Blind Image Quality Assessment Through Wakeby Statistics Model

Mohsen Jenadeleh(✉) and Mohsen Ebrahimi Moghaddam

Faculty of Computer Science and Engineering,
Shahid Beheshti University G.C, Tehran, Iran
{m_jenadeleh,m_moghadam}@sbu.ac.ir

Abstract. In this paper, a new universal blind image quality assessment algorithm is proposed that works in presence of various distortions. The proposed algorithm uses natural scene statistics in spatial domain for generating Wakeby distribution statistical model to extract quality aware features. The features are fed to an SVM (support vector machine) regression model to predict quality score of input image without any information about the distortions type or reference image. Experimental results show that the image quality score obtained by the proposed method has higher correlation with respect to human perceptual opinions and it's superior in some distortions comparing to some full-reference and other blind image quality methods.

Keywords: Blind image quality assessment · Natural scene statistics of special domain · Wakeby distribution model · Support vector machine

1 Introduction

Image quality assessment (IQA) algorithms are widely used in many image processing and video applications, such as watermarking, ton mapping, compression and enhancement. Today, the most trustworthy way of evaluating an algorithm is subjective human perception [1]. Subjective IQA is the most reliable approach because the end user always would be a human. Thus, subjective assessments offer high correlation with human vision system. Subjective methods are time consuming, expensive, and cannot be performed in real-time applications [2]. It is therefore necessary to define an objective criterion that can calculate the human-like judgment score difference between a reference image and its distorted version. Ideally, such an objective metric should be highly correlated by the perceived difference between distorted and reference images and should be varied linearly with the subjective quality assessment. Based on the availability of the reference image, the objective image quality methods are categorized into three classes [1]: full-reference methods that need both original and distorted images to compute quality of input image [3], reduced reference methods that besides the input image, need an access to some of the information from original image to calculate quality score [4] and finally, no-reference or blind methods are those which designed to compute the quality metric of a distorted image without any kind of need to access the original image's data [5]. The point is, reference image or its extracted features-information may not be always available. For instance, think of shared images

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in social networks on the internet. As the original image would not be accessible, the only way to assess quality of them is using blind image quality assessment approaches.

2 Related Works

Most of no-reference image quality assessment (NR-IQA) methods are based on prior knowledge of the distortion type, called distortion-specifics [6, 7]. This constraint limits the algorithm applications. For example, in the real world, images are usually corrupted by more than one distortion, and the distortion type is usually unknown. Recently, some methods proposed to overcome this problem. Such methods make no assumption about the type of distortions. In [8] a NR-IQA algorithm which operates in DCT domain is proposed. In this method, features are computed from natural scene statistics (NSS) of block DCT coefficients. Then quality aware features based on modeling these NSS are calculated and fed to a regression SVM to predict quality of the input image. This method is a good achievement but requires nonlinear sorting of the block based natural scene statistic features which makes it slow for real time applications. BRISQUE [5] is another recent state of the art method using suitable quality-aware NSS features in the spatial domain to learn human opinion scores on databases including some sort of distortions, even large ones [9]. Saad et al. [10] Proposed BLIINDS-II image quality method which extracts NSS of discrete cosine transform (DCT) using a single-stage framework. Liu et al. [11] proposed dubbed spatial–spectral entropy based quality metric (SSEQ) to predict image quality blindly. SSEQ utilizes local spatial and spectral entropy features of distorted images to form quality aware features. The features then feed to a regression machine to predict image quality. The problem of these methods is the limitation of possible applications caused by limited range of distortion types they have been trained on. Consider their performance is directly affected by the ability of distortions that they are familiar with.

In this work, Wakeby distribution –also known as advanced distribution- is used to modeling the NSS coefficients and extracting quality aware feature vectors. This distribution has a couple of scale and shape parameters (four parameters), which makes it more flexible in comparison to the other distribution models used in the state of the art methods. These parameters let us form a feature vector that is very sensitive to changes in an NSS coefficient's empirical distribution which causes more accurate model fitting and better prediction of image quality score.

