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A Brief Review on Blind Image Quality Evaluation Methods

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ABSTRACT
Image Quality Assessment plays an important role in various image processing applications. It is still an active area of research. A great deal of effort has been made in recent years to develop objective image quality metrics that correlate well with perceived human quality measurement or subjective methods. Image quality assessment means estimating the quality of an image and it is used for many image processing applications. Image quality can be measured in two ways, subjective and objective method. In Subjective image quality assessment the evaluation of quality by humans is obtained by mean opinion score (MOS) method where in objective evaluation of quality is done by algorithms. It concerned with how image is perceived by a viewer and gives his or her opinion on a particular image and judge quality of the multimedia content. The human eyes extract structural information from the viewing field, so the human visual system is highly adapted for this purpose.

General Terms
Security, Pattern Recognition, Algorithms etc

Keywords
Image quality assessment, objective & subjective method

1. INTRODUCTION
With the development of imaging and multimedia technologies, visual information, recorded by images has become the main source for knowledge acquisition. In the process of visual information acquisition, processing, transmission, and storage, some artifacts or noise may be introduced to images which degrade the visual quality. In a typical digital imaging system, the image is captured and transformed into digital signal by the sensor .This raw digital image signal is then processed to reduce the noise and is compressed for storage or transmission. When the image is finally displayed on the screen to the end user, it might not be same as the original version because it has been exposed to various kinds of distortions.

The sources of distortion could be ranged from motion blurring, Gaussian noise, sensor inadequacy, compression, error during transmission or the combination of many factors. To improve the performance of visual information acquisition, transmission, processing, and storage systems, it is essential to assess visual qualities of the images; so that it can maintain, control and possibly enhance the quality of the image before storage or transmission. The objective of image quality assessment is to provide computational models to measure the perceptual quality of a given image. Recently, a number of techniques have been designed to evaluate the quality of images and videos.

The accurate prediction of quality from an end-user perspective has received increased attention with the growing for compression and communication of digital image and video services over wired and wireless networks. Image quality methods can be categorized in two parts subjective and objective. The subjective assessment of image is done on the bases of subjective experiments. While objective image quality assessment methods were mainly based on some mathematical measures. The past five years have demonstrated and witnessed the tremendous and imminent demands of visual quality assessment metrics in various applications.

2. IMAGE QUALITY ASSESSMENT METHODS
Objective quality assessment is a very complicated task, and even full-reference QA methods have had only limited success in making accurate quality predictions. Researchers therefore tend to break up the problem of NR QA into smaller, domain-specific problems by targeting a limited class of artifacts-distortion-specific IQA.

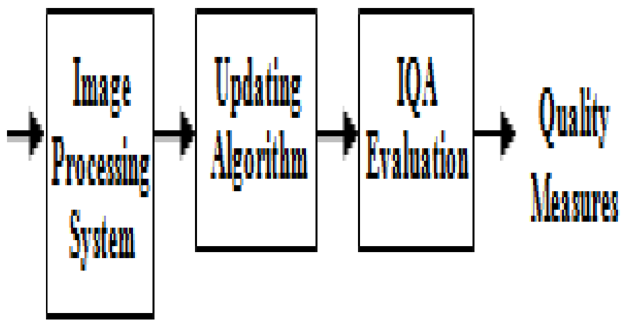

Fig 1: Block diagram of Image Quality Assessment.

The most common being the blocking artifact, which is usually the result of block-based compression algorithms running at low bit rates. At live we have conducted research into NR QA for blocking distortion as well as pioneering research into NR measurement of distortion introduced by Wavelet based compression algorithms based on Natural Scene Statistics modeling. Following are the methods of image quality assessment.

2.1 Natural Image Quality Evaluator (NIQE)
Natural Image Quality Evaluator (NIQE) blind image quality assessment (IQA) is a completely blind image quality analyzer that uses only measurable deviations from statistical regularities observed in natural images, without training on human-rated distorted images, and, indeed without any exposure to distorted images. However, all current state-of-

the-art general purpose no reference (NR) IQA algorithms require knowledge about anticipated distortions in the form of training examples and corresponding human opinion scores.

