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EFFECTIVE FEATURE ANALYSIS TOTALLY BLIND IMAGE QUALITY VALUATION

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Abstract:

In our daily life, digital visual information is attached. Various distortions are introduced during the sharing, transmission or storage of digital information. Image quality evaluation refers to determination of image quality because various image processing applications depend on information. There are two ways to measure subjective and objective picture quality. People use the Mean Opinion Score (MOS) method to determine the subjective method of image quality. In recent years there has been growing interest in developing an objective image quality assessment (IQA) model that not only monitors image quality degradation and baseline image processing system but also helps to optimize various image and video processing algorithms and systems there. Past performance is worthy of praise, but there are some important issues to face when applying existing IQA models to real world applications. For this, there are issues such as greatly reducing the complexity of the existing IQA algorithm, making it easy to use and easy to understand.

Introduction:

In the current research, image processing technologies such as acquisition, transmission, compression, restoration, expansion are attracting attention, and the quality evaluation method is also increasing. A human being the final judge of image quality, the judgment did not take time. However, we need automatic evaluation called customer's evaluation. Objective evaluation can be categorized as a full reference (FR), reduced-reference (RR) and non-reference (NR) image quality evaluation. The quality of the FR model image is achieved by accessing the original image completely. The RR model evaluates the image quality by extracting some special features from the original image. Generally, we use the image loss factor by simulating the behavior of cortical neurons to construct the RR feature. To evaluate the image quality, they used the statistics of Distortion measure obtained from natural images using multiscale multi-orientation normalized transformation to obtain SSIM features. The RF and RR Image Quality Assessment (IQA) method provide a useful or effective way to evaluate the quality of distorted images, but in some cases, the reference image or a part thereof may not be available, in this case, NR IQA method is required.

Methodology:

This model is derived from statistics of natural scenes and is based on building a set of natural features that are suitable for the multivariate Gaussian Model (MVG) model. The quality of the evaluated distorted image is expressed as the distance between the MVG fit of the feature extracted from the distorted image and the MVG model of the natural feature extracted from the natural image.

MSCN and Log-Derivative Statistics Based Features:

The MSCN coefficients and the five log-derivatives are modeled following a zero mode Asymmetric Generalized Gaussian Distribution (AGGD) (Mittal *et al.*, 2012a; Lasmar *et al.*, 2009):

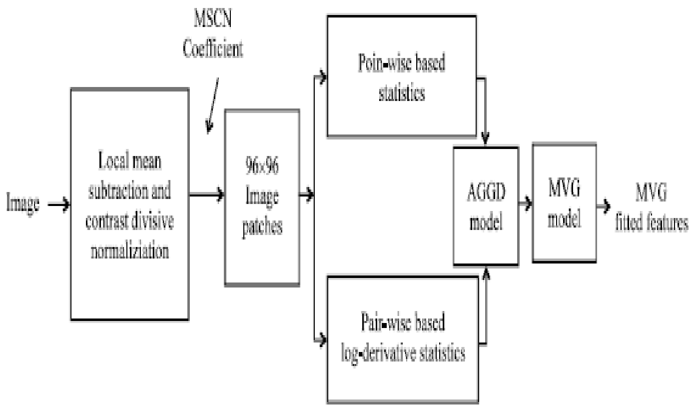

Figure 1: Block diagram of the proposed algorithm for features extraction. Where MSCN stands for mean subtraction and contrast divisive normalization, AGGD is asymmetric generalized gaussian distribution and MVG represents multivariate gaussian model

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

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

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

The five-log parameter and (γ, β 1, β r) of MSCN represent the extracted 18 features. These functions are computed on two scales characterizing multiscale operation and are filtered and downsampled twice by lowpass filtering, resulting in 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. 1is used here for extracting these features.

Multivariate Gaussian Model (MVGM):

The features obtained by Eq. 1for image patches were fitted with an MVG density, to give their rich representation (Mittal *et al*., 2013):

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

Where υ and Σ are the mean and covariance matrix of the MVGM, respectively, x_1,...x_k are the features extracted by Eq. 1.

Natural Scene Statistic (NSS) MVGM:

NSS MVGM is calculated based on 125 natural images selected from the free version of Flickr data and the Berkeley image segmentation database (Martin et al., 2001). A distributed field of rich image information that quantifies the local image sharpness.Selected features that correspond to sharper patches. Choose a sharper patch with an average variance greater than 75% of the sharpness of the peak patch on the image. This function is suitable for the MVG model in eq.2

Quality Assessment:

The proposed indicator calculates 36 features from the image (distortion) patch under test and fit them to the MVGM in the equation. 2 and compare fit MVG and natural MVG model. Quality is evaluated as the distance between the NSS MVGM and the MVGM of the test image by the following Equation 3.

$$D(\upsilon_1,\upsilon_2,\Sigma_1,\Sigma_2) = \sqrt{(\upsilon_1-\upsilon_2)^T\left(\frac{\Sigma_1+\Sigma_2}{2}\right)^{-1}(\upsilon_1-\upsilon_2)} \tag{3}$$

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.

Conclusion:

We have introduced a new BIQA approach to the "blind" IQA concept. The New Model IL-NIQE extracts five types of NSS features from a set of raw natural images to learn the multivariate Gaussian (MVG) model of the original image and a reference model that predicts its quality. In the patch image it is a patch image quality assessment and then averages the patch quality scores to generate the overall quality score. Many experiments show that IL-NIQE provides better predictive performance than all competing approaches. An important message from this work is that BIQA models that do not know "totally blind" opinions can compete with models that actually express their opinions. In the near future, I would like to develop a BIQA model that does not accept more opinions.

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