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No-reference quality assessment of deblocked images

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ABSTRACT

JPEG is the most commonly used image compression standard. In practice, JPEG images are easily subject to blocking artifacts at low bit rates. To reduce the blocking artifacts, many deblocking algorithms have been proposed. However, they also introduce certain degree of blur, so the deblocked images contain multiple distortions. Unfortunately, the current quality metrics are not designed for multiply distorted images, so they are limited in evaluating the quality of deblocked images. To solve the problem, this paper presents a no-reference (NR) quality metric for deblocked images. A DeBlocked Image Database (DBID) is first built with subjective Mean Opinion Score (MOS) as ground truth. Then a NR DeBlocked Image Quality (DBIQ) metric is proposed by simultaneously evaluating blocking artifacts in smooth regions and blur in textured regions. Experimental results conducted on the DBID database demonstrate that the proposed metric is effective in evaluating the quality of deblocked images, and it significantly outperforms the existing metrics. As an application, the proposed metric is further used for automatic parameter selection in image deblocking algorithms.

1. Introduction

With the explosive increase of digital images, the relevant quality assessment has been an attractive research field in the past decade [1]. Image quality assessment (IQA) is fundamental in many image processing problems, such as image/video coding [2], image forensics [3–5] and image restoration. According to the amount of reference information required in the quality assessment, the current methods can be classified into three categories: (1) full-reference (FR) metrics that need the whole reference image [6–9]; (2) reduced-reference (RR) metrics that need partial information of the reference image [10,11]; and (3) no-reference (NR) metrics that do not need any reference information [12,13]. The FR and RR metrics require complete/partial information of the reference image to achieve quality evaluation, which is usually not available in real-world applications, so NR metrics are highly desired.

JPEG is the most popular image compression standard. In JPEG compression, an image is divided into non-overlapping 8×8 blocks, which are compressed independently without taking into account the high correlations of adjacent blocks. Due to the quantization, JPEG images are easily subject to blocking artifacts at low bit rates. To improve the quality of JPEG compressed images, deblocking algorithms have been developed [14–19]. These approaches have achieved notable success in alleviating the blocking artifacts in JPEG images. Meantime, all deblocking algorithms are based on the underlying idea of smoothing out the high-frequency artifacts, so the deblocking process will inevitably introduce additional blur. As a result, the distortion in deblocked images is usually a combination of blocking artifacts and blur. In other words, deblocked images typically contain multiple distortions. However, the current quality metrics are not designed for multiply distorted images. Although various general-purpose NR quality metrics have been proposed to deal with different distortions types, they are not effective in evaluating the quality of images with multiple distortions. The quality evaluation of deblocked images is still an open problem.

In the literatures, many approaches have been proposed to evaluate blocking artifacts [20–28] and blur [29–36] in images. However, the deblocked images contain multiple distortions, i.e, both blocking artifacts and blur. Therefore, a single blocking artifact metric or blur metric is not expected to perform well on deblocked images. To the best of our knowledge, very few work has been done for the quality evaluation of deblocked images. Specifically, Yim et al. [37] proposed to include a blockiness term in the commonly used Peak Signal-to-Noise Ratio (PSNR), producing the PSNR-B model. PSNR-B is a full-reference (FR) approach, which requires the undistorted image as a reference. However, such an undistorted image is usually not available in practice.