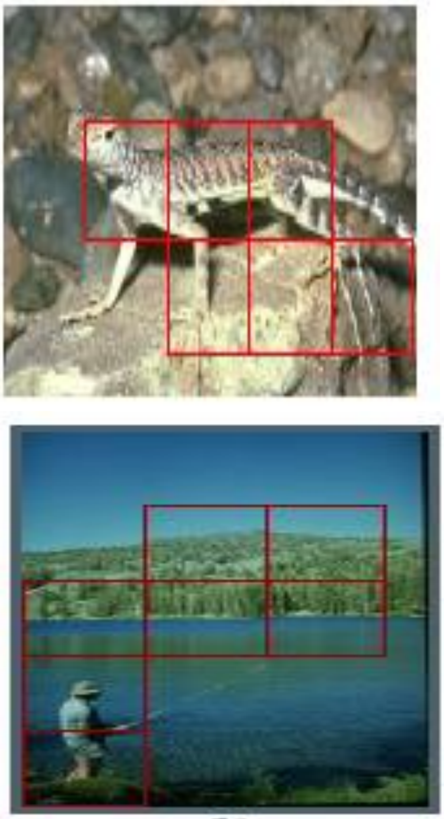

Fig 2: Patch Selection

It depends on the construction of a quality aware collection of statistical features that are based on a simple and successful space domain of natural scene statistic (NSS) model. We use a simple device to preferentially select from amongst a collection of natural patches those that are richest in information and less likely to have been subjected to a limiting distortion. This subset of patches is then used to construct a model of the statistics of natural image patches.The variance field has been largely ignored in the past in NSS based image analysis, but it is a rich source of structural image information that can be used to quantify local image sharpness. Letting the P×P sized patches be indexed b =1,2,3,….B, a direct approach is to compute the average local deviation field of each patch indexed b:

$$\delta(b) = \sum\sum_{(i,j)\epsilon patc\ hb} \sigma(i,j)$$

Given a collection of natural image patches selected as above, their statistics are characterized by 'quality aware' NSS features computed from each selected patch [3]. Prior studies of NSS based image quality have shown that the generalized

Gaussian distribution effectively captures the behavior of the coefficients of natural and distorted versions of them. The generalized Gaussian distribution (GGD) with zero mean is given by:

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

The parameters of the GGD (α,β), can be reliably estimated using the moment-matching based approach proposed. The signs of the transformed image coefficients have been observed to follow a fairly regular structure. However, distortions disturb this correlation structure. This deviation can be captured by analyzing the sample distribution of the products of pairs of adjacent coefficients computed along horizontal, vertical and diagonal orientation.

These natural scene statistic features are derived from a collection of natural, undistorted images. Experimental results show that the new index delivers performance comparable to top performing NR IQA models that require training on large databases of human opinions of distorted images. This method uses only two types of the NSS features. It uses a single global MVG model to describe the test image

2.2 BLind Image Integrity Notator using DCT-Statistics (BLIINDS)

BLIINDS is one of the efficient, general-purpose, non-distortion specific, blind that is no-reference image quality assessment (NR-IQA) algorithm that uses natural scene statistics models of discrete cosine transform (DCT) coefficients to perform distortion-agnostic NR IQA. We derive a generalized NSS-based model of local DCT coefficients, and the model parameters are transform into features suitable for perceptual image quality score prediction. The statistics of the DCT features vary in a natural and predictable manner as the image quality changes. We will refer to undistorted images captured by imaging devices that sense radiation from the visible spectrum as natural scenes, and statistical models built for undistorted natural scenes as NSS models. Deviations from NSS models, caused by the introduction of distortions to images, can be used to predict the perceptual quality of the image.

The model-based NSS-IQA approach developed here is a process of feature extraction from the image, followed by statistical modeling of the extracted features. Purely NSS-based IQA approaches require the development of a distance measure between a given distorted test image and the NSS model. This leads to the question of what constitutes appropriate and perceptually meaningful distance measures between distorted image features and NSS models. The Kullback– Leibler divergence as well as other distance measures have been used for this purpose, but no perceptual justification has been provided for its use.

