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Fully Blind Image Quality Assessment Algorithm

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Abstract: Most general purpose no-reference image quality assessment algorithms need prior knowledge about expected distortions and their corresponding human opinion scores. All distortion types may not be available when creating the model. In this study, a blind/no-reference opinion unaware distortion unaware image quality assessment algorithm based on log-derivative statistics of natural scenes is developed. The proposed approach extracts features of both natural images and distorted image at two scales in spatial domain. Locally normalized luminance values are modeled in two forms: Point-wise based statistics for single pixels and pair wise based log-derivative statistics for the relation of adjacent pixels. Then a general Gaussian distribution model is applied whose parameters represent the features of the proposed approach. Results show that the proposed algorithm correlates well with subjective opinion scores. They also show that the proposed algorithm outperforms the full-reference Peak Signal-to-noise Ratio (PSNR) and Structural Similarity (SSIM) methods. Not only do the results compete well with the recently developed Natural Image Quality Evaluator (NIQE) model but also outperform it.

Key words: No-reference, log-derivative, image quality assessment

INTRODUCTION

Image processing techniques such as acquisition, transmission, compression, restoration and enhancement are growing interest in current research and therefore, quality assessment methods have increased demand as well. Human is the ultimate judge of image quality, however, the judgment is time consuming impractical. Hence there is need for automatic assessment which is referred to as objective assessment.

Objective assessment can be categorized into: Full-reference (FR), Reduced-reference (RR) and No-reference (NR) image quality assessment. FR modelsassess image quality by fully accessing the original image (Wang and Li, 2011; Zhang *et al*., 2011a; Sheikh and Bovik, 2006; Wang *et al*., 2004). RR models assess image quality by extracting some features from the original image. RR models (Xue and Mou, 2010; Li and Wang, 2009; Wang and Simoncelli, 2005) in general utilize image decomposition coefficients by simulating the behavior of the cortical neurons to construct RR features. Shao and Mou (2013), in order to assess image quality, they used statistics of edge patterns taken from natural images. Rehman and Wang (2012) used multi-scale multi-orientation divisive normalization transform to obtain statistical features. Distortion measure was obtained by these researchers following the SSIM philosophy.

Although RF and RR Image Quality Assessment (IQA) methods provide a useful and effective way to assess quality of distorted images, the reference image or even partial of it may not be available, in which case a NR IQA method is required.

Most existing NR IQA methods are based on prior knowledge of the distorted type, known to be distortion-specific (Gabarda and Cristobal, 2012; Zhang *et al*., 2011b; Li, 2002; Bovik and Liu, 2001; Wang *et al*., 2000). This specification limits the application of such algorithms. NR IQA algorithms which are non-distortion-specific are known as general distortion algorithms. General distortion algorithms that obtain a collection of distorted images with co-registering human scores are Opinion Aware (OA) (Mittal *et al*., 2012a; Saad *et al*., 2012; Moorthy and Bovik, 2011). Contrary to these, Opinion Unaware (OU) do not need training on databases of human judgments of distorted images (Mittal *et al*., 2012b). Among OU models, distorted images may not be available during IQA model construction or training, so models that do not require knowledge about anticipated distortions are Distortion

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Unaware (DU).They rely only on exposure to naturalistic source images or image models to direct the quality assessment process. Mittal *et al.* (2013) designed the first OU-DU Natural Scene Statistic (NSS) NR IQA model. The novelty of this work is to build no-reference OU-DU model based on log-derivative statistics and simplifying the computational process by unifying the procedure of extraction the statistical features as will be presented.

In this study the effect of point-wise based statistics for single pixel values and pair wise based log-derivative statistics for the relation of adjacent pixels on image quality assessment is examined. Derivative statistics were first studied by Huang and Murnford (1999) and motivated by the work of Zhang and Chandler (2013) and Mittal *et al.* (2012b).

MATERIALS AND METHODS

The proposed model is based on building a group of natural features which are derived from natural scene statistics and fitting them to Multivariate Gaussian Model (MVG) model. Assessing the quality of a distorted image is then expressed as the distance between MVG fit of the features extracted from the distorted image and MVG model of the natural features extracted from natural images.