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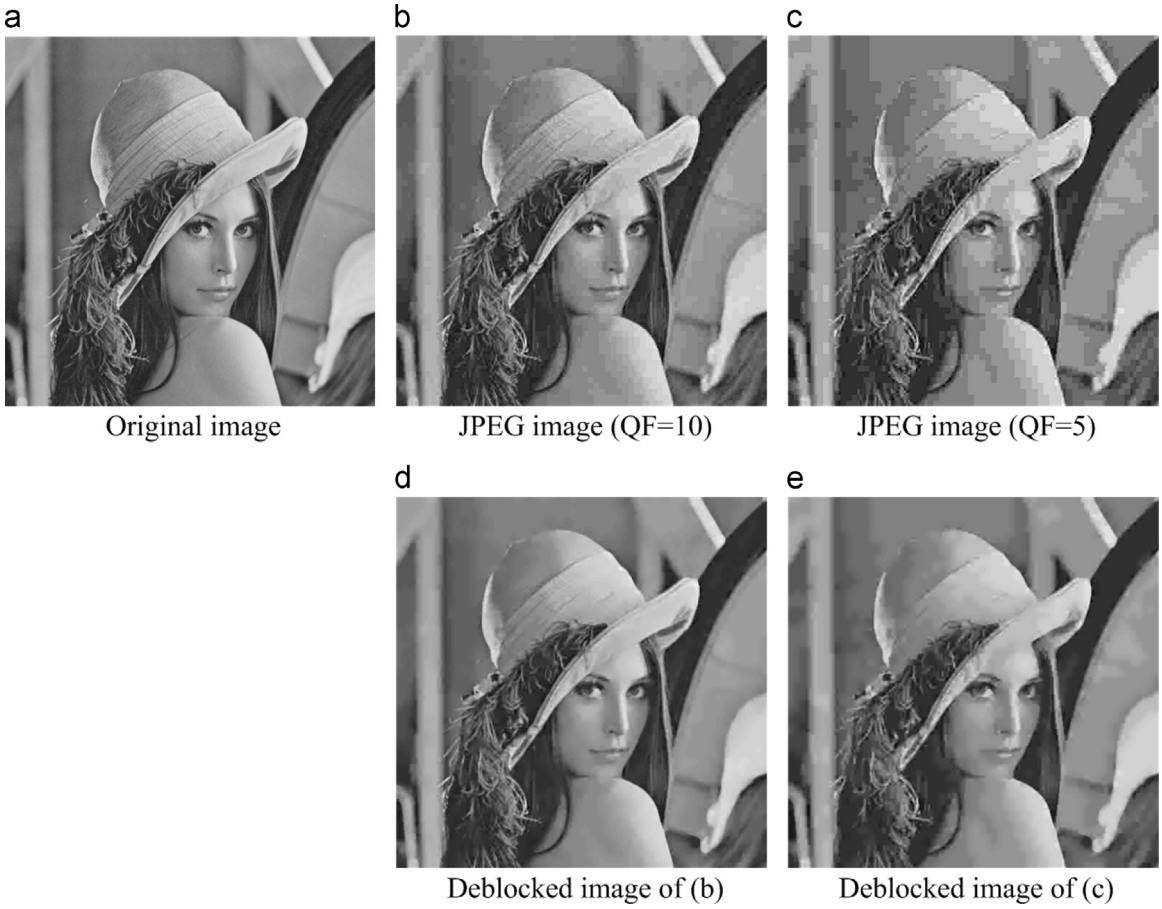

Fig. 1. An example of image deblocking. Original image (a) is compressed with JPEG quality factors 10 and 5, producing images (b) and (c); images (b) and (c) are processed using deblocking algorithm [14], producing the deblocked images (d) and (e).

Furthermore, the added term does not consider blurring effect, and the PSNR itself does not perform very well on blur, which we believe is also important for deblocked image quality assessment. Therefore, a NR metric for effective quality evaluation of deblocked images is needed, which is the focus of this work.

Fig. 1 shows an example of image deblocking. The deblocked images are contaminated by both blocking artifacts and blur. Blocking artifacts mainly affect the quality of smooth regions and blur mainly affects the quality of textured regions. Based on these observations, this paper presents a NR moment-based DeBlocked Image Quality (DBIQ) metric. Discrete Tchebichef moments are adopted to evaluate both blocking artifacts and blur in deblocked images. With the consideration that a standard database is desired for benchmarking deblocked image quality models and there is not one publicly available, a DeBlocked Image Database (DBID) is constructed. Then the performance of the proposed method is tested on DBID database. Experimental results demonstrate the advantages of the proposed metric.

The contributions of this work are summarized as follows: (1) a deblocked image database is constructed through subjective test, which is then used to evaluate the performances of image deblocking algorithms; (2) the multiply distorted nature of deblocked images is analyzed, based on which we propose a new moment-based NR deblocked image quality metric by simultaneously measuring blocking artifacts in smooth regions and blur in textured regions; (3) we use the proposed metric for parameter tuning of image deblocking algorithms.

2. Deblocked image database (DBID)

As mentioned above, in order to systematically test the performance of a quality metric, a benchmarking database is needed, where the ground truth is rated by human subjects. So far, no standard database for deblocked image quality assessment is available. In this section, we build such a database[1], which will be used to evaluate the performances of both image deblocking algorithms and the proposed deblocked image quality metric.

2.1. Selection of images and deblocking algorithms

Twenty natural images with size 512×512 are used to build the database, which are shown in Fig. 2. These images are selected to cover diverse contents in natural environments, including people, plants, animals, etc. To simulate the blocking artifacts, each image is subject to JPEG compression with three different distortion levels (slight, medium and heavy), producing 60 JPEG compressed images.

Six representative image deblocking algorithms [14–19] are employed to process the 60 JPEG images. These deblocking algorithms include shape-adaptive DCT (SA-DCT) [14], kernel regression-based deblocking [15], fields of experts prior based postprocessing method [16], postfiltering in shifted windows (PSW) [17], deblocking by overlapped block transform coefficient estimation [18], and local edge regeneration based deblocking [19].

[1] We will make the DBID database available to the research community.