Our approach relies on the IQA algorithm learning how the NSS model parameters vary across different perceptual levels of image distortion. The algorithm is trained using features derived directly from a generalized parametric statistical model of natural image DCT coefficients against various perceptual levels of image distortion. The learning model is then used to predict perceptual image quality scores. Unlike much of the prior work on image/video quality assessment (QA) , we make little direct use of specific perceptual models such as area V1 cortical decompositions, masking and motion perception .Yet we consider our approach as perceptually relevant since the NSS models reflect statistical properties of the world that drive perceptual functions of the HVS. This is a consequence of the belief that the HVS is adapted to the statistics of its visual natural environment. In other words, models of natural scenes embody characteristics of the HVS, which is hypothesized to be evolutionally adapted to models conforming to natural scenes. HVS characteristics that are intrinsic to, or that can be incorporated into NSS models include:

1. Visual sensitivity to structural information
2. Perceptual masking
3. Visual sensitivity to directional information
4. Multiscale spatial visual processing and
5. Intolerance to flagrantly visible visual distortions.

In the following sections we explain how one or more of these HVS properties are embedded in the model. The framework of the proposed approach is summarized in Fig. An image the IQA "pipeline" is first subjected to local 2-D DCT coefficient computation.

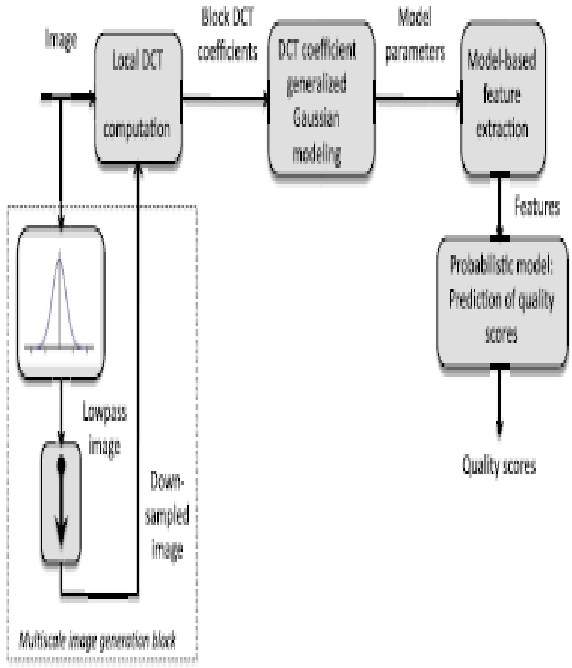

Fig 3: Overview of BLIINDS method

This stage of the pipeline consists of partitioning the image into equally sized n x n blocks, henceforth referred to as local image patches, then computing a local 2-D DCT on each of the blocks. The coefficient extraction is performed locally in the spatial domain in accordance with the HVS's property of local spatial visual processing (i.e., in accordance with the fact that the HVS processes the visual space locally). This DCT decomposition is accomplished across spatial scales. The second stage of the pipeline applies a generalized Gaussian density model to each block of DCT coefficients, as well as for specific partitions within each DCT block.

A generalized probabilistic model is applied to these features, and are used to make probabilistic predictions of visual quality. We show that the method correlates highly with human subjective judgements of quality. The contributions of this approach are as follows:

1) The proposed method inherits the advantages of the NSS approach to IQA. While the goal of IQA research is to produce algorithms that accord with human visual perception of quality, one can to some degree avoid modeling poorly understood functions of the human visual system (HVS), and resort to deriving models of the natural environment instead.

2) BLIINDS is non-distortion specific; while most NR-IQA algorithms quantify a specific type of distortion, the features used in our algorithm are derived independently of the type of distortion of the image and are effective across multiple distortion types. Consequently, it can be deployed in a wide range of applications.

3) We propose a novel model for the statistics of DCT coefficients.

4) Since the framework operates entirely in the DCT domain, one can take exploit the availability of platforms devised for the fast computation of DCT transforms.

