Image Quality Evaluation Using Gradient Statistics

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Abstract: Nowadays image quality assessment is a very important methodology in image processing applications. Image quality assessment is a process of evaluating the quality of an image and in recent years, the goal is to evaluate the image quality without the human subjective scores; therefore the accurate assessment of the image quality is necessary. Many image processing applications evaluates the quality of the image with the human opinions, whereas the main purpose of image quality assessment (IQA) method is to automate this image quality evaluation with human quality perception. This paper presents the methodology used in blind image quality assessment (BIQA) method-ILNIQE. It provides the automatic image quality scores without any requirement of reference images. An important aim behind the study of the blind image quality assessment (IQA) problem is to develop perceptual model that can be able to predict the quality of distorted images with prior knowledge of the images or their distortions.

Keywords: completely blind, no reference, image quality assessment, multivariate Gaussian

1. Introduction

As the demand for image-based applications is increasing, the need for efficient and reliable evaluation of image quality is also increasing. The image quality measurements are the fundamental jobs for numerous image processing applications, where the main aim of image quality assessment (IQA) methods is to evaluate the quality of images automatically with the equivalent results with humans. Many IQA methods have been proposed over the past years to fulfill this goal. Since in most of the multimedia applications the human observers are the ultimate users, the most accurate and reliable way of evaluating the quality of images is through subjective evaluation. However, subjective image quality evaluations are expensive and time consuming, which makes them impractical in real-world applications. Moreover, subjective image quality evaluation experiments are further complicated by many factors including type of display device, lighting condition, viewing distance, persons' vision ability, and persons' mood. Therefore, it is necessary to design mathematical models that are able to predict the quality evaluation of an average human observer. Therefore the goal of objective IQA is to design mathematical models that are able to predict the quality of an image accurately and automatically.

2. Quality-Aware NSS Features

The natural scene statistics (NSS) are good at indicating the degree of quality of an image and also image quality distortions. Using this, we can design a set of appropriate and effective Natural Scene Statistic features for the development of the opinion-unaware BIQA model. We use two types of NSS features to characterize structural distortion, which are obtained from the distribution of locally mean subtracted and contrast normalized (MSCN) coefficients and from the distribution of products of pairs of adjacent MSCN coefficients. To characterize these structural distortions more effectively and to capture contrast distortion, we use quality-aware gradient features. To extract multi-scale and multi-orientation image properties that are related to the image quality, we use log-Gabor filters and from those filter responses statistical features will be extracted. Using statistical features derived from the image intensity distribution in a logarithmic-scale opponent color space, color distortions are described. That is to make the completely blind image quality evaluator, collectively, five types of features are used.

2.1 Statistics of Normalized Luminance

Given a distorted image, first we have to compute locally normalized luminance by using local mean subtraction and divisive normalization. Ruderman concluded that by applying a local non-linear operation to log contrast luminances to remove local mean displacements from zero log-contrast and to normalize the local variance of the log contrast has a decorrelating effect. This operation can be applied to a given intensity image I(i, j) that can results in the locally normalized luminance of a natural gray-scale photographic image I is similar to a Gaussian distribution. This normalization process can be described as:

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

where *i* and *j* are spatial coordinates, and

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

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

These are the local image mean and contrast, where k= -K,.....K and l= -L,….,L. Ruderman also observed that these normalized luminance values tend towards a unit normal Gaussian characteristic for natural images. To model the contrast-gain masking process in early human vision, such an operation can be used. We use the pre-processing model in our quality assessment model development and refer to the transformed luminances Ib(i, j) as mean subtracted contrast normalized (MSCN) coefficients. Here observation can be as the coefficients $\bar{I}(i,j)$ follow a unit normal distribution on natural images that have not suffered noticeable quality distortions which then known as MSCN coefficient. When images are subjected to quality degradations which are caused by common distortions, this Gaussian model can be violate. A zero-mean generalized Gaussian distribution (GGD) is used to broadly model the distribution of I(i,j) in the presence of distortion. The density function associated with the GGD is given by

$$g(x;\alpha,\beta)=\frac{\alpha}{2\beta\Gamma(1/\alpha)}\exp(-(\frac{|x|}{\beta})^{\alpha})$$

Where Γ(.) is the gamma function

$$\Gamma(x)=\int_{0}^{\infty} t^{x-1}e^{-t}dt\ ,x>0$$

Where the parameters α and β are effective "quality-aware" features which can be reliably estimated using the moment-matching.

