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Totally Blind Image Quality Assessment Algorithm Based on Weibull Statistics of Natural Scenes

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Abstract: Non-specific distortion blind/no-reference image quality assessment algorithms mostly need prior knowledge about expected distortions by obtaining collections of these distortions with co-registered human opinion scores. No confirmation that all distortion types are available when creating the model. Practical no-reference image quality assessment algorithms formulated to predict the quality of distorted images without prior knowledge of the images or their distortions. In this study, a blind/no-reference opinion unaware distortion unaware image quality assessment algorithm using Weibull distribution as feature extractor of natural scenes is developed. The proposed algorithm uses a set of novel features to assess image quality. The features which are composed of Weibull distribution and maximum likelihood estimation parameters extracted from both natural images and distorted image in spatial domain. The features ability to capture the variations due to distortion types is investigated. Results indicate that efficient and rapid extraction of a scene's visual gist facilitated by Weibull distribution. Experiments show that the proposed algorithm correlates well with subjective opinion scores when tested on LIVE database. They also show that the proposed algorithm significantly outperforms the popular full-reference Peak Signal-to-noise Ratio (PSNR) and structural similarity (SSIM) methods. Not only do the results reasonably well compete with the recently developed state of the art no-reference Natural Image Quality Evaluator (NIQE) model but also outperform it.

Key words: No-reference, weibull distribution, 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 models assess 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) generally use image decomposition coefficients by simulating the behavior of the cortical neurons to construct RR features. Shao and Mou (2013) extracted edge patterns from natural images and used the statistics of these patterns to assess image quality. Rehman and Wang (2012) used transform of multi-scale multi-orientation divisive normalization to obtain statistical features. Distortion measure was obtained by these researchers following the structural similarity (SSIM) index 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. As example, the noise-free image is unknowable when assessing the quality of a denoising algorithm on a real-world database.

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

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human scores are Opinion Aware (OA) (Mittal *et al.*, 2012a; Saad *et al.*, 2012; Moorthy and Bovik, 2011) contrariwise algorithms that do not need training on databases of human judgments of distorted images are Opinion Unaware (OU) (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 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.

A lot of researches studded Weibull distribution and its relationship with natural images. Ghebreab *et al.* (2009) found that for natural images a large amount of visual gist information contained by Weibull contrast statistics. The spatial structure of uniform textures of many different origins completely can be characterized by Weibull distribution parameters (Geusebroek and Smeulders, 2005). Timm and Barth (2011) used Weibull distribution for defect detection in textures. Tang *et al.* (2011) used Weibull distribution to learn a mapping from them.

In this study, OU-DU approach based blind image quality measure is introduced. The proposed algorithm well perceptually correlates with human judgments with no require for prior knowledge about anticipated distortions or their corresponding opinion scores. The key contributions in this study are the investigation and development of novel features and employ them for measuring image quality blindly with low computational complexity. The features provide high ability to capture the variations due to distortion types.

MATERIALS AND METHODS

The proposed model is based on building a group of natural features, which are derived from natural scene statistics. Features of both natural images and distorted image extracted at two scales in spatial domain, where locally normalized luminance values are modeled in two aspects: Point-wise statistics for single pixels and pairwise based log-derivative statistics for the relation of adjacent pixels. Then a Weibull distribution and maximum likelihood estimation models are applied whose their parameters represent the extracted features of the proposed approach. These features are fit to Multivariate Gaussian Model (MVG) model to obtain their rich representation. 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 (pristine) images.

Normalized luminance and their log-derivatives: The normalized luminance of distorted/natural images I (i, j), computed by means of local Mean Subtraction and Contrast Divisive Normalization (MSCN) (Ruderman, 1994) defined as:

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

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

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I(i+k, j+1) \tag{2}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} \left[I(i+k, j+1) - \mu(i,j) \right]^2} \tag{3}$$

are the estimated local mean and local contrast, respectively and $w = \{w_{k,l} | k = -K, ..., K, l = -L, ..., L\}$ is a 2D circularly-symmetric Gaussian weighting function sampled out to three standard deviations (K = L = 3) and rescaled to unit volume. After computing MSCN coefficients (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 (Huang and Murnford, 1999), we first compute the logarithm of $\hat{I}(i,j)$ to create new image sub-band J given by:

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

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

$$J_x(i,j) = J(i,j+1) - J(i,j) \tag{5}$$

$$J_y(i,j) = J(i+1,j) - J(i,j) \tag{6}$$

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

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

$$J_{x \text{ and } y}(i,j) = J(i,j) + J(i+1,j+1) - J(i,j+1) - J(i+1,j) \tag{9}$$

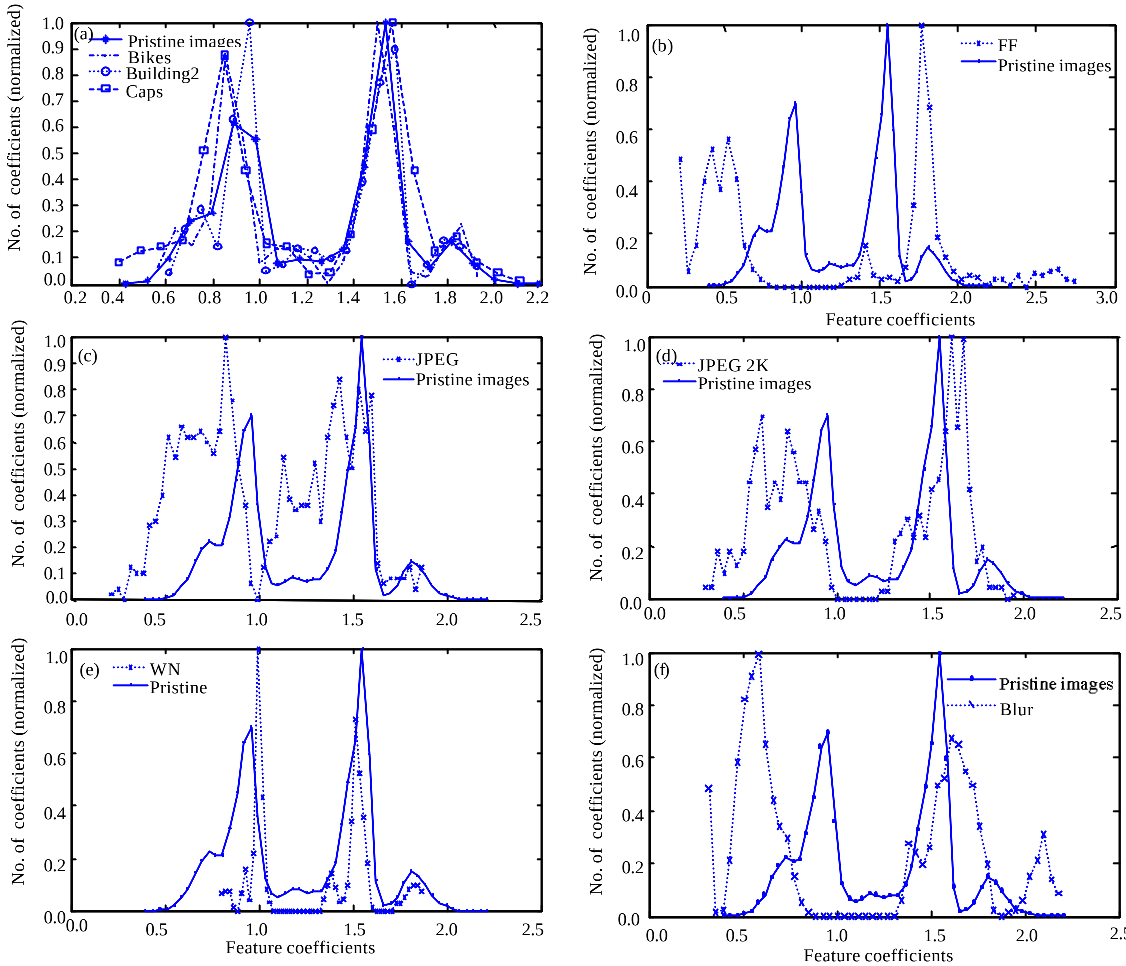

Fig. 1(a-f): Comparison of pristine (natural images) feature coefficients with, (a) Three reference images, (b) Rayleigh fast fading, (c) Joint Photographic Experts Group compression (JPEG), (d) Joint Photographic Experts Group 2000 compression (JPEG2000), (e) Additive white Gaussian noise and (f) Gaussian blur distortions of bikes image (shown in Fig. 2) from LIVE (Laboratory for Image and Video Engineering) database

The 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*., 2012b), in which hypothesis the proposed algorithm based on.

