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No Reference Image Quality Assessment: Feature Extraction Approach

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Abstract: ***In our day to day life we are accompanied with digital visual information. Various distortions are introduced during the sharing, transmission or storing of this digital information. Image quality assessment refers to the judgment of the image quality as various image processing applications depends on this information. Image quality can be measured by two ways, subjective and objective method. Subjective method where human judges the quality of image using mean opinion score (MOS) method. This method is time consuming, expensive and cannot be implemented in system where real time valuation of image quality is needed while Objective method can be implemented without human involvement and predict image quality that is reliable with human subjective observation. When quality of test images are done without the information of distortion present in that image then it is called no reference image quality assessment or blind image quality assessment. The objective of this paper is to overview the different methodologies employed for quality assessment of an image and briefly explains the no reference image quality assessment method using a feature extraction approach and analyses its performance.***

Keywords: MATLAB 2013, NSS features, IL-NIQE method, TID2013 database & GLCM features

1. Introduction

The quality of any image is lost due to the occurrence of noise and these noises occurred during the storing and transmit of information or during sharing time of information between the devices. A wide range of applications depend on this transmitted digital information. Hence quality measuring is needed for assessing and control the quality of those images. Image quality assessment refers to a model which predicts the quality of distorted images. Image quality assessment methods are categorized as: subjective assessment by humans where the evaluation of quality by humans is obtained by mean opinion score (MOS) method and other is objective assessment by algorithms which automatically predict the quality of the distorted images as would be perceived by an average human.

Depending on the amount of information that is available from the original image as a reference, the objective methods are further classified into full reference (FR), reduced reference (RR) [6] and blind or no-reference (NR) methods [6] described as follows:

FR methods: The entire original image is used as a reference image in this approach. This method compares distorted image with original image. MSE and PSNR fall into this category.

RR methods: In this case, the complete original image is not available as a reference only some features about texture or other suitable descriptive features of the original image are provided.

Blind or NR methods: These methods do not require access to the original image. It uses the pixel domain of distorted image to to search for artifacts.

Both FR and RR methods require the availability of a reference image against which the test image is compared. In many applications, however the reference image is not available to perform a comparison against the test image. This strictly limits the application domain of FR-IQA and RR-IQA algorithms and demands for reliable blind/NR-IQA algorithms.

Blind (NR IQA) is based on the principle that natural images own certain regular statistical properties that are measurably altered by the existence of distortions. This method is capable of assessing the quality of an image without any reference image.

2. Methodology

Figure1. shows a block diagram of a typical IQA model

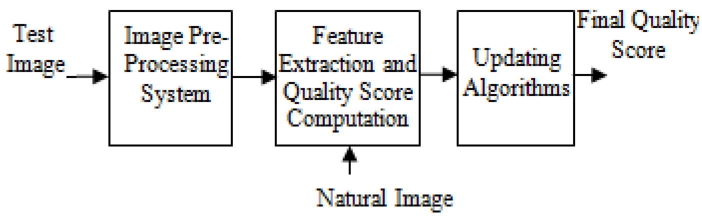

Figure 1: Block Diagram of IQA model

The test image is processed to different steps and a viewer gives his or her opinion on a particular image and evaluates quality of the multimedia content as shown in figure 1.

Any natural image can be a test image whose features are first extracted in the form of numeric values. Next a set of natural images are trained and features are extracted and stored in matrix form. Both features are then compared and accordingly ranking are done which predicts the quality of an image.

Various IQA models [5] are shown in figures 2, 3 &4.

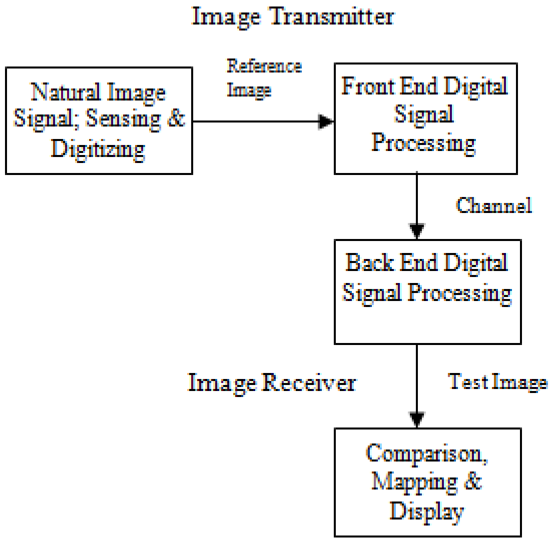

Figure 2: Block Diagram of FR IQA method

In FR IQA method, the test image is compared with the reference signal which is already available as shown in figure2. In RR IQA method part of information of the reference image is used for evaluation process as shown in figure3.

