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## SHORT COMMUNICATION

# Full reference image quality metrics for JPEG compressed images

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#### ABSTRACT

As high-resolution digital images that are used in remote sensing technologies and medical imaging, tend to be of large sizes and thereby consuming large storage space, large transmission bandwidth, and long transmission times. Therefore, image compression is required before storage and transmission. JPEG2000 and JPEG is the widely used compression standard offering best compression performance. However, compression leads to loss of data and may lead to erroneous results. Thus, there is a need for image quality assessment (IQA) of compressed images at various compression stages. In this paper, we address the full-reference (FR) image quality metric (IQM) for JPEG compressed images and we present a new effective and efficient IQA model, called LSDBIQ (local standard deviation based image quality). The approach is based on the comparison of the local standard deviation of two images. The proposed metrics is tested on four well-known databases available in the literature (TID2013, TID2008, LIVE and CSIQ). Experimental results show that the proposed metrics outperforms other models for the assessment of image quality and have very low computational complexity.

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#### 1. Introduction

High resolution images that are used in geographic information systems are generally very large in size, therefore compression of the images is a must before storing and transmitting to save storage space and to reduce the transmission cost. Lossy image compression techniques allow high compression rates, but only at the cost of some perceived degradation in image quality. For lossy JPEG compressed images, the main distortion that might be introduced is blurring and ringing. Therefore, it become imperative to develop a quality assessment method that can evaluate perceptual image quality as good as human subjective evaluation. This necessitates the development of objective IQA approaches that can automatically predict perceived JPEG-compressed image quality [1–5].

#### 2. Image quality assessments

IQA techniques can be divided into two groups, namely subjective and objective. The best way for assessing the quality of an image is the subjective quality measurement recommendations given by the ITU [6], which consists of mean opinion score (MOS) from a number of expert observers by looking at image. However, for most

http://dx.doi.org/10.1016/j.aeue.2014.09.002 1434-8411/© 2014 Elsevier GmbH. All rights reserved. applications the MOS method is inconvenient because MOS evaluation is slow and costly, since it employs a group of people in the evaluation process [7].

In order to solve this problem i.e. the need for people in the evaluation process, an objective approach is required. Such objective quality assessment system has great potential in a wide range of application environments. Usually the objective image quality approaches can be categorized into three groups depending on the availability of the original image. (1) Full reference (FR) methods perform a direct comparison between the image under test and a reference or original image. (2) No reference (NR) metrics, are applied when the original image is unavailable. (3) Reduced reference (RR) metrics lie between FR and NR metrics and are designed to predict image quality with only partial information about the reference image [2]. Focusing on FR metrics, the methods can be targeted to estimate the quality of JPEG-compressed images.

#### 3. Related work

The conventional pixel-based metrics such as mean square error (MSE), signal-to-noise ratio (SNR) and peak signal-to-noise ratio (PSNR) are most widely used in image processing as these metrics are simple to calculate and easy to use. However, these pixel based metrics do not correlate well with human subjective evaluation, and researchers have been devoting much efforts in developing advanced human visual system (HVS) IQA models [8,9]. Recently,





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Wang et al. [1] proposed structural similarity index (SSIM) based on the assumption that HVS is highly accustomed to extract structural information from an image. After the great success of SSIM, number of IQA metrics has been developed with an attempt to mimic the HVS. However, until now not even a single IQA metric can completely impersonate HVS for evaluation purpose. A comprehensive evaluation and survey of FR-IQA is available in [10–13]. It is still a challenging task to achieve 100% consistency with a human perception in IQA under different circumstances. Therefore, the objective of this research work is to develop such a quality assessment metric for JPEG compressed images, which can evaluate the quality effectively and efficiently.

In practice, an IQA model should not be only effective but also efficient. Unfortunately, accuracy and efficiency are difficult to achieve simultaneously. Most of the previous IQA algorithms can achieve only one of the two goals. To fulfill this need, in this paper we have considered the case of JPEG-distorted images, and we have proposed a model based on a local standard deviation of an image called a LSDBIQ model. Proposed model aim is to estimate the existence of a specific image distortion i.e. JPEG-artifact, ringing, colorfulness, texture distortion, etc. Traditional methods such as GMSD, FSIM, SSIM and PSNR overall perform well. However, these methods require large computational expensive and memory.

The paper is organized as follows: in Section 4 the proposed LSDBIQ technique is presented. Section 5 gives the experimental results (in terms of correlation coefficients and computational complexity). Finally, the conclusions are drawn in Section 6.

#### 4. Proposed LSDBIQ technique

A schematic overview of the LSDBIQ approach proposed here is shown in Fig. 1.

#### 4.1. Local standard deviation of an image

Measures of local standard deviation have been widely used in image processing for texture measures and studies of spatial image structure [14,15]. Its numerous applications vary from remote sensing, automated inspection and object recognition to contentbased image retrieval. To calculate local standard deviation of an image *I*, a local standard deviation filter (stdfilt) is available in MAT-LAB software [16]. This tool performs a local standard deviation filter on a raster image, i.e. it calculates the standard deviation within a neighboring area around each grid cell. A local standard deviation ( $\sigma$ ) can be used to emphasize the local structure in an image and defined as:

$$\sigma = \sqrt{\frac{\sum (l-t)^2}{N}} \tag{1}$$

where  $\sigma$  is standard deviation and *N* is number of pixels.

The local standard deviation of the reference  $(I_r)$  and distorted  $(I_d)$  images is defined as:

$$I_r = stdfilt(I_r)$$

 $I_d = stdfilt(I_d)$ 

with the help of  $I_r$  and  $I_d$  standard deviation maps, we define the local quality map (LQM) between two images  $I_r$  and  $I_d$  as:

$$LSM = \frac{2I_{r}I_{d} + T}{I_{r}^{2} + I_{d}^{2} + T}$$
(2)

where *T* is a small positive constant to stabilize the result and its proposed value is 0.0010. From Eq. (2), if  $I_r$  and  $I_d$  are equal, then LSM will achieve the maximum value 1.

#### 4.2. Quality score measurement

We have applied our quality score measurement method to LSM values using standard deviation. The proposed metrics is named as LSDBIQ and is calculated as:

$$LSDBIQ = \left[\frac{1}{N}\sum_{i=1}^{N} (LSM(i) - LSM)^2\right]^{1/2}$$
(3)

where LSM is

$$L\overline{SM} = \frac{1}{N} \sum_{i=1}^{N} LSM(i)$$
(4)

where *N* is number of pixels in the image.

Values of objective LSDBIQ and human subjective Difference Mean Opinion Scores (DMOS) score also measures distortion, lower the value better will be the image quality.

#### 5. Experiment result

#### 5.1. Demonstrative results

Fig. 2 shows some representative results from the CSIQ database where flower image with different levels of JPEG2000 compression are compared. The subjective ratings of quality in term of DMOS are also shown for comparison. As can be seen in Fig. 2(a)–(f), the level of JPEG2000 compression distortion increases and so does the DMOS subjective ratings of quality. This makes the LSDBIQ can predict quality of these images in a manner that is highly correlated with the subjective ratings of quality.



Fig. 1. Overview of our LSDBIQ model.

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