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A no-reference sharpness metric based on the notion of relative blur for Gaussian blurred image

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ABSTRACT

This work presents a no-reference sharpness metric for Gaussian blurred image. The metric is based on the notion of relative blur. The key concept is that the judgement on the sharpness closely relates to the degree of convenience for recognizing image objects on a certain scale. Based on this concept, the proposed metric is defined as relative blur with respect to certain object scale using an absolute blur measure. The object scale is characterized by a granularity analysis of image content. And the absolute blur is built on an analysis of edge local gray level distribution. The performance of the metric is tested and compared with some outstanding existing metrics in this field on three widely used databases. The experiment results show that the proposed metric can predict the sharpness of images in varying databases with high accuracy and reliability.

1. Introduction

An image is usually degraded by various factors, which makes it necessary to assess image quality for device surveillance, parameter controlling, etc. It is most reliable to assess an image in the subjective way that is commonly implemented by subjective rating of image quality to derive the Mean Opinion Score (MOS). However, the subjective assessment is time-consuming, costly, and infeasible. Thus interest in reliable objective quality metrics is increasing recently.

The objective metrics can be divided into three categories: full-reference (FR), reduced-reference (RR), and no-reference (NR) [1]. The FR utilizes all information of a reference image, and the RR uses features or partial information of a reference image. In contrast, the NR does not need any reference information; hence it is widely used but is challenging simultaneously.

The particular interest of this work is the NR sharpness assessment for Gaussian blurred images. The metrics most related to ours were presented in [2–5]. They were based on perceptual blur and were implemented by analyzing the grayscale distribution of edge region. In detail, the metric proposed in [2] utilized the notion of just noticeable blur across contrasts at edges and a probability summation over space. It was based on the metric in [4] which computed the edge spread at each edge and averages all the spreads. The spread at an edge was computed as the span of the edge transition that was defined as the profile section between the local maximum and minimum points around the edge. And the metric proposed in [5], which was also based on the edge spread and the study of human blur perception, utilized a probabilistic model to estimate the probability of blur detection at each edge.

In this paper, a novel algorithm is proposed to assess the sharpness of Gaussian blurred images. We found that the HVS tolerance to the blur decreases dramatically when image objects are small and even comparable to the blur extent. This means the perceptual blur depends not only on absolute blur, but also on object scale. Some real images with almost the same blur extent but different object scales are shown in Fig. 1. In Fig. 1(a), it can be seen that the perceptual blur varies with the rows since the images in the first row contain large-scale objects but the ones in the second row are quite reverse. Further, we conducted a subjective experiment to test the image perceptual sharpness (blurriness) when the image objects varied in scale (size). And the observation is validated by the experimental result (detailed in Section 4). Based on the observation above, the proposed metric integrates the notion of relative blur which is a concept of blur perception across scales of image objects. For large objects, there is more tolerance to blur, and vice versa.

As an important component, the scale indication (also called as granularity in this paper) is derived from a granularity analysis. This indication tunes an absolute blur measure to derive the