3 Proposed Method

A novel method to assess quality of natural images based on NSS modeling is proposed in the presented model, the natural features are extracted from input images that would be a composition of the local mean subtraction and contrast divisive normalization (MSCN) coefficients. Additionally, the product of MSCN coefficients in four directions (horizontal, vertical and two diagonals) is calculated and used as a part of the feature vector. Wakeby distribution has been adapted for modeling of the MSCN coefficients and their relative products. This model is achieved by estimating the distribution parameters obtained by the best fitting trials of MSCN coefficients. Then the estimated parameters of Wakeby distribution has been used to form the quality aware feature vector. Since the range of raw data values vary widely, in order to obtain faster converges, the range of all features should be normalized between [-1, 1] so we make a fair deal between each feature's contribution. The feature vectors of the training samples are fed to an SVM to form the model. Then the SVM model and feature vector of each testing sample is being used as a prediction module to find a blind approximation of quality score for the test image.

3.1 Natural Scene Statistics Extraction

The statistics of natural images, have been studied for more than 50 years by vision scientists and television engineers. The idea is simple: All natural images share some common statistical behaviors regularities related to the real world. One of the best examples of NSS is MSCN coefficients where its histogram is approximately Gaussian like for a natural image [12]. Figure 1 shows the behavior of these statistics in presence of different distortions is predictable. It helps the reader to have a better imagination of the relation between NSS and severity of distortions. As it is shown in Fig. 1 each distortion affects each image distribution in a distinguishable way and all the behaviors are independent of image contents. For example, presence of JPEG2000 and JPEG distortions, makes the distributions highly picked but JPEG makes it sharper and when it comes to white noise, we see the distribution is more Gaussian like. By generating models based on these regular behaviors, presence and severity of the distortions are objectively sensible. To model the statistical regularities observed in natural images, the local mean subtraction and contrast divisive normalization (MSCN) coefficients are calculate by the Eq. (1):

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

Where $i \in (1, 2, .., M)$ and $J \in (1, 2, .., N)$ are spatial indices of a natural image's pixels with size of, $M \times N$ and d is a small value to prevent division by zero. μ and σ can be calculated by Eqs. (2) and (3) respectively:

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=L}^{L} \omega_{k,l} I_{k,l}(i,j) \tag{2}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=L}^{L} \omega_{k,l} [I_{k,l}(i,j) - \mu(i,j)]^2} \tag{3}$$

Where is $\omega_{k,l} | k = -K, \ldots, K, l = -L, \ldots, L$ is a 2D circularly symmetric Gaussian weighting function.

3.2 Wakeby Distribution Model

The MSCN coefficients can be modeled by different statistical distributions, in [5], zero-mean general Gaussian distribution (GGD) with two parameters and in [13] Weibull distribution with three parameters is used to model the MSCN coefficients. Both of these distributions have some inabilities to fit the coefficients efficiently, and it encouraged us to use a more flexible distribution with more degree of freedom to model MSCN coefficients. Therefore, our choice comes to the advanced continuous Wakeby distribution [20] with five parameters for modeling and extract quality aware features. The Wakeby distribution's mathematic definition is shown in Eq. (4):

$$x(F) = \zeta + \frac{\alpha}{\beta}\left(1 - (1 - F)^{\beta}\right) - \frac{\gamma}{\delta}\left(1 - (1 - F)^{-\delta}\right) \tag{4}$$

$x(F)$ represents Wakeby distribution with shape parameters β and δ, scale parameters α and γ, and location parameter ζ. Where $F = F(x) = P(X \leq x)$ is non-exceedance probability and $x(F)$ is F corresponding quantile value. Also the following conditions are necessary to satisfy:

$$\alpha \neq 0 \ or \ \gamma \neq 0$$

$$\beta + \delta > 0 \ or \ \beta = \lambda = \delta = 0$$

$$if \ \alpha = 0 \ then \ \beta = 0$$

$$if \ \gamma = 0 \ then \ \delta = 0$$

$$\gamma \geq 0 \ and \ \alpha + \gamma \geq 0$$

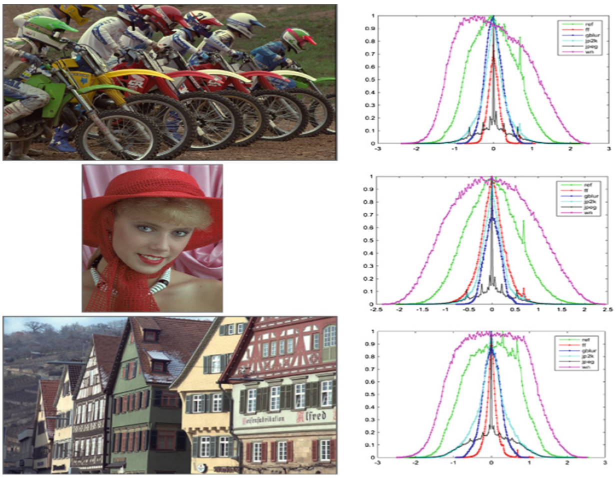

Fig. 1. Empirical histograms of the MSCN coefficients of three random reference images from LIVE database and their distorted versions.

