ARTICLE IN PRESS
JID: CAEE [m3Gsc;January 4, 2016;16:11]

Computers and Electrical Engineering 000 (2016) 1–15

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

No-reference image quality assessment based on gradient histogram response☆

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ARTICLE INFO

Article history:
Received 8 October 2014
Revised 6 November 2015
Accepted 6 November 2015
Available online xxx

Keywords:
Gradient histogram response
Object input
Object output
Local image transform
No-reference image quality assessment

ABSTRACT

In view of the fact that objects with different natures usually respond differently to the same external stimulus, this paper proposes a no-reference image quality assessment based on gradient histogram response (GHR). GHR is the gradient histogram variation of an image object under a local transform. In the metric, through preprocessing, a test image is transformed to a noise image and a blur image, which are taken as two image objects. Each image object is exerted with a local transform as an object input, and its GHR as an object output is extracted in multiscale space. The two GHRs compose a global feature vector and are mapped to an image quality score. Experiments show that GHR outperforms state-of-the-art no-reference metrics statistically in the condition that test images are degraded by different types of distortions. Especially, the metric is feasible for the quality assessment of the images degraded by mixed distortions though the types of these images are not included in the training database.

1. Introduction

Image quality assessment (IQA) is widely used in the fields of image preprocessing, fusion, transmission, etc. IQA metrics can be roughly categorized into two groups: subjective metrics and objective metrics. Subjective metrics are simple, intuitive and accurate. But they cannot work without human's participation. They are infeasible in the condition that there are masses of images to be assessed. Therefore, it is indispensable to attach importance to objective metrics. Objective metrics are further categorized into full-reference (FR) metrics, reduced-reference (RR) metrics and no-reference (NR) metrics. FR metrics are based on the following assumption: the reference image is an available image with the highest quality. With FR metrics, the perceptual quality of a test image is assessed by calculating the similarity between the test image and its reference image [1,2]. RR metrics access partial reference information instead of the full reference image. With RR metrics, the similarity or difference between the test image and its reference image also need to be calculated when assessing the quality of a test image [3,4]. Thus, if the access to any reference information is unavailable, FR and RR metrics cannot work. Compared with FR and RR metrics, NR metrics can assess image quality based on the test image itself, so the reference image is unnecessary [5–18]. In terms of application, NR metrics have more promising prospects. Hence, the research of NR metrics has become the study focus both at home and abroad.

According to their feasibilities for specific types of distortions, NR metrics follow two approaches: distortion-specific NR metrics and general (distortion-unspecific) NR metrics. Distortion-specific NR metrics are only applicable to one or more specific types of distortions, such as blocking [7], noise [8], blur [9], etc. They probe into the mechanism of a special type of distortion,

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Area Editor Dr. E. Cabal-Yepez.

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http://dx.doi.org/10.1016/j.compeleceng.2015.11.007
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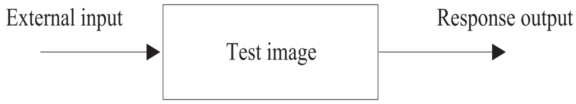

Fig. 1. IQA framework.

and assess image quality only if the distortion type is known in advance. However, in most practical applications, the distortion type is unknown, which limits the applications of the metrics. It is desirable to design a general NR metric which performs well for various types of distortions even without the prior knowledge of distortion type.