2.2 Statistics of MSCN Products

The MSCN coefficients have characteristic statistical properties which are changed by the presence of distortion, and that by quantifying these changes will make it possible to predict the type of distortion which affects an image as well as its perceptual quality. Image quality information can obtained by the distribution of the products of pairs of adjacent MSCN coefficients, in particular $I(i,j)I(i,j+1)$, $I(i,j)I(i+1,j)$, $I(i,j)I(i+1,j+1)$, and $I(i,j)I(i+1,j-1)$. These products are well modeled on both pristine and distorted images, as following a zero mode asymmetric GGD (AGGD) is

$$g_{\alpha}(x;\gamma,\beta_l,\beta_r)=\begin{cases}\dfrac{\gamma}{(\beta_l+\beta_r)\left(\Gamma\frac{1}{\gamma}\right)exp\left(-\left(\frac{-x}{\beta_l}\right)^{\gamma}\right)}, & \forall x\le 0\\[2ex] \dfrac{\gamma}{(\beta_l+\beta_r)\left(\Gamma\frac{1}{\gamma}\right)exp\left(-\left(\frac{-x}{\beta_r}\right)^{\gamma}\right)}, & \forall x>0\end{cases}$$

The mean of the AGGD is

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

The parameters (γ, β_l, β_r, η) are also powerful "quality-aware" features.

2.3 Gradient Statistics

An image gradient is a directional change in the intensity or color in an image. The gradient of the image is one of the fundamental building blocks in image processing. It is also one of the rich descriptor of local image structure as well as local image quality. The gradient of an image measures how that image is changing. It provides two pieces of information. First the magnitude of the gradient which tells us how quickly the image is changing, while the direction of the gradient tells us in which direction the image is changing most rapidly. As the distortion to an image is introduced, the distributions of its gradient components (partial derivatives) and gradient magnitudes get changed.

Fig.1(a)

Fig.1(b)

Fig.1(c)

Fig.1(d)

Fig.1(e)

Fig. 1. (a) A reference image. Distorted versions of (a): (b) minor Gaussian blur, (c) severe Gaussian blur, (d) minor JPEG2K compression, and (e) severe JPEG2K compression.

To demonstrate this fact. Fig. 1 shows five selected images. Fig1(a) is a reference image while the other four are distorted versions of it: 1(b) with minor Gaussian blur, 1(c) with severe Gaussian blur, 1(d) with minor JPEG2K compression, and 1(e) with severe JPEG2K compression. The subjective scores are recorded on each image. Higher the subjective score, better the perceptual quality. In Fig. 2(a), we plot the histograms of the gradient components of the five images in Fig. 1, while in Fig. 2(b) we plot the histograms of their gradient magnitudes.

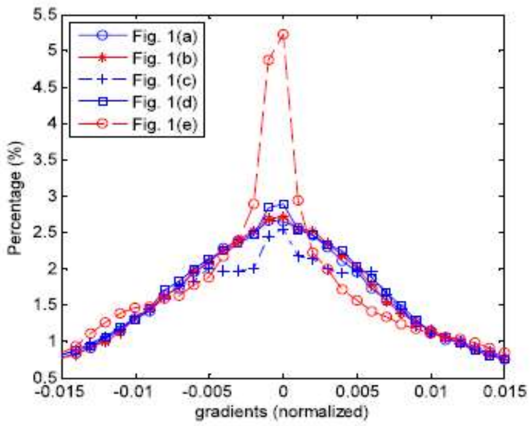

Fig.2(a) Histograms of the gradient components

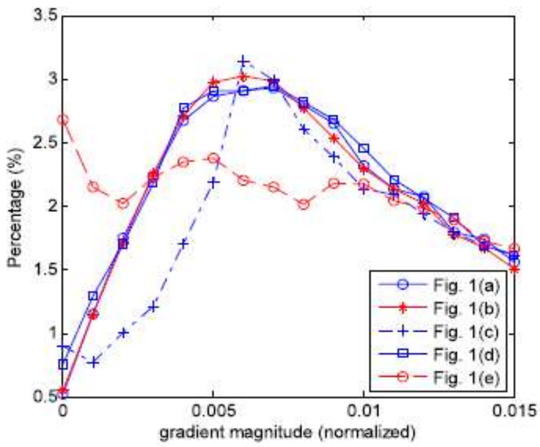

Fig.2(b) Histograms of gradient magnitudes

Fig.2(a) shows that the distortions applied to the images in Figs. 1(b) and 1(d) are less severe than distortions present in Figs. 1(c) and 1(e). By convolving image I with two Gaussian derivative filters in both the horizontal and vertical directions, respectively, gradient component images are derived, denoted by I_h and I_{v111},. The gradient magnitude image is computed as $\sqrt{{I_h}^2+{I_v}^2}$. The gradient magnitudes of natural images can be derived as following Weibull distribution:

$$P(x;a,b)=\begin{cases}\frac{a}{b^a}x^{a-1}exp\left(-\left(\frac{x}{b}\right)^a\right) & ,x\geq 0\\ 0 & ,x<0\end{cases}$$

As values of the parameter a are larger, it corresponds to the texture in gradient magnitude graph whereas values of b are larger, it corresponds to more local contrast.