Normalized luminance and their log-derivatives: The model begins with computing the normalized luminance of distorted/natural images. For an image I (i, j), normalized luminance $\hat{I}(i,j)$ which is computedby means of local Mean Subtraction and Contrast Divisive Normalization (MSCN) (Ruderman, 1994) defined as:

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

where, $i \in \{1, 2, ..., M\}$ and $j \in \{1, 2, ..., N\}$ are indices of spatial domain, M and N are the dimensions of the image and:

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I(i+k, j+l) \quad (2)$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} \left[I(i+k, j+l) - \mu(i,j) \right]^2} \quad (3)$$

are the estimated local mean and local contrast, respectively and $w = \{w_{k,l} | k = -K,\dots, K, l = -K,\dots, L\}$ is a 2D circularly-symmetric Gaussian weighting function sampled out to three standard (K = L = 3) and rescaled to unit volume. After computing MSCN coefficients Eq. 1, the image is divided into patches of 96×96 each. Features are calculated through the coefficient of each patch. To extract features using derivative statistics, the logarithm of $\hat{I}(i,j)$ is computed to create new image sub-band J given by:

$$J(i,j) = \log\left(\hat{I}(i,j) + 0.1\right) \quad (4)$$

The small constant 0.1 prevents $\hat{I}(i,j)$ from being zero. Then the five types of log-derivatives are computed. Horizontal, vertical, main-diagonal, secondary-diagonal and combined-diagonal log-derivatives are given in Eq. 5-9 below:

$$J_x(i,j) = J(i, j+1) - J(i, j) \quad (5)$$

$$J_y(i,j) = J(i+1, j) - J(i, j) \quad (6)$$

$$J_{xy}(i,j) = J(i+1, j+1) - J(i, j) \quad (7)$$

$$J_{yx}(i,j) = J(i+1, j-1) - J(i, j) \quad (8)$$

$$J_{xandy}(i,j) = J(i,j) + J(i+1, j+1) - J(i, j+1) - J(i+1, j) \quad (9)$$

The proposed algorithm is based on the hypothesis that statistics of MSCN coefficients and their log-derivatives significantly change in presence of distortion in the spatial domain (Zhang and Chandler, 2013; Mittal *et al.*, 2012a).

Zhang and Chandler (2013) found that the MSCN statistics and their five types of log-derivatives statistics are effective in modeling natural images. Their profiles alter in the presence of different spatial domain distortions. These alterations areused to estimate the quality.

As indicated in section above much literature concentrates on modeling natural scene statistics in spatial domain (Mittal *et al.*, 2012b, 2013) and this study is an extension of such literature. Figure 1 shows a block diagram to extract features of the proposed algorithm in spatial domain.

MSCN and log-derivative statistics based features: The MSCN coefficients in Eq. 1 and the five log-derivatives in Eq. 5-9 are modeled following a zero mode Asymmetric Generalized Gaussian Distribution (AGGD) (Mittal *et al.*, 2012a; Lasmar *et al.*, 2009):

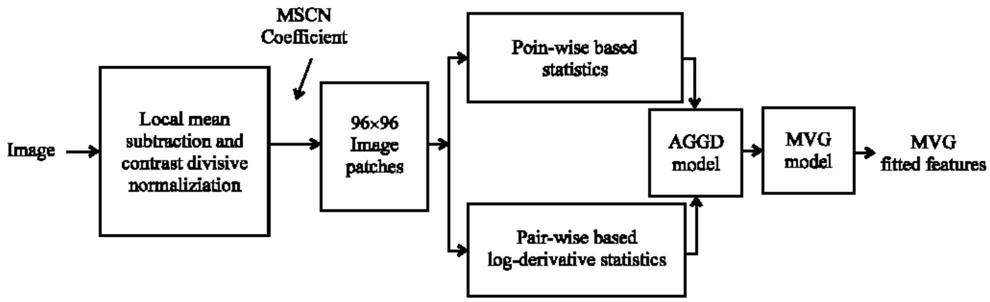

Fig. 1: Block diagram of the proposed algorithm for features extraction. Where MSCN stands for mean subtraction and contrast divisive normalization, AGGD is asymmetric generalized gaussian distribution and MVG represents multivariate gaussian model

$$f(x;\gamma,\beta_l,\beta_r)=\begin{cases}\dfrac{\gamma}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{\gamma}\right)}\exp(-(\frac{-x}{\beta_l})^{\gamma})\forall x\le 0\\ \dfrac{\gamma}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{\gamma}\right)}\exp(-(\frac{x}{\beta_r})^{\gamma})\forall x\ge 0\end{cases}\quad(10)$$

$\Gamma(\cdot)$ is the gamma function:

$$\Gamma(a)=\int_0^{\infty}t^{a-1}e^{-t}dta\succ 0\quad(11)$$

The parameters, (γ, β_l, β_r) of the MSCN and the five log-derivatives represent the extracted 18 features. These features are computed at two scales to portray multi-scale behavior, by low pass filtering and down sampling by a factor of two, this process leads to a set of 36 features. All features are extracted in the spatial domain. Unlike the approach of using two or more equations to extract features as demonstrated by Mittal *et al*. (2013) and Zhang and Chandler (2013), only one Eq. 10 is used here for extracting these features.

