRDPF-IQA and other NR-algorithms on LIVE, TID2008, CSIQ databases, we analyze their computational complexity. The comparison of runtime requirements (sec) percentage is calculated for MSCN, GGD and AGGD in step wise as shown in Table 5. To evaluate the computational complexity of each of the four feature types, we measure their relative percentage of time required to compute the quality of a 512×768 image on a 2.8 GHz intel core i3 PC with 4GB RAM shown in Table 6. The probability plot for the normal distribution using the approach is shown in Fig. 1. This is mainly because of normalization, a relatively time consuming process required for computing the NRDPF-IQA algorithm.

Table 1: Results of one sided t-test performed between srocc values of various iqa algorithms

Variables	PSNR	SSIM	MS-SSIM	CBIQ	LBIQ	BLINDS-II	DIIVINE	BRISQUE	NRDPF-IQA (proposed)
PSNR	0	-1	-1	-1	-1	1	-1	-1	-1
SSIM	1	0	-1	1	1	1	1	-1	-1
MS-SSIM	1	1	0	1	1	1	1	1	1
CBIQ	1	-1	-1	0	-1	1	-1	-1	-1
LBIQ	1	-1	-1	1	0	1	-1	-1	-1
BLIINDS-II	1	-1	-1	1	1	0	-1	-1	-1
DIIVINE	1	1	-1	1	1	1	0	-1	-1
BRISQUE	1	1	-1	1	1	1	1	0	-1
NRDPF-IQA (proposed)	1	1	-1	1	1	1	1	1	0

A value of "1" indicates that the row algorithm is statistically superior to the column algorithm; "-1" indicates that the row is worse than the column; a value "0" indicates that the two algorithms are statistically indistinguishable

Table 2: Mean and median classification accuracy across 1000 train-test trails

Variables	JPEG2000	JPEG	WN	Blur	ALL
PSNR	0.825	0.876	0.918	0.934	0870.000
SSIM	0.963	0.935	0.817	0.960	0.902
BRISQUE	0.832	0.924	0.829	0.881	0.896
NRDPF-IQA (proposed)	0.974	0.942	0.921	0.973	0.921

Table 3: Median Spearman Rank Ordered Correlation Coefficient (SROCC) across 1000 train-test combinations on the live iqa database (bold indicate proposed algorithm)

Classification accuracy (%)	JPEG2000	JPEG	WN	Blur	FF	ALL
Mean	94.82	93.12	100.00	96.24	91.36	94.04
Median	**95.12**	**94.38**	**100.00**	**97.12**	**92.12**	**94.12**

Table 4: Spearman's Rank Order Correlation Coefficient (SROCC) on the tid2008 database. Bold indicate NR-IQA algorithms and others are FR-IQA algorithm

Variables	JPEG2000	JPEG	WN	Blur	FF	ALL
NRDPF-IQA (proposed)	**0.9886**	**0.9814**	**0.9863**	**0.9612**	**0.9462**	**0.9585**

Table 5: Informal complexity analysis of nrdpf-iqa. Tabulated values reflect the percentage of time devoted to each of the steps of NRDPF-IQA

Steps	Percentage of time
MSCN	48.7
GGD	8.1
Pairwise products and AGGD	36.4

Table 6: Complexity analysis of nrdpf-iqa: a comparison of the amount of time taken to compute various quality measures for a 512×768 image on a 2.8GHz intel core i3 PC with 4GB ram

Algorithms	Time (sec)
PSNR	0.05
DIIVINE	104.12
BLIINDS-II	35.12
BRISQUE	1.81
NRDPF-IQA	1.24

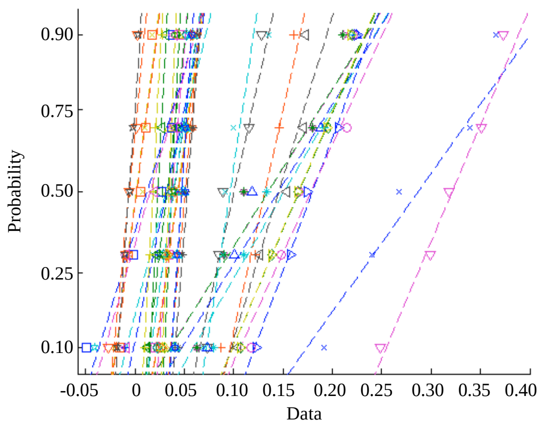

Fig. 1: Probability plot for normal distribution using NRDPF-IQA (CSIQ, TID2008, LIVE databases)

CONCLUSION

We proposed No reference Distortion Patch Feature Image Quality Assessment algorithm which perform better results in all available databases like LIVE, TID, CSIQ. No distortion specific features such as ringing, blur were modeled in the algorithm. We detailed the algorithm and demonstrated with the human perception like Spearman and Pearson. We then under took a evaluation of the NRDPF-IQA index in terms of correlation with human perception and NRDPF-IQA is statistically better than BRISQUE and other models.

REFERENCES

Chen, M.J. and A.C. Bovik, 2011. Fast structural similarity index algorithm. J. Real-Time Image Process., 6: 281-287.

Li, C., A.C. Bovik and X. Wu, 2011. Blind image quality assessment using a general regression neural network. IEEE Trans. Neural Networks, 22: 793-799.

Mittal, A., G.S. Muralidhar, J. Ghosh and A.C. Bovik, 2012. Blind image quality assessment without human training using latent quality factors. IEEE Signal Process. Lett., 19: 75-78.

Mittal, A., R. Soundararajan and A.C. Bovik, 2013. Making a completely blind image quality analyzer. IEEE Signal Process. Lett., 20: 209-212.

Moorthy, A.K. and A.C. Bovik, 2010. A two-step framework for constructing blind image quality indices. IEEE Signal Process. Lett., 17: 513-516.

Moorthy, A.K. and A.C. Bovik, 2011. Blind image quality assessment: From natural scene statistics to perceptual quality. IEEE Trans. Image Proces., 20: 3350-3364.

Saad, M.A., A.C. Bovik and C. Charrier, 2010. A DCT statistics-based blind image quality index. IEEE Signal Proces. Lett., 17: 583-586.

Saad, M.A., A.C. Bovik and C. Charrier, 2011. DCT statistics model-based blind image quality assessment. Proceedings of the 18th IEEE International Conference on Image Processing, September 11-14, 2011, Brussels, pp: 3093-3096.

Saad, M.A., A.C. Bovik and C. Charrier, 2012. Blind image quality assessment: A natural scene statistics approach in the DCT domain. IEEE Trans. Image Process., 21: 3339-3352.

Seshadrinathan, K. and A.C. Bovik, 2010. Motion tuned spatio-temporal quality assessment of natural videos. IEEE Trans. Image Process., 19: 335-350.

Sheikh, H.R. and A.C. Bovik, 2006. Image information and visual quality. IEEE Trans. Image Proc., 15: 430-444.

Sheikh, H.R., A.C. Bovik and L. Cormack, 2005. No-reference quality assessment using natural scene statistics: JPEG2000. IEEE Trans. Image Process., 14: 1918-1927.

Soundararajan, R. and A.C. Bovik, 2012. RRED Indices: Reduced reference entropic differencing for image quality assessment. IEEE Trans. Image Process., 21: 517-526.