An analytical technique based on probability-weighted moments [21] is used to estimate $(\beta, \delta, \alpha, \gamma, \zeta)$ parameters of the Wakeby distribution. Also, mean and variance (m, v) of best Wakeby distribution fitted of MSCN coefficients are calculated and used for the Wakeby distribution modeling.

3.3 Quality Aware Feature Extraction

In addition to the MSCN coefficients that have been modeled in previous section, the statistical relationships between adjacent pixels are also modeled. A study [5] shows that the MSCN coefficients are more homogenous for original natural images, and the product values of adjacent coefficients exhibit a regular structure that changes in presence of different distortions. Same to BRISQUE [5], To model this regular structure between neighbor coefficients, pairwise products on a distance of one pixel along four orientations (horizontal, vertical, main diagonal and secondary diagonal) between adjacent MSCN coefficients, are calculated by Eqs. (5), (6), (7) and (8) respectively. Figure 2 shows the neighboring MSCN coefficients which are computed along four directions and their horizontal (i,j) histograms for a sample image and its distorted versions.

$$\text{Horizontal } (\mathrm{i,j}) = \hat{I}(i,j) \times \hat{I}(i,j+1) \tag{5}$$

$$\text{Vertical } (\mathrm{i,j}) = \hat{I}(i,j) \times \hat{I}(i+1,j) \tag{6}$$

$$\text{Main diagonal } (\mathrm{i,j}) = \hat{I}(i,j) \times \hat{I}(i+1,j+1) \tag{7}$$

$$\text{Secondary diagonal } (\mathrm{i,j}) = \hat{I}(i,j) \times \hat{I}(i+1,j-1) \tag{8}$$

In each orientation, for each paired products the Wakeby distribution parameters (β, δ, α, γ, ζ) are estimated. Due to independency of position parameter to distortions, this parameter is not used in the feature vector. Therefore, the 22 quality aware features are a composition of these four parameters: $(\beta, \delta, \alpha, \gamma)$ (from modeling MSCN coefficients) and 16 elements obtained from the products of adjacent MSCN coefficients along the four directions, and the last two elements are (μ, v). The features are extracted over two scales and this yields 44 features that extracted from each image and forms the quality aware feature vector. This is done because the human visual system (HVS) extracts structural information from the natural images, therefore by modeling the structural similarities, a good approximation of image quality is obtained. In [14] multiscale nature of HVS and the affection of distortions on natural images are described.

3.4 SVM Model and Prediction

In this paper, a support vector machine (SVM) regression (SVR) [15] is used to predict the quality score of the test images. LIBSVM [16] package is used beside the implementation of this algorithm as the regression machine, implementing SVR with radial basis function (RBF) kernel that makes the suggested SVM model. The feature vectors

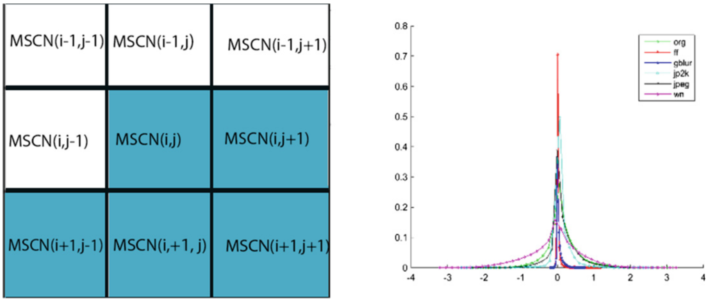

Fig. 2. Left: Pairwise products of MSCN coefficients are computed along four directions, Right: Horizontal(i,j) histograms of buildings reference image and its five distorted versions from LIVE II database that shows the product values of adjacent coefficients exhibit a regular structure.

of training samples (described in previous section), and corresponding differential mean opinion score (DMOS) (described in Sect. 4.1) are fed to the SVR to generate the suggested SVM model. Then the prediction module uses the SVM model and the test image feature vector to estimate quality score. The prediction module is also implemented in the LIBSVM package.

