No Reference Based Image Quality Assessment Using Feed Forward Neural Network

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ABSTRACT

With the increasing demand for image-based applications, the efficient and reliable evaluation of image quality has increased in importance. Blind image quality assessment (BIQA) aims to predict perceptual image quality scores without access to reference images. State-of-the-art BIQA methods typically require subjects to score a large number of images to train a robust model. In past few years many successful algorithms for full reference quality assessment have been developed but general purpose no-reference approaches still lags as 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. This limits their application domain. To overcome this limitation a new model for no-reference image quality assessment based on feed forward neural network is discussed.

Keywords:- *Image quality assessment, No reference image, Blind Image, Neural Network*

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.

Quality measuring is needed for numerous computer vision, computer graphics, and image processing applications. 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.

Quality can be measured in two ways subjective and objective. 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. 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.

Several methods have been used for the objective quality assessment i.e. depending on the presence of reference image they are classified in to full reference, reduced reference, and no reference approaches.[7]

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

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 an auxiliary channel or by incorporating some information in the distorted stimulus (such as a watermark).

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

In the signal and image processing literature, the most common measure for judging image quality are straightforward measure such as PSNR (Peak-Signal-To-Noise), yet, it is well known that PSNR does not correlate well with perceptual quality. Furthermore many measures require a reference image for comparison, making them useful only in limited situations. In most practical cases, a reference image is not available, and image quality assessment is more difficult.

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. Recent approaches have used labeled data and machine learning to model perceptual image quality.

2. RELATED WORK

Huixuan Tang, Neel Joshi and Ashish Kapoor proposed a neural network approach [1] 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. Overall, the model is a multi-layer network that learns a regression function from images to a single scalar quality score for each image. 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.

Chaofeng Li, Alan Conard Bovik, Xiaojun Wu [2] proposed a model that 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. 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.

Anush Krishna Moorthy, Alan Conard Bovik proposed NSS based NR IQA model [3], dubbed the Distortion Identification-based Image INtegrity and Verity Evaluation (DIIVINE) index, deploys summary statistics derived from an NSS wavelet coefficient model, using a two stage framework for QA: distortion-identification followed by distortion-specific QA. 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. The DIIVINE index performs quite well on the LIVE IQA database, achieving statistical parity with the full-reference structural similarity (SSIM) index.

Anish Mittal, Anush Krishna Moorthy, and Alan Conrad Bovik [4] proposed a Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE) which utilizes an NSS model framework of locally normalized luminance coefficients and quantifies ‘naturalness’ using the parameters of the model. BRISQUE introduces a new model of the statistics of pair-wise products of neighboring (locally normalized) luminance values. The parameters of this model further quantify the naturalness of the image. Claim is that characterizing locally normalized luminance coefficients in this way is sufficient not only to quantify naturalness, but also to quantify quality in the presence of distortion.

3. PROPOSED WORK

The goal of the proposed framework is to provide a measure of image quality from the relevant features extracted from images. Specifically, for the purpose of this paper we extracted the same set of image features as the LBIQ measure [6]. These features include univariate and cross-scale histograms and statistics of complex wavelet transform of images (the real part, absolute value, and phase) as well as a few direct blur and noise measures.