5) The method requires minimal training, and relies on a simple probabilistic model for quality score prediction. This leads to further computational gains.

6) Finally, the method correlates highly with human visual perception of quality and yields highly competitive performance, even with respect to state-of-the-art FR-IQA algorithms.

2.3 Distortion Identification-based Image Verity and Integrity Evaluation (DIIVINE)

DIIVINE is a distortion-agnostic approach to blind IQA that utilizes concepts from natural scene statistics (NSS) to not only quantify the distortion and hence the quality of the image, but also qualify the distortion type afflicting the image. The Distortion Identification-based Image Verity and Integrity Evaluation (DIIVINE) index utilizes a 2-stage framework for blind IQA that first identifies the distortion afflicting the image and then performs distortion-specific quality assessment.

Our computational theory for distortion-agnostic blind IQA is based on the regularity of natural scene statistics (NSS); for example, it is known that the power spectrum of natural scenes falloff as (approximately) 1/f^b , where f is frequency. NSS models for natural images seek to capture and describe the statistical relationships that are common across natural (undistorted) images. Our hypothesis is that, the presence of distortion in natural images alters the natural statistical properties thereby rendering the image 'un-natural'. NR IQA can then be accomplished by quantifying this 'un-naturalness' and relating it to perceived quality.

In order to extract statistics from distorted images we utilize the steerable pyramid decomposition. The steerable pyramid is an over complete wavelet transform that allows for increased orientation selectivity. The choice of the wavelet transform was motivated by the fact that the scale-space orientation decomposition that the wavelet transform performs mirrors models of spatial decomposition that occurs in area V1 of the primary visual cortex. The steerable pyramid has been previously used for FR IQA as well as RR IQA with success. Note that we do not use the complex version of the steerable pyramid as in, but that used in. Given an image whose quality is to be assessed, the first step is to perform a wavelet decomposition using a steerable pyramid over 2 scales and 6 orientations. We have found that an increased degree of orientation selectivity is beneficial for the purpose of QA - more so than selectivity over more than 2 scales. The choice of steerable filters was also motivated by its increased orientation selectivity.

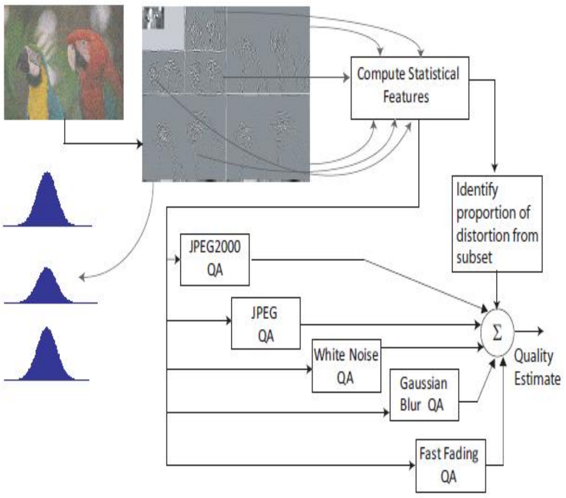

Fig 3: Distortion identification-based Image Verity and Integrity Evaluation (DIIVINE) index

The Distortion Identification-based Image Verity and Integrity Evaluation (DIIVINE) – divines the quality of an image without any need for a reference or the benefit of distortion models, with such precision that its performance is statistically indistinguishable from popular FR algorithms such as the structural similarity index (SSIM). The DIIVINE approach is distortion-agnostic, since it does not compute distortion-specific indicators of quality, but utilizes an NSS-based approach to qualify as well as quantify the distortion afflicting the image. The approach is modular, in that it can easily be extended beyond the pool of distortions considered here. This method assume that the distortion types in the test images are represented in the training dataset, which is, however, not the case in many practical applications.