4 Experimental Results

4.1 Database

LIVE II IQA database [17] consists of images with five types of distortions including JPEG2000, JPEG, white noise (WN), Gaussian blur (Blur) and fast fading channel distortion (FF). All of them derived from 29 reference images. In this database the differential mean opinion score (DMOS) of each distorted image is included. DMOS scores are in range [0, 100], where lower DMOS indicates higher quality.

4.2 Performance Evaluation

Two commonly used performance metrics, Pearson Linear Correlation Coefficient (PLCC) and Spearman Rank-Order Correlation Coefficient (SRCC) as suggested in [18] are employed to evaluate the proposed algorithm. First, 80 % of LIVE database are randomly selected as training samples. To prove method's content independency, we made sure there is no content overlap between train and test samples. We conducted performance comparisons between the proposed method and six other state of the art image quality assessment methods: Three full reference algorithms including (PSNR [19], SSIM [3], MS-SSIM [14]), and other three no-reference (blind) algorithms including (SSEQ [11], BRISQUE [5], BLIINDS-II [10]). All of them tested via the mentioned performance evaluation metrics. To make a fair comparison, we performed random 20 % test and 80 % training samples for 100 times. Then we employed mean of all 100 times repeated tests as the final performance of the algorithms, since the FR algorithms do not need training, mean of 100 runs on the test samples' results are reported. Table 1 shows PLCC metric across all train-test trials on the LIVE II IQA database for the proposed and other six mentioned state of the art method. The PLCC metric shows that the proposed method has a more accurate performance in presence of all distortions of the LIVE II IQA database. Table 2 shows the performance of the proposed method with the metrics SRCC. This metric also demonstrates our method is superior in total on LIVE II IQA database. The best results in the full references and the blind methods are highlighted in all tables.

Table 1. PLCC metric across 100 train-test trials on the LIVE II IQA database.

Methods	JPEG2k	JPEG	WN	Blur	FF	ALL
PSNR	0.8814	0. 9112	0.9221	0.8134	0.8933	0.8781
SSIM	0.9555	0.9531	**0.9832**	0.9143	0.9518	0.9165
MS-SSIM	**0.9689**	**0.9733**	**0.9832**	**0.9592**	**0.9501**	**0.9573**
SSEQ	0.9492	**0.9595**	0.9709	0.9445	0.9033	0.9310
BRISQUE	0.9486	0.9407	**0.9891**	**0.9450**	0.9101	0.9239
BLIINDS-II	0.9358	0.9399	0.9637	0.9102	0.8994	0.9198
Proposed method	**0.9540**	0.9330	0.9716	0.9219	**0.9186**	**0.9414**

Table 2. SRCC metric across 100 train-test trials on the LIVE II IQA database

Methods	JPEG2k	JPEG	WN	Blur	FF	ALL
PSNR	0.8577	0.9014	0.9398	0.7776	0.8803	0.8665
SSIM	0.9399	0.9500	0.9601	0.9112	0.9369	0.9088
MS-SSIM	**0.9665**	**0.9801**	**0.9760**	**0.9502**	**0.9411**	**0.9533**
SSEQ	0.9443	0.9454	0.9770	**0.9443**	0.9104	0.9358
BRISQUE	0.9246	**0.9699**	**0.9803**	0.9433	0.8888	0.9370
BLIINDS-II	0.9519	0.9220	0.9655	0.9207	0.9021	0.9359
Proposed method	**0.9575**	0.9410	0.9737	0.9406	**0.9135**	**0.9437**

5 Conclusion

In this paper a novel general purpose blind image quality assessment model is presented, which uses MSCN spatial natural scene statistics of the input images. A feature vector with 44 dimensions is then extracted based on the Wakeby distribution modeling. Then an SVM is trained to predict image quality scores from these feature vectors. We then evaluated performance of the proposed method in terms of correlation with human perception. The experimental results have shown this method is statistically better than the full reference PSNR and SSIM metrics as well as highly competitive to all state of the art blind image quality methods.

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