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A no-reference image blurriness metric in the spatial domain

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ABSTRACT

This paper presents a no-reference image quality metric for Gaussian blurred image. The metric is implemented in the spatial domain without the need of data conversion or training. It utilizes the just noticeable blur (JNB) model to estimate the amount of blurriness at each edge in the image. Then the probability distribution histogram of edge blurriness is built to calculate the final blur metric of entire image. The performance of the metric is demonstrated by comparing it with existing no-reference blurriness metrics. And the experimental results on multiple image quality assessment databases show that the proposed metric is highly consistent with the subjective quality evaluations.

1. Introduction

Image quality is an important index to compare the performance of different image-processing algorithms and to optimize the parameter settings of the systems. Therefore, developing effective image quality metrics plays a central role in the field such as image acquisition, compression, transmission and restoration etc. [1]. Since human beings are the ultimate receivers in most image-processing applications, subjective quality metric is considered to give the most reliable results [2]. While subjective evaluation method involving human observers is usually time-consuming and impractical for real-time implementation and system integration. The objective image quality assessment research is to predict perceived image quality automatically based on appropriate computational models. And its goal is to achieve the measurement consistent with human subjective evaluation.

Depending on the availability of a reference image, the objective evaluation may be classified into full reference, reduced reference and no reference methods [3]. The full reference and reduced reference methods need the information about original image, which limit their application since many practical systems do not have access to the reference images. While no reference methods overcome this limitation, it can assess the image quality without any reference. Most existing no reference metrics are aimed at the specifically distortion types, such as blocking, ringing, blurring and jitter motion, etc. [4]. Of particular interest to this work is no reference image quality assessment targeted towards blurring distortion.

The traditional image sharpness/blurriness measurements, such as statistical method, derivative-based method, histogram-based method and so on, have been proposed [5]. While these metrics cannot predict well the relative blurriness in images with different contents. This imposes obvious limitations on the applications that such metrics can be used for. In recent years, various algorithms have been proposed to measure the sharpness/blurriness of images. A common

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technique of sharpness/blurriness estimation involves measuring the spread of edges in the image. The metric proposed by Marziliano et al. [6,7] was based on the smoothing effects of blur on edges. They estimated overall blurriness based on the average edge width along vertical edges in an image. Ong et al. [8] further improved Marziliano's work, they characterized the amount of image blur by the average extent of the slope's spread of an edge in the opposing gradients' directions. To improve the reliability of a blur metric, Ferzli and Karam [9] introduced the notion of just noticeable blur (JNB). They proposed a perceptual-based image sharpness/blurriness metric by integrating the concept of just noticeable blur into a probability summation model. Narvekar and Karam [10] built on the work of Ferzli and Karam [9] and proposed an improved blur metric which utilized the concept of just noticeable blur (JNB) together with a cumulative probability of blur detection (CPBD).

A number of sharpness/blurriness metrics involving data conversion or training were also proposed. Caviedes and coworkers [11,12] built a block-based sharpness estimator using the kurtosis of the DCT coefficients of each block, and the overall sharpness metric was given by the average of the sharpness of the blocks in the edge profiles. In Ref. [13], a sharpness estimator called FISH was proposed by using a three-level separable discrete wavelet transform (DWT). Vu et al. [14] designed an algorithm to measure the local perceived sharpness in an image, which utilized both spectral and spatial properties of the image. In Ref. [15], sharpness was identified as strong local phase coherence (LPC) evaluated in the complex wavelet transform domain. And in Ref. [16], Anish et al. proposed a transform-free method, BRISQUE, by using locally normalized luminance coefficients, and calibrated the regressor module by performing a training.

A blur estimation which is based on the spatial data without any kind of conversion or training is the main motivation for our proposed blur metric. In this paper, we analyze the deficiency of related work and propose an improved method. The essential idea is to pool the information obtained from single edge together to estimate the perceived blurriness. First, the amount of blurriness at each edge in the image is estimated based on the just noticeable blur (JNB) model. Then the probability distribution histogram of edge blurriness is built to calculate the final blur metric of entire image.

The rest of the paper is organized as follows. Some related work and improvement is described in Section 2, while Section 3 gives a detailed implementation of the proposed blur metric. Experiment results are presented in Section 4 and the conclusion is drawn in Section 5.

2. Related work and improvement

The method proposed by Marziliano et al. [6,7] is one of the early attempts to assess image blurriness in the spatial domain. It is based on the smoothing effects of blur on edges. Marziliano et al. first identify vertical edges in an image and then estimate overall blurriness based on the average edge width. While the metric has not taken the feature of HVS into account, it does not correlate well with respect to human perception.

Later, Ferzli and Karam [9] introduce the notion of just noticeable blur (JNB) through subjective testing. The concept of JNB is proposed based on the visual masking effect of HVS, which is defined as the threshold with which a human can perceive blurriness around an edge given a contrast higher than the just noticeable difference. Knowing that the HVS tolerance is subject-dependent, the JNBs can be determined in function of the local contrast. By introducing the concept of JNB, the probability of detecting blur for a single edge can be measured by psychometric function. Then the blurriness of image is pooled over edge blocks with a Minkowski metric based on a probability summation model.

For the JNB method, it is based on a model assuming that the blur impairment increases when the probability of blur increases. However, it ignores the fact that the blur is not likely to be perceived when it is below the JNB. Therefore, Narvekar and Karam [10] propose an improved no-reference blur metric which utilizes the concept of just noticeable blur (JNB) together with a cumulative probability of blur detection (CPBD). In the metric, the probability of detecting blur at each edge in an image is estimated. Then the entire image sharpness is pooled based on the CPBD, which is obtained from the normalized histogram of the probability of blur detection of the processed edges. The CPBD is the cumulative probability of edges at which blur cannot be detected, corresponding to the percentage of sharp edges in an image.

As analyzed above, CPBD method separates the image edges into two types by judging whether or not the blur of the edge can be perceived. Then the sharpness of entire image is described as the probability of the edges at which blur cannot be detected (in a probabilistic sense). However, it ignores to consider the amount of blurriness at each edge. For this, an improved metric is proposed. In which, the amount of blurriness at each edge is estimated and the probability distribution histogram of edge blurriness is built to calculate the final blur metric of entire image. The following section will describe it in detail.

3. Proposed blur metric

The block diagram of the proposed no-reference blur metric is shown in Fig. 1. The main idea of the metric is calculating the amount of blurriness at each edge and pooling it to estimate the blurriness of the entire image. The blurriness of the image edge is determined by the spread width and the JNB width. Details of implementation are explained below.