Multivariate gaussian model (MVGM): The features obtained by Eq. 10 for image patches were fitted with an MVG density, to give their rich representation (Mittal *et al*., 2013):

$$f_X(x_1,\ldots,x_k)=\frac{1}{(2\pi)^{k/2}|\Sigma|^{1/2}}\times\exp(-\frac{1}{2}(x-\upsilon)^T\Sigma^{-1}(x-\upsilon))\quad(12)$$

where υ and Σ are the mean and covariance matrix of the MVGM, respectively, x_1,...x_k are the features extracted by Eq. 10.

Natural scene statistic (NSS) MVGM: The NSS MVGM computed from 125 natural images which were selected from copyright free Flickr data and from the Berkeley image segmentation database (Martin *et al*., 2001). The variance field in Eq. 3 is rich of image information that can quantify local image sharpness (Mittal *et al*., 2013). The features corresponding to the sharper patches were selected. Sharper patches that had average of variance greater than 75% of the peak patch sharpness over the image are selected. The features then fitted to MVG model, Eq. 12.

Quality assessment: The proposed index computes 36 features from patches of the tested (distorted) image, fitting them with the MVGM in Eq. 12 and then compares the fit MVG to the natural MVG model. Quality is assessedas the distance between NSS MVGM and MVGM of the tested image in Eq. 13 below:

$$D(\upsilon_1,\upsilon_2,\Sigma_1,\Sigma_2)=\sqrt{(\upsilon_1-\upsilon_2)^T\left(\frac{\Sigma_1+\Sigma_2}{2}\right)^{-1}(\upsilon_1-\upsilon_2)}\quad(13)$$

The mean vectors and covariance matrices of the NSS MVGM and the tested image MVGM are υ_1, υ_2 and Σ_1, Σ_2, respectively.

RESULTS AND DISSCSSION

Testing: LIVE IQA database has been used to evaluate the performance of the proposed algorithm (Sheikh *et al*., 2006). There are 29 reference images included in this database with a total of 779 distorted images. These distorted images are classified into five different kinds of distortions. These distortions can be a result of JPEG and JPEG 2000 (JPEG2K) compression or introduced as Gaussian blur (blur). The imgae transmission through a Rayleigh channel also corrupts the image and is termed as fast fading distortion. One of the common types of distortion is the additive white Gaussian noise (WN).

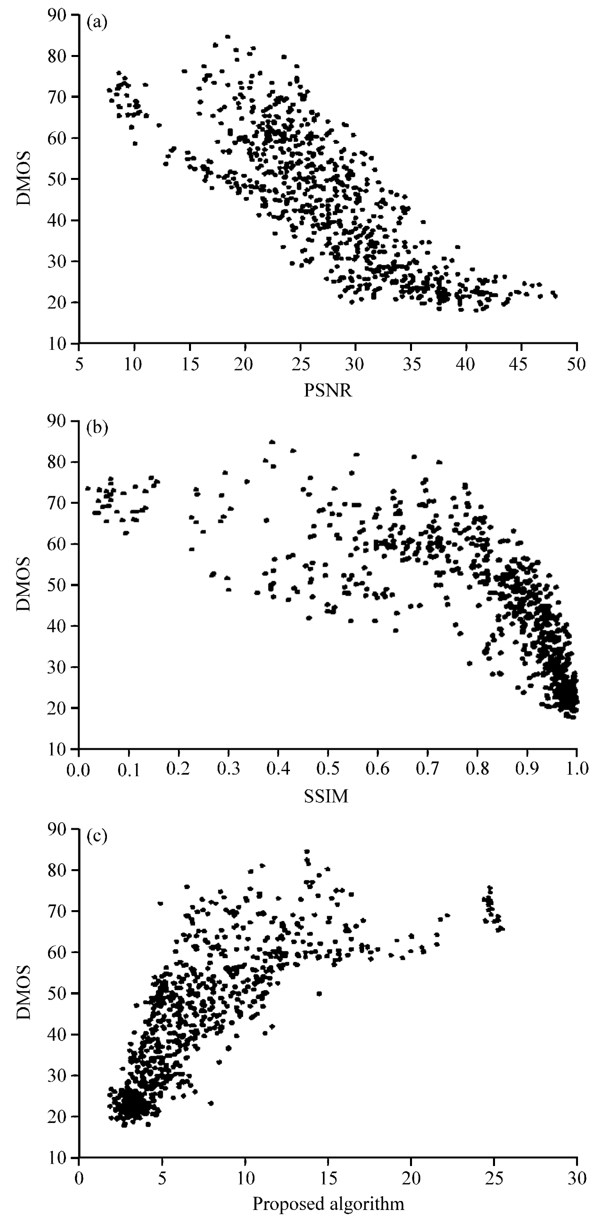

Fig. 2(a-c): Comparing DMOS (differential mean opinion score) with PSNR (peak signal-to-noise ratio), SSIM (structural similarity) and the proposed algorithm (a) DMOS vs. PSNR (b) DMOS versus SSIM and (c) DMOS vs. proposed algorithm

