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A Survey on Different Approaches Used For Blind Image Quality Assessment

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Abstract

Image quality Assessment signifies the process of estimating a quality of an image and it is used for many image processing applications. The field of perceptual quality assessment has gone through a wide range of developments and it is still growing. General purpose blind image quality assessment has been recently attracting significant attention in the field of image processing. This paper presents a survey on latest published research work in the area of Blind Image quality assessment. The methods of visual quality assessment of blind image considered for survey are differed from each other based on the types of methodologies used for the underlying processing employed for quality estimation.

Keywords: *Image quality assessment, No reference image, Blind image, Objective method.*

1. Introduction

There has been a tremendous progress recently in the usage of digital images for an increasing number of applications. With this huge increase in the exposure of image to the human eye, the interest in delivering quality of experience (QoE) may increase naturally. The quality of visual media can get degraded during capturing, compression, transmission, reproduction, and displaying due to the distortions that might occur at any of these stages.

In an image when the distortions take place it results into degradation of quality. Quality measuring is needed for numerous computer vision, computer graphics, and image processing applications, for example if the designer of a medical device want to decide from which device get the better results so he want to measure the quality of the images from those devices. The measurement of “quality” cannot be easily defined, as it often depends on context and personal preferences. It is a challenging task to compute a perceptual image quality due to variations in image content and the underlying image distortion process.

A simple, scalar measure of perceptual image quality can inform a number of algorithms in computer vision and computer graphics. Such a measure can be used for evaluating image processing methods, driving image compression techniques, or filtering out low quality images before image recognitions tasks. In order to maintain, control, and enhance the quality of images, it is essential for image communication, management, acquisition, and processing systems to assess the quality of images at each stage. Image Quality Assessment (IQA) plays an important role in visual signal communication and processing.

2. Image Quality Assessment

Image Quality Assessment methods can be categorized into subjective and objective methods. The legitimate judges of visual quality are humans as end users, whose opinions can be obtained by subjective experiments. Subjective experiments involve a panel of participants which are usually non-experts, also referred to as test subjects, to assess the perceptual quality of given test material such as a sequence of images. Subjective experiments are typically conducted in a controlled laboratory environment. Careful planning and several factors including assessment method, selection of test material, viewing conditions, grading scale, and timing of presentation have to be considered prior to a subjective experiment.

Due to the time-consuming nature of executing subjective experiments, large efforts have been made to develop objective quality metrics, alternatively called as objective quality methods. The goal of such objective IQA is to design mathematical models that are able to predict the quality of an image accurately and also automatically.[8]

Based on the availability of a distortion-free, perfect quality reference image, objective IQA methods can be classified into three categories: Full reference, Reduced reference, and No reference approaches.

A. ***Full-reference*** **(FR)** algorithms are provided with the original undistorted visual stimulus along with the distorted stimulus whose quality is to be assessed.[2]

B. ***Reduced-reference*** **(RR)** approaches are those in which the algorithm is provided with the distorted stimulus and some additional information about the original stimulus, either by using a auxiliary channel or by incorporating some information in the distorted stimulus (such as a watermark). [2]

C. ***No-reference*** **(NR)**/blind approaches to quality assessment are those in which the algorithm is provided only with the distorted stimulus. [2]

Objective IQA methods can also be categorized based on their application scope: General purpose methods and Application specific methods.

A. **General Purpose Methods** are the ones that do not assume a specific distortion type. Therefore, these methods are useful in a wide range of applications.[8]

B. **Application Specific Methods** are the ones that are designed for specific distortion types. Examples of these methods are the algorithms designed for image compression applications. Many quality metrics in image compression are designed for block-DCT or wavelet-based image compression. [8]

Blind measures of image quality, i.e., those that do not require ground truth reference images, are challenging to create but are much more desirable than those that require a reference image.

3. Literature Survey

In the following subsections, we will comprehensively describe five NR-IQA/BIQA Algorithms. The selected methods are widely cited in the literature, and have been reported to have good performance by researchers

3.1 BIQA Using Semi-Supervised Rectifier Network:

It is a neural network approach that defines the kernel function as a simple radial basis function on the output of a deep belief network of rectified linear hidden units. It first pre-trains the rectifier networks in an unsupervised manner and then fine-tunes them with labeled data. Finally it models the quality of images with Gaussian Process regression.

There are two specific components of the model: the first component is a Gaussian Process that regresses the final quality score given activations from a trained neural network. The second component is a neural network whose goal is to provide a feature representation that is informative for image quality assessment.

Experiments show that the method leads to significant improvement over previous methods (both blind and non-blind) for two challenging datasets, and robustness to reduction of labels.[1] the overall performance of the method is 0.841, and it is much better than state-of-the-art methods: LBIQ is 0.74 and BRISQUE is 0.61. Though it is not as good as the original LBIQ metric for a few distortion types. [1] This is because the Gaussian process in trying to reconcile among the 17 distortion types, sacrifices the performance on individual distortion types.

