p-ISSN: 2348-6848
e-ISSN: 2348-795X
Volume 03 Issue 12
August 2016

A Review on Blind Image Quality Assessment

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Abstract

Image quality is a distinctive characteristic of an image that calculates the observed image degradation. There are numerous methods to assess quality of an image, categorized as no-reference (NR) methods and full-reference (FR) methods. Blind image quality assessment states to the problem of calculating the visual quality of an image without any reference. In this paper we endeavor to search and give analysis on the various algorithms used to assess the blind image. At the end problem is formulated out of the literature review on various algorithms used for assessing blind image quality.

Key Words: Image quality assessment, Blind image quality assessment.

1.1 Introduction

An image may be defined as a two-dimensional function, $f(x, y)$, where x and y are spatial plane coordinates, and the amplitude of at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When (x, y), and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. A digital image is a numeric representation (normally binary) of a 2-D (x, y) image.

Image processing is a technique to transform an image into digital form and perform some actions on it, in order to acquire an enhanced image or to extract some valuable information from it.

1.2 Image Quality Assessment

The main objective of quality assessment (QA) is to design algorithms whose quality estimation is good as compared with subjective analysis from human observers, mainly it is of two types [1].

- Subjective Quality Assessment
- Objective Quality Assessment

1.2.1 Subjective Quality Assessment

Human eyes are decisive viewer in subjective quality assessment and Mean Opinion Score is alternative type of subjective quality assessment. MOS is the most broadly used subjective quality assessment measure. MOS calculates the quality of an image by using opinion score as per P.800 ITU-T Reference. Depends upon the quality features to be evaluated, MOS can be classified assessments accordingly [2].

1.2.2 Objective Quality Assessment

SNR, PSNR, SSIM, MSE are the various parameters of Objective Quality Assessment for analysis of quality assessment of its algorithm [1].

Depending upon available parameters about original image objective quality assessment is classified into three categories [3].

- Full reference (FR)
- Partial reference (PR)

- No reference or Blind image quality assessment (NR)

In FR image quality assessment approach, the quality of a given image is measured by comparing it with a reference image that is assumed to have perfect quality [3]. So in FR image quality assessment all the quality parameters of original reference image are known. While in PR image quality assessment parameters are partially given e.g. Resolution, contrast, size of referred original image is given from these known partial parameters quality of test image is to be assessed [3].

Blind image quality assessment states to the problem of measuring the visual quality of an image without any reference. It addresses a fundamental distinction between fidelity and quality, i.e. human vision system usually does not need any reference to determine the subjective quality of a target image. NR metrics try to assess the quality of an image without any reference to the original one [1] [3] [4].

2.1 Literature Review

In 2014, Huixuan Tang [5] presented a Blind Image Quality Assessment using Semi-supervised Rectifier Networks. It is often desired to calculate images quality with a perceptually applicable measure that does not need a reference image. Recent methods to this problematic use human delivered scores for quality with machine learning to study a measure. The biggest difficulties to achieve these efforts are: 1) the difficulty of generalizing diverse kinds of distortions and 2) gathering the human scored exercise data that is required to learn the measure. Huixuan Tang presented a novel blind image quality measure that works on these problems by learning a strong, nonlinear kernel regression function by using a rectifier neural network. The technique is to pre-train with unlabeled data and then fine-tuned with labeled data. It simplifies across a large set of distortion types and images without the requirement of large amount of labeled data. Huixuan Tang assess our method on two standard datasets and displays that it not only outdoes the existing state of the art in blind image quality assessment, but also over performs the state of the art in non-blind measures. Additionally, Tang displays that semi supervised method is healthy to use variable amounts of labeled data. The achievement of such approaches depends on the kernel function to sufficiently insert the training data into a quality relevant sub space. It also entails a sensible quantity of training data to demonstrate the image quality measure. Tang propose to signify the kernel function for image quality assessment with a rectifier neural network. It allows to signify the structure of image distortions with elasticity. The capability to achieve unsupervised pre training of the model consents us to use large size of unlabeled image data to train the model without being limited by the restricted access to human scores [5].

3.1 Problem Formulation

The objective image quality assessment parameters like MSE, SNR, PSNR, SSIM did not take into interpretation human visual structure in the logic that eye will see. Also some of the earlier described procedures do not score image quality according to the kind of an error, as well as according to the position of an error in spatial domain. For e.g., for JPEG and JPEG2000 compressed images errors will be located in the higher wavelet subbands even though images with Fast fading degradations and Gaussian blur will also have errors in lower subbands [5]

[6]. White noise too equally distributed in all subbands.

PSNR and MSE are easy and simple to compute but do not relate well with the human observation quality. SSIM is more accurate than PSNR and MSE. Computation wise PSNR and MSE are faster. But not a single image quality metric, works for practically each and every type of error and is computationally faster.

As future work, Tang only increase no. of unlabeled samples in the feature of reference images [7] [8]. Consequently, it is not clear how that method can be extended to handle the increased sorts of distortion. However, that Tang model can grasp some hidden distortion types to some expanse as it attains arithmetical codependences across abundant sorts of distortion [9] [10]. Addressing and sightseeing the above limitations is a hopeful direction for future work.

4.1 Objectives

All the former described objective image quality assessment metrics didn't take into account HVS. None of them rates the image quality as per type of an error, as well as position of an error in spatial domain. Our key objective is to develop a novel blind image quality assessment measure based on DWT in different wavelet subbands. The novel image quality assessment metric should analyze the quality of an image using DWT decomposition and rate quality liable on the wavelet Subband in which error occurs. This novel image quality assessment must consider properties of human visual system and deliver better outcomes in terms of precision and computationally faster image quality score than some other quality procedures like SSIM, UQI, etc.

Conclusion. This paper gives review on algorithms used to assess the blind image quality and formulates problem for future research work. Our novel blind image quality assessment delivers better outcomes in terms of precision and computationally faster image quality score than other image quality assessment algorithms.

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