An ideal general NR metric should perform well for various common types of distortions. As is known, any metric is to be implemented with two phases: feature extraction and quality assessment. Feature extraction is vital to IQA, but it is difficult to choose the types of features which are the most useful to depict image quality. Quality assessment maps the features to a quality score through intelligent algorithms. Statistical models based on natural scene statistics (NSS) are common feature extraction approaches [1,2,10–17]. They assume that natural scenes possess certain statistical properties, and distortion affects these properties. Generalized Gaussian distribution (GGD) statistical model and asymmetric generalized Gaussian distribution statistical (AGGD) model are often used to depict image signal distributions, and reveal the marginal statistics of image signals [10–12,14–17]. The parameters of the estimated models can be used as features to be mapped to quality scores through support vector regression (SVR) [10,12], deep learning [17], etc. Codebook-based model is another common feature extraction approach for NR metrics [13,18]. A codebook is constructed from the local features extracted from labelled training images, and is used for feature space quantization. Local features extracted from the test image are encoded as a vector through quantization. Image quality is assessed by mapping the vector to a quality score using SVR [13,18], example-based method [18], etc. But efforts should still be made to reduce the gaps between subjective scores and objective predicted scores to meet the requirements of actual applications. The present NR metrics work well mainly in the condition that images are degraded by one type of distortion. In the conditions that the images are degraded by different types of distortions or mixed distortions, there is great improvement space in accuracy and stability for NR metrics.

This paper proposes a new NR metric—gradient histogram response (GHR). GHR refers to the gradient histogram variation between an image and its counterpart under a local image transform. GHR is extracted in multiscale space to improve the metric's performance. The metric is irrelevant to the distortion type and the image content. To keep the metric adaptable to different types of distortions, a test image is transformed to a noise image and a blur image through preprocessing. Each of the two images is taken as an unknown image object, and its corresponding local image transform and GHR are taken as its input and output respectively. The two GHRs of the two image objects compose a global feature vector, and are mapped to an image quality score. The rest of this paper is organized as follows. Section 2 establishes an IQA framework, which exerts an image input to the test image, and assesses image quality based on its image response output. Section 3 introduces gradient histogram. Section 4 introduces GHR and feature descriptions. Section 5 investigates the relationship between GHR and noise/blur distortion in detail. Further, Section 6 adjusts the gradient definition and puts forward a NR metric based on GHR. In Section 7, experiments are carried out to verify GHR's assessment performance. Finally, conclusions are presented in Section 8.

2. Image quality assessment framework

Objects with different natures often response differently to the same stimulus input. For an unknown object, its essential nature can be acquired by analyzing the object's response outputs. In the real world, the assessment (investigation) of an unknown object is a commonly-confronted problem. In control field, a controlled object is an unknown object when its transfer function is measured; in software design field, a new software is an unknown object when its reliability and stability are assessed; in medical field, a patient is an unknown object when his pathologies are diagnosed. In the above fields, to acquire the essential nature of an unknown object, an external stimulus as an input is exerted to the unknown object, and its response output is then analyzed to probe into its intrinsic essential nature [19–21]. A test image to be assessed can be taken as an unknown object, which lays the very foundation for a new IQA framework as shown in Fig. 1. With the test image taken as an unknown object, an external image input is exerted to the object, and then the quality of the object is assessed based on its response output. Here, the image's external stimulus input is a local image transform (with which an original test image changes into a transformed image); its response output is the corresponding feature variation between the original test image and the transformed image.

There are many ways to classify distortions. According to their producing mechanism, they can be classified into JPEG2000, JPEG, WN, GBLUR, FF (Fast Fading), etc. [22]. According to their effects on the local correlation of neighboring pixels, they can be classified into three groups: noise distortion, blur distortion, and noise–blur distortion. Noise distortion such as Gaussian noise distortion weakens the correlation of image neighboring pixels. Blur distortion such as Gaussian-smoothing distortion reinforces the correlation of neighboring pixels. JPEG2000 distortion mainly makes image blur, and also belongs to blur distortion. Noise–blur distortion indicates that the distortion has both noise effects and blur effects. Noise–blur distortion may be shown in many forms. For example, an image can be degraded by noise distortion and blur distortion successively. Then the distortion produced from multiple types of distortions is defined as mixed distortion, which is a common form of noise–blur distortion. JPEG and FF distortions also belong to noise–blur distortion. The edges of the blocks in a JPEG image destroy the correlation of neighboring pixels, while the inner parts of the blocks reinforce the correlation. FF distortion is produced through different proportions of

Please cite this article as: T. Sun et al., No-reference image quality assessment based on gradient histogram response, Computers and Electrical Engineering (2016), http://dx.doi.org/10.1016/j.compeleceng.2015.11.007