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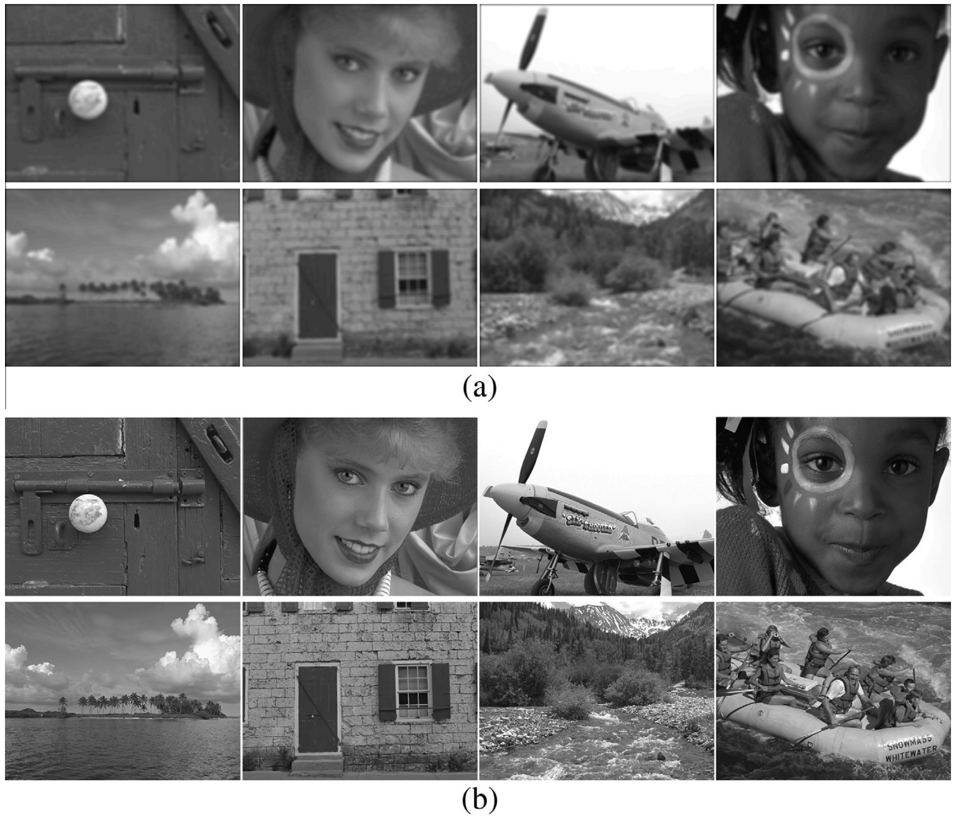

Fig. 1. Image samples with almost the same blur extent but different scale in (a) where the structures in images of the second row are much finer than that of the first row. The reference images are presented in (b).

relative blur. To obtain the absolute blur measure, we mainly adopt the edge spread measure based on [4]. However, we improve it by using a truncated edge profile instead of the whole one. It is much more robust since the gray level near an edge usually changes. Thus the whole edge profile is not very appropriate for indicating the blur extent (analysis and validation are detailedly provided in Sections 3.2 and 4.4).

This paper is organized as follows. Section 2 presents an overview of the related work. Section 3 describes the proposed metric. Performance results are presented in Section 4. And we conclude this paper in Section 5.

2. Related work

The main existing FR and RR metrics were introduced in [6]. An overview of early NR sharpness metrics was given in [2]. It summarized some metrics that were content-dependent and were mainly developed for "auto-focus" applications. We give an overview of content-independent sharpness metrics in two categories: frequency domain and spatial domain. In frequency domain, the most important principle is that natural images exhibit statistical regularities [7]. A so-called Natural Scene Statistic (NSS) model is used to capture these regularities and to measure the departure when blur occurs, which is based on the learning-based framework. In [8,9] a NR quality assessment algorithm (BLIINDS-II) in the context of the NSS was proposed. The approach relied on learning the nonlinear mapping between the NSS model parameters and the perceptual levels of image distortion. Some metrics based on local phase coherence were proposed in [10–12]. The authors showed that exactly localized features such as step edges result in strong local phase coherence across scales and spaces in complex wavelet domain, while the blur leads to loss of such coherence. Some global phase coherence based metrics [13,14] compared the image with all possible alternatives sharing the same Fourier power spectrum in terms of their likelihood.

The metrics in spatial domain generally utilize the information on grayscale distribution. Several metrics based on the kurtosis in DCT or wavelet domain were put forward in [15–17]. The metrics in [18–20] were built on a wavelet-based local structure tensor, the Riemannian tensor, and a tensor based on local gradient, respectively. The metrics based on human blur perception [2–5] analyzed the distribution of edge local grayscale.

Summarily, the learning-based metrics usually necessitate intensive computation. In addition, they are inadequate on image sharpness modeling, which goes against further researches on image sharpness. More widely, the existing metrics did not take global image content into account. As mentioned above, the perceptual blur depends not only on the absolute blur, but also on the object scales. With this global consideration, performance can be promoted, especially when the scales of image objects vary largely.

3. The proposed algorithm

The proposed metric is based on relative blur that is a concept of perceptual blur with respect to (w.r.t.) scale of image object where blur occurs. It is based on the observation that the HVS tolerance to image blur varies with object scale and falls dramatically when the object scale gets finer than the blur. This has been mentioned in Section 1. It is seen in Fig. 1 that some real images with almost the same blur extent but different object scales show varying perceptual blur. We conducted a subjective experiment using some images with varying object scales to validate the observation (detailed in Section 4).