Weibull distribution based extracted features: The MSCN coefficients in Eq. 1 and the five log-derivatives in Eq. 5-9 are modeled with Weibull (10), this gives 12 features.

$$f(x;\lambda,\gamma,\mu)=\begin{cases}\dfrac{\gamma}{\lambda}\left(\dfrac{x-\mu}{\lambda}\right)^{\gamma-1} e^{-\left(\frac{x-\mu}{\lambda}\right)^{\gamma}} & x\geq 0\\ 0 & x<0\end{cases} \quad (10)$$

where, λ is the scale parameter, γ is the shape parameter, and μ the origin of the contrast distribution. For natural images (as the case in this study) the origin μ is usually close to zero, however, this parameter eliminated by stretching the contrast (Timm and Barth, 2011).

The Weibull parameters are estimated with Maximum Likelihood Estimation (MLE). Both Weibull parameters and the estimated model parameters used as features. By employing MLE, extra 12 features are obtained at yielding 24 overall. 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 48 features. All features are extracted in the spatial domain.

To investigate the validity of the features that extracted from the natural images (pristine images) for giving perfect quality measurement, these features are compared with features extracted from three random reference images, as in Fig. 1a. The plot shows that, the

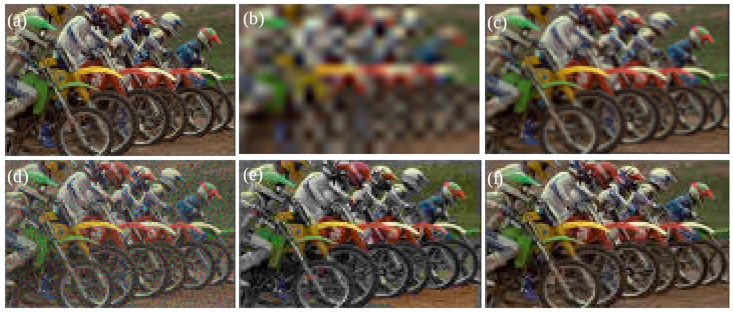

Fig. 2(a-f): Reference bikes image and its five distorted versions in the LIVE (Laboratory for Image and Video Engineering) database, (a) Reference image, (b) Rayleigh fast fading, (c) Gaussian blur, (d) Gaussian white noise, (e) Joint Photographic Experts Group compression (JPEG) and (f) Joint Photographic Experts Group 2000 compression (JPEG2000)

features extracted from the natural images consistent with those of the features extracted from reference images. Figure 1b-f shows how the natural images base-features suffer from changes due to various distortion types. The propose model follow these changes and measure them to evaluate the quality. Figure 2 shows the distorted images from LIVE database which their features are plotted in Fig. 1.

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

$$f_X(x_1,\ldots,x_k) = \frac{1}{(2\pi)^{k/2}|\Sigma|^{1/2}} \times \exp\left(-\frac{1}{2}(x-\upsilon)^T \Sigma^{-1}(x-\upsilon)\right) \quad (11)$$

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

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 (11).

Quality assessment: The proposed index computes 48 features from patches of the tested (distorted) image, fitting them with the MVGM in Eq. 11 and then compares the fit MVG to the natural MVG model. Quality is assessed as the distance between NSS MVGM and MVGM of the tested image in Eq. 12 below:

$$D(\upsilon_1,\upsilon_2,\Sigma_1,\Sigma_2) = \sqrt{(\upsilon_1-\upsilon_2)^T\left(\frac{\Sigma_1+\Sigma_2}{2}\right)^{-1}(\upsilon_1-\upsilon_2)} \quad (12)$$

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 DISCUSSION

To evaluate the proposed algorithm performance, LIVE IQA database (Sheikh *et al*., 2005) of 29 reference images and 779 distorted images is used. LIVE database has five different distortion categories: JPEG and JPEG2000 (JPEG2K) compression, additive white Gaussian noise (WN), Gaussian blur (Gblur) and Rayleigh fast fading channel distortion (FF).

Figure 3 shows scatter plots of Differential Mean Opinion Score (DMOS) versus Peak Signal-to-noise Ratio (PSNR) (a), DMOS versus 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.