2.4 Statistics of Log-Gabor Filter Responses

The statistics of multi-scale, multi-orientation filter responses to an image are also very useful for generating image quality-aware BIQA features. Here we use log-Gabor filters to accomplish multi-scale, multi-orientation filtering. A 2D log-Gabor filter can be expressed in Fourier domain as:

$$G(\omega,\theta)=e^{-\frac{\left(\log\left(\frac{\omega}{\omega\theta}\right)\right)^2}{2\sigma_r^2}}.e^{-\frac{(\theta-\theta_j)^2}{2\sigma_\theta^2}}$$

Where $\theta_j=j\pi/J$ $,j=(0,1,\ldots.j-1)$ is the orientation angle, J is the number of orientation, ω_0 is the center frequency, the filter's radial bandwidth is controlled by σ_r , the angular bandwidth of the filter is determined by σ_θ . Applying log-Gabor filters which have *N* different center frequencies and *J* different orientations to filter an image f(x) produces 2NJ responses.

$\{(e_n,j(x),o_n,j(x)):\ |n=0,1,\ldots N-1,j=0,1,\ldots\ldots J-1\}$

With given 2NJ response map we extract another set of NSS features using scheme as follows:

a) To model the distributions of $\{e_n,j(x)\}$and $\{o_n,j(x)\}$,The GDD is used and also used to extract the best fit model parameters α and β as NSS features.

b) Use GDD to model the gradient components o $\{e_n,j(x)\}$and $\{o_n,j(x)\}$ and use the retrived best fit model parameter as feature.

c) Similarly, use the Weibull distribution to model the gradient components of $e_n,j(x)\}$ and $\{o_n,j(x)\}$ and use best fit model parameters as extracted features.

2.5 Statistics of color

To further obtain the stastical properties that are pertain to color in images, we use s simple but classical NSS model. Ruderman showed that in a logarithmic-scale opponent color space, the distributions of photographic image data conform well to a Gaussian probability model.An RGB image having three channels R(i, j), G(i, j), and B(i, j) is given,it is first converted into a logarithmic signal with mean subtracted as follows:

$$R_1(i,j)=\log R(i,j)-\mu_R$$
$$G_1(i,j)=\log G(i,j)-\mu_G$$
$$B_1(i,j)=\log B(i,j)-\mu_B$$

Where μ_R , μ_G and μ_B are the mean values of log R(i, j), log G(i, j), and log B(i, j) respectively, over the entire image. Then, image pixels expressed in (R_1,G_1,B_1) space are projected onto an opponent color space as follows:

$$l_1(x,y)=(R_1+G_1+B_1)/\sqrt{3}$$
$$l_2(x,y)=(R_1+G_1-2B_1)/\sqrt{6}$$
$$l_3(x,y)=(R_1-G_1)/\sqrt{2}$$

Thus, we use Gaussian model to fit the empirical density function of *l*1, *l*2 and *l*3:

$$f(x;\tau,\rho^2)=\frac{1}{\sqrt{2\pi}\rho}exp\left(\frac{-(x-\tau)^2}{2\rho^2}\right)$$

We derive two parameters τ and ρ^2 for each of the channels and then use these parameters as NSS features. To show how the distributions of *l*1, *l*2 and *l*3 differs as a function of distortion, we use the following example. Fig.3(a) shows the reference image.Fig.3(b) and fig.3(c) indicates the distorted versions of reference image. Fig.3(b) shows additive noise in color component while fig.3(c) shows contrast compression.Fig.3(d), fig.3(e) and fig.3(f) are the histograms of *l*1, *l*2 and *l*3. It is observed that by the presence of distortion, distributions of *l*1, *l*2 and *l*3 are modified. This shows the effectiveness of the NSS features for quality evaluation.