2.4 Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)

Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) is a natural scene statistic (NSS)-based distortion-generic blind/no-reference (NR) image quality assessment (IQA) model which operates in the spatial domain. It does not compute distortion specific features such as ringing, blur or blocking, but instead uses scene statistics of locally normalized luminance coefficients to quantify possible losses of 'naturalness' in the image due to the presence of distortions, thereby leading to a holistic measure of quality.The underlying features used derive from the empirical distribution of locally normalized luminances and products of locally normalized luminance under a spatial natural scene statistic model. No transformation to another coordinate frame (DCT, wavelet, etc) is required, distinguishing it from prior no reference IQA approaches. Despite its simplicity, we are able to show that BRISQUE is statistically better than the full-reference peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM) and highly competitive to all present-day distortion-generic NR IQA algorithms. BRISQUE has very low computational complexity, making it well suited for real time applications. BRISQUE features may be used for distortion identification as well.

To illustrate a new practical application of BRISQUE, we describe how a non-blind image denoising algorithm can be augmented with BRISQUE in order to perform blind image denoising. Results show that BRISQUE augmentation leads to performance improvements over the state-of-the-art. The model proposed in extracts three sets of features based on the statistics of natural images, distortion textures, and blur/noise; three regression models are trained for each feature set and finally a weighted combination of them is used to estimate the image quality.

2.5 No-Reference Quality Assessment algorithm for Block-Based compression artifacts

Perhaps the most common distortion type that one comes across in real-world applications is the distortion introduced by lossy compression algorithms, such as JPEG (for images) or MPEG/H.263 (for videos). These compression algorithms are based on reduction of spatial redundancies using the block-based Discrete Cosine Transform (DCT). When these algorithms are constrained to increase the amount of compression, a visible 'blocking' artifact can be seen. Blocking resulting from DCT based compression algorithms running at low bit rates has a very regular profile. It manifests itself as an edge every 8 pixels (for the typical block-size of 8 x 8 pixels), oriented in the horizontal and vertical directions. The strength of the blocking artifact can be measured by estimating the strength of these block-edges. At LIVE, we have developed frequency domain algorithms for measuring blocking artifact in images compressed by JPEG, with the algorithm having no information about the reference image.

2.6 No-Reference Quality Assessment for JPEG2000 Compressed Images using Natural Scene Statistics

Not all compression algorithms are block-based. Recent research in image and video coding algorithms has revealed that a greater compression can be achieved for the same visual quality if the block-based DCT approach is replaced by a Discrete Wavelet Transform (DWT). JPEG2000 is a recent image compression standard that uses DWT for image compression. However, DWT based algorithms also suffer from artifacts at low bit rates, specifically, from blurring and ringing artifacts. Blurring and ringing artifacts are image dependent, unlike the blocking artifact, whose spatial location is predictable.

This makes the task of quantifying distortion resulting from DWT based compression algorithms (such as the JPEG2000) much harder to quantify. At LIVE we have proposed a unique and innovative solution to the problem. We propose to use Natural Scene Statistics models to quantify the departure of a distorted image from "expected" natural behavior.

2.7 A No Reference Image Quality Assessment by using a general regression neural network (GRNN)

The general regression neural network is a powerful regression tool that has a dynamic network structure. It is based on established statistical principles, and asymptotically converges with an increasing number of samples to the optimal regression surface. It extract image quality-related statistical features in both the spatial and frequency domains. In the spatial domain, locally normalized pixels and adjacent pixel pairs were statistically modeled using log-derivative statistics; and in the frequency domain, log-Gabor filters were used to extract the fine scales of the image. Based on the observation that image local contrast features convey important structural information that is related to image perceptual quality, a BIQA model utilizing the joint statistics of the local image gradient magnitudes and the Laplacian of Gaussian image responses is found. GRNN has been observed to yield better results than the back-propagation network or RBF (radial basis function) network in terms of prediction performance. The GRNN was implemented using the MATLAB function new GRNN. The four perceptually motivated features can be used as inputs to the GRNN:

1) The mean value of the phase congruency image of distorted image (MPC),
2) The entropy of the phase congruency image of distorted image (EPC),
3) The entropy of the distorted image (EDIS), and
4) The mean value of the gradient magnitude of the distorted image (MGDIS).

3. ACKNOWLEDGMENTS

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