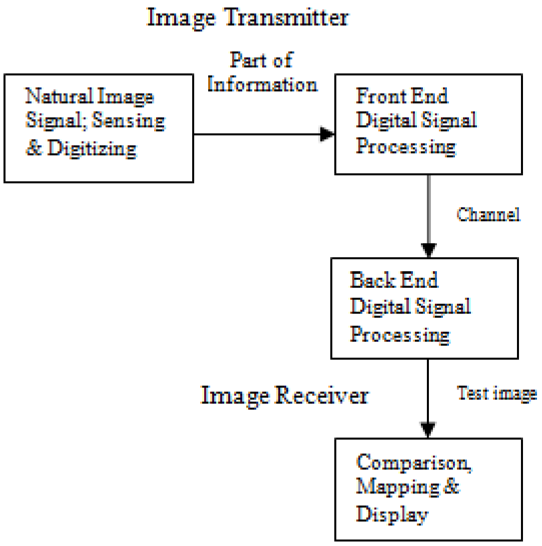

Figure 3: Block Diagram of RR IQA method

BIQA (NR IQA) method does not need any distorted model of images or human subjective scores for training as shown in figure4, yet experiment show its better quality-prediction performance and hence make it suitable for assessment of image quality.

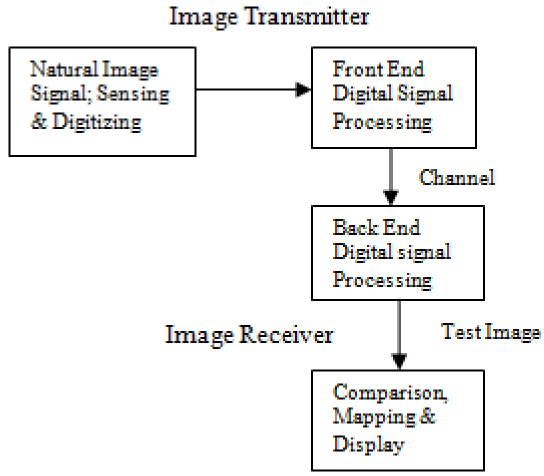

Figure 4: Block diagram of BIQA (NR IQA) method

3. Categories of BIQA

Blind Image Quality Assessment (BIQA) methods are categorised as: Opinion aware methods in which a large number of training samples are used and the distortion types is also known and uses a human subjective scores to predict the quality of distorted images. The second category is Opinion unaware methods which do not use any distorted sample images or human subjective scores for training.

Various Opinion aware methods are:
1) BIQI
2) DIIVINE
3) BLIINDS& BLIINDS-II
4) BRISQUE
5) CORNIA

Various Opinion unaware methods are:
1) NIQE
2) QAC
3) IL-NIQE

In first opinion aware method called BIQI, some statistics (features of an image) of test image is first extracted and used to classify the test image into n distortions. Same statistics set of natural image are then used to evaluate the quality of test image.

Later BIQI method is modified and named as Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE) method [1] in which enriched number of natural scene features are used. It uses two stage QA frame work: identification of distortion followed by distortion-specific QA. It does not use any distortion and reference models and evaluate the quality of an image. Its evaluation performance is précised and statistically incomparable from previous popular FR algorithm such SSIM. The DIIVINE approach is distortion-agnostic as it adopts Natural Scene Statistic based approach to qualify and compute the distortion afflicting the image rather than computing distortion –specific indicators of quality. The approach is modular, in that it can easily be extended beyond the group of distortions considered here. DIIVINE approach cannot be applied to compute quality in real time as it is difficult to calculate huge number of features.

Then a new opinion aware BIQA model is proposed that works in the DCT domain and is named BLIINDS [9]. A probabilistic model first extracts contrast and structure features in Discrete Cosine Transform (DCT) domain and then train this new model. A small number of efficient features are computed from a NSS model of block DCT coefficients and is fed to a regression function that delivers precise QA predictions. This method relies on a simple probabilistic model for quality score prediction and requires minimal training. This leads to further computational gains. Also, this method correlates highly with human subjective scores of quality and gives highly competitive performance, even with respect to state-of-the-art FR-IQA algorithms. BLIINDS-II model is an extension of BLIINDS model which uses more NSS based DCT features.