Fig.3(a)

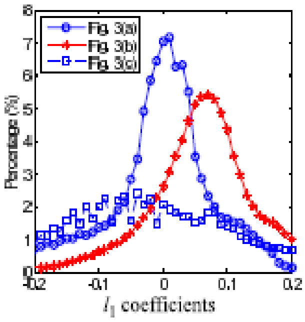

Fig.3(d)

Fig.3(b)

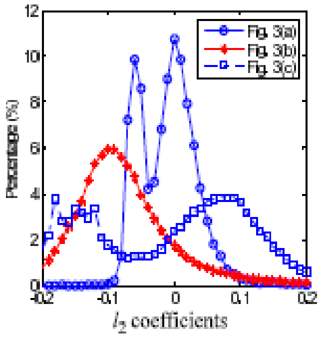

Fig.3(e)

Fig.3(c)

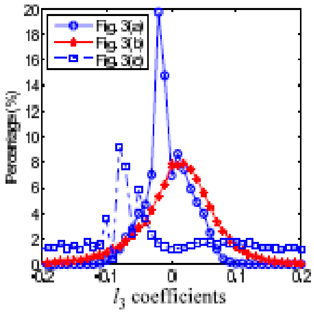

Fig.3(f)

Fig. 3.1.3- Image with distorted versions and their histograms

3. Main Modules

- **Learn MVG model for Pristine Database:**
  We learn a pristine MVG model to create a good representation of the extracted NSS features of natural

pristine images. In IL-NIQE that is Integrated Local Natural Image Quality Evaluator, the MVG model serves as a "reference" model against which the quality of a given natural image patches is to be evaluated. To learn this MVG model, we have collected a set of high quality natural images from the Internet sources.

- **NSS Feature Extraction:**

From the given image patches, NSS features are extracted from each patch. To make these extracted NSS features more meaningful for image quality prediction, only a subset of the patches are used. This prediction is based on a measure of patch contrast. The contrast at each pixel of the patch is computed, after which the patch contrast is computed as the sum of contrasts within each patch. Only those patches which are having a supra-threshold contrast greater than a threshold are selected to learn the MVG model.

Here the threshold is empirically determined by 78% of the peak patch contrast over each image. In order to enhance the image quality prediction performance of IL-NIQE, all of the NSS features are computed over two scales (by down-sampling the images by a factor of 2) to capture multi-scale attributes of the images. Each selected patch produces a d-dimensional feature vector by stacking all the NSS features extracted from it. As might be expected, some of the NSS features will be correlated with others. Therefore, to remove this correlation effects, we apply PCA to the feature vector to reduce its dimension. As a result of this, the computational cost gets reduced and the quality prediction process becomes more efficient.

- **MVG model:**

The MVG model (μ_i, Σ_i) can be constructed using the NSS feature vectors that is estimated from neighboring patches. However, this can be very costly. For simplicity, we use the NSS feature vector y'_i as μ_i, and the empirical covariance matrix of the feature set $\{y'_i\}$ as Σ_i. That is, all patches share the same covariance matrix, denoted by Σ'. Then the MVG model (y'_i, Σ'). is assignd to the patch i.

- **Compute Quality Score for Test Image:**

After learning the pristine MVG model (μ, Σ), we can then use it to measure the quality of any patch in a given test image. From each patch I of the given test image extract a d-dimensional natural scene statistics feature vector y_i, then reduce the dimension of y_i using the pre-learned projection matrix Φ:

$$y'_i = \Phi^T y_i, \quad y'_i \in \mathcal{R}^{m\times 1}, \ i = 1, \dots, k.$$

After obtaining the feature set $\{y'_i\}_{i=1}^{k}$ of a given test image, we can now predict its quality score. Previous IQA studies have proved that different local regions of an image can provide different contributions to the evaluation of the overall image quality. Therefore, each patch i is fitted by an MVG model, denoted by (μ_i, Σ_i), which is then compared with the pristine MVG model (μ, Σ), that produces a quality prediction value of the local quality score of patch i. Then the overall image quality score of the test image can be obtained by pooling the quality scores of all patches. Here we use simple average pooling. We use the following formula to measure the distortion level of patch i:

$$q_i = \sqrt{(\mu - y'_i)^T \left(\frac{\Sigma + \Sigma'}{2}\right)^{-1} (\mu - y'_i)} \quad \dots\dots\dots\dots(1)$$

Which is a modified Bhattacharyya distance that is also used in NIQE. In summary, Eq. 1 measures the difference of the statistics of patch i from the reference statistics that are prelearned from high quality natural images. Finally, the overall quality score of the given test image is pooled as the mean of {qi}.

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