Correlation with differential mean opinion score (DMOS): Figure 2 shows scatter plots of DMOS versus peak signal-to-noise ratio (PSNR) (a), DMOS versus structural similarity (SSIM) index (b) and DMOS versus the proposed algorithm (c). The figure indicates that although the proposed method is a blind/NR, it correlates better than FR PSNR and SSIM model with differential mean opinion score.

Table 1: Comparison of SROCC[1] of the proposed algorithm against FR-PSNR[2] and FR-SSIM3 algorithms and NR-NIQE[4] algorithm. Bold italic indicates best-performing algorithm between no-reference algorithms

	FF[5]	G Blur[6]	WN[7]	JPEG[8]	JPEG2K[9]	All
FR-PSNR	0.7817	0.8086	0.6858	0.8478	0.8424	0.7933
FR-SSIM	0.6535	0.6536	0.6430	0.8086	0.8014	0.7120
Proposed	0.7582	**0.7623**	0.7608	**0.8743**	0.8460	0.8003
NR-NIQE	**0.7860**	0.7602	**0.8636**	0.8669	**0.8571**	**0.8268**

[1]Spearman's rank ordered correlation coefficient, [2]Full-reference peak signal-to-noise ratio algorithm, [3]Full -reference structural similarity index, [4]No-reference natural image quality evaluator, [5]Fast fading distortion, [6]Gaussian blur distortion, [7]Additive white gaussian noise distortion, [8]Joint photographic experts group compression distortion, [9]Joint photographic experts group 2000 compression distortion

Table 2: Comparison of PLCC[1] of the proposed algorithm against FR-PSNR[2] and FR-SSIM[3] algorithms and NR-NIQE[4] algorithm. Bold italic indicates best-performing algorithm between no-reference algorithms

	FF[5]	G Blur[6]	WN[7]	JPEG[8]	JPEG2K[9]	All
FR-PSNR	0.7440	0.7572	0.7643	0.8271	0.8265	0.7838
FR-SSIM	0.7442	0.7871	0.8193	0.7840	0.7668	0.7803
Proposed	0.8505	0.9065	0.7394	**0.8898**	**0.8983**	**0.8569**
NR-NIQE	**0.8592**	**0.9102**	**0.8025**	0.7520	0.8931	0.8434

[1]Pearson's linear correlation coefficient, [2]Full -reference peak signal-to-noise ratio algorithm, [3]Full -reference structural similarity index, [4]No -reference natural image quality evaluator, [5]Fast fading distortion, [6]Gaussian blur distortion, [7]Additive white Gaussian noise distortion, [8]Joint photographic experts group compression distortion, [9]Joint photographic experts group 2000 compression distortion

Performance measurement: To assess the prediction monotonicity, Spearman's Rank Ordered Correlation Coefficient (SROCC) is usedwhile Pearson's Linear Correlation Coefficient (PLCC) is employed to evaluate the prediction accuracy of the proposed algorithm. Before calculating PLCC, the objective scores passed through a logistic non-linear function (Sheikh *et al*., 2006) (where its parameters are found numerically using the MATLAB function 'fminsearch' in the optimization toolbox) to maximize the correlations between subjective and objective scores.

Table 1 and 2 show that the proposedalgorithm performs better than the popular FR PSNR and SSIM (Wang *et al*., 2004) methods. Not only does the proposed algorithm compete well with the recently developed OU-DU Natural Image Quality Evaluator (NIQE) model (Mittal *et al*., 2013) but also outperform it.

CONCLUSION

Constructing no-reference models that do not train on features extracted from distorted images and human opinion scores is a big challenge for researchers.A newlow computational complexity NR OU-DU method is introduced based on log-derivative statistics. The proposed algorithm extracts features at two image scales in spatial domain where no transform (e.g., DCT, wavelet, etc.) is required. The results presented above of this study show that this method outperforms FR PSNR and SSIM (Wang *et al*., 2004) IQA models. Not only do the results compete well with the recently developed NIQE model (Mittal *et al*., 2013) but also outperform it.

Future work concentrates on developing OU-DU algorithm which extracts features of natural images using appropriate mechanism that facilitate efficient and rapid extraction of a scene's gist.

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