BLIINDS-II is more efficient than DIIVINE but it requires non-linear sorting of block based NSS features which slows it considerably.

The new model Blind/Reference less Image Spatial Quality Evaluator (BRISQUE) [9] is an another opinion aware BIQA model that predict the quality of image by using the scene statistics of pair-wise products of neighboring (locally normalized) luminance coefficient values to quantify possible losses of naturalness in the image due to the presence of distortions. BRISQUE [9] has very low computational complexity and may be used for distortion-identification which makes it suitable for real time applications

Later an unsupervised feature learning framework BIQA model called CORNIA is proposed that extract the local feature and maintain a codebook and accordingly assign subjective scores of its quality.

After then the first opinion unaware method called Natural Image Quality Evaluator (NIQE) [3] is proposed that extracts local features from an image and fits the feature vectors to a single global Multivariate Gaussian Model (MVG) and predicts the quality by the distance between MVG‟s model of pristine image and of natural image. Another model is trained which first partitioned the test image into overlapped patches and learn a set of quality aware centroids and use them as a codebook to infer the quality of an image patch. This model is trained from the dataset using patch based clustering and percentile pooling strategy to estimate the quality of each patch.

A powerful opinion unaware method called IL-NIQE is a recent methodology which uses quality aware NSS [2] features of natural pristine images. In IL-NIQE [1] method, first a pristine multivariate Gaussian model of NSS features is learned from a collection of stored pristine images. Then from each patch of a given test image, an MVG model is fitted using the feature vector and then its local quality score is computed by comparing it with the learned pristine MVG model. Finally, the overall quality score of the test image is obtained by pooling the quality scores obtained by its feature vectors.

3.1 Proposed Method

The proposed methodology utilizes a powerful opinion unaware BIQA method called IL-NIQE method with a large number of GLCM features such as Homogeneity feature, angular second moment feature, inverse difference moment feature, correlation and inertia as a texture features along with features such as features of local structure, contrast, multi-scale and multi-orientation decomposition and color based features to characterize the image quality distortion.

3.2 NSS Features Used

The Natural Scene Statistics features used in the proposed model are as follows:
a) Structural features.
b) Contrast.
c) Multi-scale and multi-orientation decomposition.
d) Distortion in image color space.
e) Homogeneity
f) Angular Second Moment
g) Inverse difference Moment
h) Entropy
i) Inertia

All these features are described as follows:

3.2 (a) Structural features
To characterize structural distortion, two types of NSS [2] features are adopted which is derived from distribution of local mean subtract and contrast normalized (MSCN) coefficients and from the distribution of product of pairs of adjacent MSCN coefficients. On both pristine and distorted images, these products are modelled as zero mode asymmetric GGD (AGGD) [7].

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

where $\beta_l=\sigma_l\sqrt{\dfrac{\Gamma(1/\gamma)}{\Gamma(3/\gamma)}}$

$$\beta_r=\sigma_r\sqrt{\frac{\Gamma(1/\gamma)}{\Gamma(3/\gamma)}}$$

The shape parameter γ controls the shape of the distribution while β_l and β_r are scale parameters that control the spread of the mode on each side respectively.

3.2 (b) Contrast
To capture contrast distortion, quality aware gradient features are used. The distributions of its gradient

components (partial derivatives) & gradient magnitudes are changed by introducing distortions to an image. The gradient components denoted by I_h and I_v are computed by convolving I with two Gaussian derivatives filter along the horizontal and vertical directions. Gradient components [10] are modelled as generalized Gaussian distribution. Gradient magnitude of natural image is modelled using weibull distribution expressed as

$$f(x:a,b)=\begin{Bmatrix} 0x<0 \\ \frac{a}{b^a}x^{a-1}\exp\left(-\left(\frac{x}{b}\right)^a\right)x\geq 0 \end{Bmatrix}$$

where a is scale parameter and b is shape parameter.

3.2 (c) Multi-Scale and Multi-Orientation Decomposition

To extract quality related multiple scale and multi-orientation property of an image, log Gabor filters are used that extract statistical features from filter responses.