To assess the prediction monotonicity, Spearman's Rank Ordered Correlation Coefficient (SROCC) is used while Pearson's Linear Correlation Coefficient (PLCC) is employed to evaluate the prediction accuracy of the proposed algorithm. Before PLCC is calculated, 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 proposed algorithm performs better than the FR PSNR and SSIM

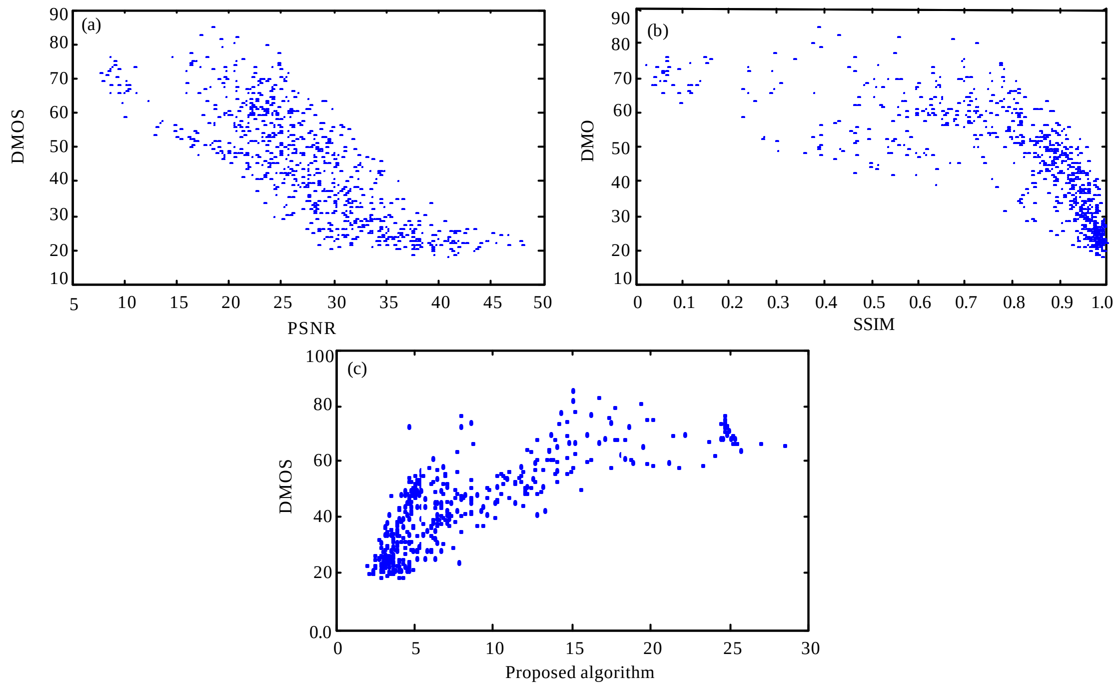

Fig. 3(a-c): Comparing differential mean opinion score (DMOS) with peak signal-to-noise ratio (PSNR), Structural Similarity (SSIM) index and the proposed algorithm. DMOS versus: (a) PSNR, (b) SSIM and (c) proposed algorithm

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

Variables	FF[5]	GBlur[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	0.7766	0.7739	0.7608	0.8738	0.8559	0.8082
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 of the proposed algorithm against FR-PSNR and FR-SSIM algorithms and NR -NIQE algorithm. Bold italic indicates best-performing algorithm between no-reference algorithms

Variables	FF[5]	GBlur[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	0.8033	0.9354	0.7506	0.8826	0.9141	0.8572
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

(Wang *et al*., 2004) methods. Not only does the proposed algorithm reasonably well compete the recently developed OU-DU NIQE model (Mittal *et al*., 2013) but also outperform it.

CONCLUSION

Devising perceptual no-reference models that do not train on features extracted from distorted images and human opinion scores is a big challenge for researchers. However choosing the appropriate features play significant role in measuring image quality. In this study, novel low level features are extracted and investigated. These features are employed to devise a new blind OU-DU image quality assessment evaluator. The study shows that the extracted features which are from the scene's gist, capable to capture the variations due to distortion types. The proposed approach is low computational complexity NR OU-DU method which extracts features in spatial domain where no transform (e.g., DCT, wavelet, etc.) is required. The results presented in this study shows that this method correlates well with mean opinion score and has a good performance.

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