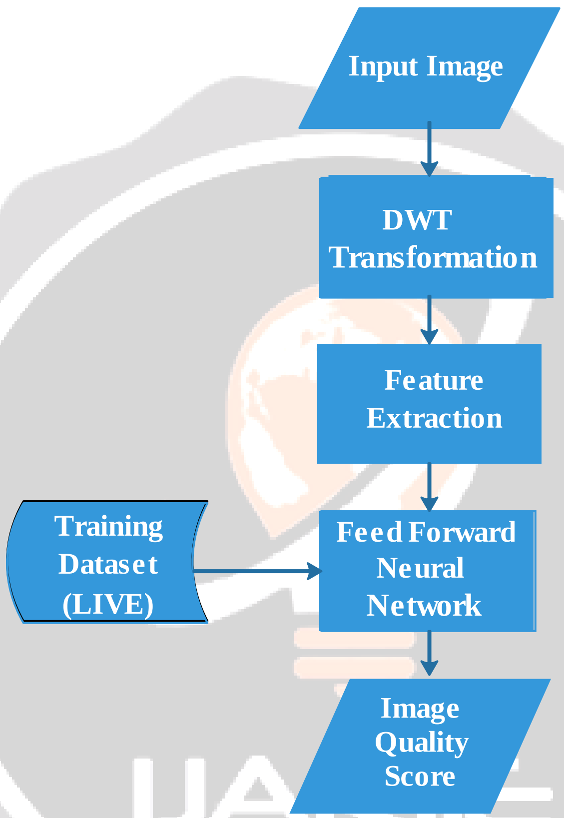


Fig.1: Flow Diagram of NR-IQA using Feed-Forward Neural Network

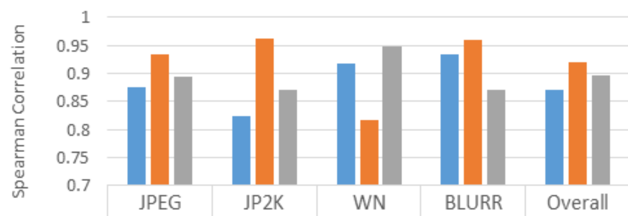
Overall, our model is a multi-layer network that learns a regression function from images to a single scalar quality score for each image. Fig. 1 shows the configuration of our model. There are three specific components of the model: the first component is a DWT Transformation that transform an input image into three level of DWT transformation. The second component is a Feature Extraction that extract the interesting feature point of an image. The third and last component is feed forward neural network whose goal is to provide a quality score for an input image.

4. RESULT ANALYSIS

We used the LIVE IQA database [10] to test the performance of the model, which consists of 29 reference images with 779 distorted images spanning five different distortion categories – JPEG2000 (JP2K) and JPEG compression, additive white Gaussian noise (WN), Gaussian blur (Blur), and a Rayleigh fast-fading channel simulation (FF). Each of the distorted images has an associated difference mean opinion score (DMOS) which represents the subjective quality of the image.

The indices used to measure performance of the algorithm are the Spearman's rank ordered correlation coefficient (SROCC) between the predicted score and the DMOS. A value close to 1 for SROCC indicates superior correlation with human perception.

We also report the performance of two FR IQA algorithms PSNR and the SSIM. The former has been used as a measure of quality for many years, and the latter is now gaining popularity as a good-yet-efficient assessor of perceived image quality.



	JPEG	JP2K	WN	BLURR	Overall
PSNR	0.876	0.825	0.918	0.934	0.87
SSIM	0.935	0.963	0.817	0.96	0.919
NRIQA	0.894	0.872	0.948	0.872	0.897

PSNR SSIM NRIQA

Fig.2: Median Spearman's Rank Ordered Correlation Coefficient (SROCC) On the LIVE Image Quality Assessment Database

It should be clear that proposed model performs well in terms of correlation with human perception. Remarkably, proposed model also trumps the *full-reference* PSNR, for each distortion separately as well as across distortion categories. However, the most salient observation from Fig.2 is that the proposed *no-reference* approach is competitive with the *full-reference* SSIM index. This is no mean achievement, since the SSIM index is currently one of the most popular FR IQA algorithms.

5. CONCLUSION

After surveying many research methodology for No-reference quality assessment approaches it seems that existing approaches are either distortion specific this means they could only remove a specific type of distortion which limits their application domain or less accurate. So there is a wide scope of implementing general purpose No-reference quality assessment approach that accurately assesses the quality of a blind image. We proposed a no-reference image based quality assessment algorithm using feed forward neural network that assesses the quality of an image without need for a reference across a variety of distortion categories

6. REFERENCES

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