A one dimensional Log-Gabor function whose frequency response is expressed as:

$$G(f)=\exp\left\{\frac{-(\log(f/f_0))^2}{2(\log(\sigma/f_0))^2}\right\}$$

where σ and f_0 are the parameters of the filter. σ affects the bandwidth of the filter. f_0 is the center frequency of the filter. It is useful to maintain the same shape while the frequency parameter is varied.

3.2 (d) Distortion In Image Colour Space

These features can be derived from intensity distribution of an image in a logarithmic scale opponent colour space [1]. In a logarithmic-scale opponent color space, the distributions of photographic image data match to a Gaussian probability model (showed by Ruderman). Consider RGB image with *R (i, j)*, *G (i, j)* and *B (i, j)* as three image channels; first convert it into a logarithmic signal with mean subtracted:

$$R(i,j) = \log R(i,j) - \mu_R$$

$$G(i,j) = \log G(i,j) - \mu_G$$

$$B(i,j) = \log B(i,j) - \mu_B$$

where μ_R, μ_G and μ_B are the mean of logarithmic scale of three channels i.e log R (i, j) , log G (i, j) and log B (i, j) over the entire image. Then, image pixels expressed in (R, G, B) space is projected onto an opponent color space:

$$l_1(x,y)=(R+G+B)/\sqrt{3}$$

$$l_2(x,y)=(R+G-2B)/\sqrt{6}$$

$$l_3(x,y)=(R-G)/\sqrt{2}$$

The distributions of the coefficient l_1, l_2 and l_3 of natural images conform to a Gaussian probability law.

3.2 (e) Homogeneity

Homogeneity measures the closeness of distribution of the elements in GLCM

$$\text{Homogeneity}=\sum_{i,j}\frac{P(i,j)}{1+|i-j|}$$

3.2(f) Angular Second Moment:

Angular second moment measures the sum of squared elements in the GLCM

Angular Second Moment $=\sum_{i,j}P(i,j)^2$

3.2(g) Inverse Difference Moment:

Inverse difference Moment is the local homogeneity whose value is high when local gray level is uniform. It is computed as:

$$\text{IDM}=\sum_{i,j=0}^{G-1}\frac{1}{1+(i-j)^2}\ P(i,j)$$

3.2(h) Entropy

Entropy is the amount of information coded for by the compression algorithm. It is given as:

Entropy = $-\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j)\log(P(i,j))$

3.2(i) Correlation

Correlation measures the linear statistical relationship between specified pixel pairs means how correlated a pixel to its neighbor pixel over the entire image.

Correlation = $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{\{i*j\}*P(i,j)-(\mu_x*\mu_y)}{\sigma_x\sigma_y}$

4. Performance Analysis

TID2013 dataset is used to evaluate the performance of IQA methods. To evaluate the performances of both BIQA methods Spearman rank order correlation coefficient (SRCC) [6] is used which operates only on the rank of the data points and not on the relative distances between data points. In IL-NIQE, five types of features including MSCN based features, MSCN product based features, log-Gabor responses based features, gradient based features and color based features were used [1] and in the proposed method along with these features angular second moment, homogeneity, inverse difference method, entropy ,correlation and inertia features are used. SRCC is used as the performance metric to compare both BIQA models..

The results of performance of both methods on all features are reported in Table I.

Table 1: Performance (SRCC) Of Each of the Five Types of Features Used In IL-NIQE

Distortion Type	*IL-NIQE Method*	*Proposed Method*
1. Additive Gaussian Noise	0.1185	0.1369
2. Gaussian Blur	0.5163	0.5279
3. JPEG Compression	0.2879	0.3167
4.JPEG2K Compression	0.1592	0.2169
5. Non Eccentricity Pattern Noise	0.2819	0.3604
6.Local Block-wise Distortions	0.2508	0.3185
7. Mean Shift	0.2923	0.3677
8. Change of Color Saturation	0.5854	0.6446

The results lead to the following conclusion that if the number of features extracted to predict the quality of any image is increased then the performance of an assessment method also increased. This method is an efficient method as it does not require any dataset of distorted samples for training as well as human subjective scores to predict the quality of an image.

5. Conclusion

Comparisons of both BIQA methods show that although opinion unaware methods have a good generalization ability but the prediction of quality of distorted images are not accurate than opinion aware methods. An approach which uses natural scene statistics model for feature extraction of distorted image without the need of any distorted sample images or subjective scores for training can be more précised if more features of an image can be used so that high correlation can be achieved.

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