3.2 Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE):

This approach to blind image quality assessment (IQA) is based on the hypothesis that natural scenes possess certain statistical properties which are altered in the presence of distortion, rendering them un-natural; and that by characterizing this un-naturalness using scene statistics, one can identifies the distortion afflicting the image and perform no-reference (NR) Image Quality Assessment. Based on this theory, they propose an (NR)/blind algorithm—the Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE) index—that assesses the quality of a distorted image without need for a reference image.

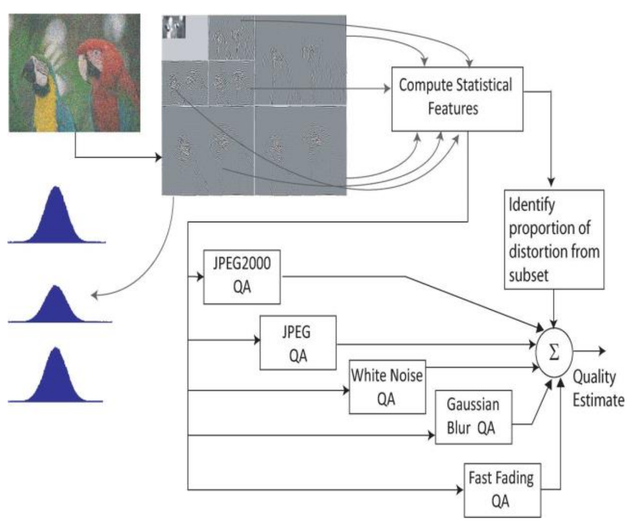

Fig. 1 DIIVINE Diagram[2]

DIIVINE is based on a 2-stage framework which first identifies the distortion present in the image and then performs distortion-specific quality assessment to provide an ostensibly distortion-independent measure of perceptual quality, using extracted natural scene statistic features. Figure 1 shows the detailed diagram of the DIIVINE. DIIVINE is capable of assessing the quality of a distorted image across multiple distortion categories, as against most NR IQA algorithms that are distortion-specific in nature.[2] By comparing the performance of DIIVINE with two standard full-reference QA algorithms: the PSNR and the single-scale SSIM, it can be said that DIIVINE is statistically superior to the FR PSNR and statistically indistinguishable from the FR SSIM. To the best of our knowledge, DIIVINE is the only IQA algorithm that not only assesses quality across a range of distortions, but also correlates with human perception judgments at a level that is statistically equivalent to good FR measures of quality.[2]

3.3 BIQA Using a General Regression Neural Network:

The proposed model develops a no-reference image quality assessment (QA) algorithm that deploys a general regression neural network (GRNN). The given algorithm is trained on and successfully assesses image quality, relative to human subjectivity, across a range of distortion types.[3] The features deployed for QA include the mean value of phase congruency image, the entropy of phase congruency image, the entropy of the distorted image, and the gradient of the distorted image. Image quality estimation is accomplished by approximating the functional relationship between these features and subjective mean opinion scores using a GRNN. The experimental results show that the proposed method accords closely with human subjective judgment.[3]

3.4 IQA: From Error Visibility To Structural Similarity:

Under the assumption that human visual perception is highly adapted for extracting structural information from a scene, The proposed model introduce an alternative complementary framework for quality assessment based on the degradation of structural information. As a specific example of this concept, they develop a Structural Similarity Index and demonstrate its promise through a set of intuitive examples, as well as comparison to both subjective ratings and state-of-the-art objective methods on a database of images compressed with JPEG and JPEG2000.[4]

3.5 No-Reference Image Quality Assessment Using Blind Image Quality Indices:

Most of the blind approaches are distortion specific this means they could only remove a specific type of distortion that may be blockiness, blur or ringing.[5] This limits their application domain. To overcome this limitation a new two step framework for no-reference image quality assessment based on Natural scene statistics (NSS) is discussed.

The structure works as follows. First step is to fetch a distorted image; the type of distortion in image is then predicted by a set of algorithm. It should be noted that it is not necessary that there should be only one type of distortion present in a image, in some cases there can be many type of distortion in a single image too. The amount of distortion present within the image is predicted by the probability estimation which is provided by the Support Vector Machine (SVM). The probability of each distortion that is present in the image is measured & is denoted by pi , {i=1,…5}. The second stage will now measure the quality of image along each of these distortions. The quality scores for each distortions are denoted by qi , {i=1,…5}.[5]

4. Conclusions

The growing demands for digital image technologies in applications like medical imaging, biomedical systems, monitoring, and communications has highlighted the need for accurate quality assessment methods. Many processes can affect the quality of images, including compression, transmission, display, and acquisition. Therefore, accurate measurement of the image quality is an important step in many image-based applications.

In this paper, an overview of objective IQA of blind image was presented. By studying the various method of blind image quality assessment we found that most of the traditional methods are distortion specific and gives poor performance when applied to large set of distortions.

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