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No-reference blur assessment based on edge modeling ☆

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ABSTRACT

This paper presents a no-reference objective blur metric based on edge model (EMBM) to address the image blur assessment problem. A parametric edge model is incorporated to describe and detect edges, which can offer simultaneous width and contrast estimation for each edge pixel. With the pixel-adaptive width and contrast estimations, the probability of detecting blur at edge pixels can be determined. Also, unlike previous work, we advocate using only the salient edge pixels to simulate the blur assessment in Human Visual System (HVS). Finally, the blur metric is obtained by cumulating the probability of blur detection. Various images with different blur distortions are tested to demonstrate the effectiveness of the proposed metric.

1. Introduction

Benefiting from the widespread use of imaging devices such as digital cameras and smartphones, millions of photographs are taken every day. Especially, the emergence of Internet has enabled sharing of photographs on a truly massive scale. Distinguishing the high perceptual quality images from the distorted poor ones in a subjective way is burdensome for human, and infeasible in real-time applications. Hence, developing objective assessment metrics to automatically find the high quality images is getting more and more attention as they are crucial for many fields such as image processing and multimedia.

A number of objective quality assessment metrics have been proposed, which can be classified into full-reference, reduced-reference and no-reference metrics based on the availability of the original image [1]. A full-reference quality assessment metric requires the whole original information of the reference image to give a quality score [2–5]. The reduced-reference metrics only need part of the original information [6–14], and the no-reference metrics are the solutions in situations where the reference images are unavailable. Apparently, the no-reference metrics are more promising in applications and also more challenging.

In this work, we only focus on the image blurring problem which is one of the most common distortions and results in the loss of details in images. Blurring is mostly caused by the unideal imaging situation during acquisition process or the inappropriate filtering/compression during postprocessing process. Recently, there exist some no-reference objective assessment algorithms [15–28] that attempted to interpret the perceptual quality in terms of image blurriness. Hassen et al. [15,16] proposed a metric to achieve image blur assessment on the basis of Local Phase Coherence (LPC) in the wavelet domain. Since edges in an image vary in LPC, a sharpness index can be obtained by quantifying the degree of LPC for each edge pixel. Vu and Chandler [17] also proposed a wavelet based sharpness metric by decomposing the image via discrete wavelet transform (DWT). The image sharpness is measured via a weighted average of the log-energies of the DWT subbands. Blanchet et al. [18] defined a metric named Global Phase Coherence (GPC) based on the regularity of random phase images. Such metric was improved in [19] by using Gaussian random field to reduce the computational complexity. In [20], Marziliano et al. presented a blur metric to measure the spread of the edges based on the smoothing or smearing effect of filtering or compression in JPEG2000 images. The edge width is calculated by counting the number of pixels with increasing grayscale values from one side and the number of pixels with decreasing grayscale values from the other side. Tang et al. [21] proposed a metric based on the low-level features to predict the quality of blur images. The low-level features are derived from a learning framework to correlate

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with the perceptual image quality. Mittal et al. [22] built the quality-aware visual words by clustering features such as SIFT computed from multiple patches across all collected images based on natural scene statistics (NSS). Then, the image quality was determined by examining the distributions of visual words.

To simulate well with the Human Visual System (HVS), some no-reference objective image blur metrics [23,24] were proposed based on the concept of Just Noticeable Blur (JNB). The pioneering work was done in Just Noticeable Blur Metric (JNBM) [23] which indicated that HVS is able to mask blurriness around an edge up to a certain threshold. This threshold corresponds to the maximum amount of blurriness without being perceived by human eyes at a specific contrast, and thus is referred as "Just Noticeable Blur". Through a lot of subjective experiments, the authors found the JNBs under different contrasts and derived a metric based on the probability summation model. Since JNBM missed the fact that the blur below JNB is unlikely to be perceived, Narvekar and Karam [24] presented an improved blur metric named Cumulative Probability of Blur Detection (CPBD) by introducing the concept of JNB into a cumulative probability model.

As the most important cues of images, edges are vital to the performance of image blur assessment. In this paper, we propose an improved objective metric by integrating the concept of edge modeling into JNB. To overcome the limitation of edge detection in JNBM and CPBD, a parametric edge model is incorporated for edge description and detection. Benefiting from this model, all edges in an image are depicted parametrically. The width and contrast for each edge pixel (see Section 2.2 for details) can be computed simultaneously. Compared to the integer pixel-level width defined in CPBD and JNBM, the width here originates from the standard deviation of the blurring distortion and is more accurately floating-point. Moreover, edge model offers contrast estimation for each edge pixel. Thus our algorithm is simpler and does not need to perform block by block. More importantly, JNB is assigned to each pixel adaptively according to its contrast. Finally, with the aid of edge model, all edges can be detected well including the horizontal ones missed in CPBD and JNBM. Unlike previous work, we advocate using only the salient edge pixels that refer to the ones with large contrast for quality assessment. Because the salient edges are normally located at the boundary area containing two adjacent parts with distinct color and thus grab most attention from human visual perception.

2. The algorithm

2.1. JNB-based metrics

The aim of this paper is to overcome the limitation of conventional JNB-based image blur metrics like JNBM and CPBD by modeling edges in a parametrical way. So we shall first give a brief review about how they perform image blur assessment. JNBM and CPBD are very similar in the workflow where the image is first divided into blocks with the size of 64×64. Then the divided blocks are classified into edge blocks and smooth blocks based on the percentage of edge pixels. The smooth ones are skipped in the quality assessment. Dividing an image into blocks can help determine the contrast, and the contrast of each block is fixed by subtracting the maximum value to the minimum value. According to the subjective test in [23], the JNB of each edge in a block are measured to be 5 for block contrast that is below or equal to 50 and 3 for block contrast is above 50.

Similar to [20], the width of each edge pixel is obtained in pixel level by counting the number of pixels with increasing grayscale values from one side and the number of pixels with decreasing grayscale values from the other side. With edge width, the probability of detecting a blur distortion for each edge pixel can be calculated as:

$$P_{BLUR}(e_i) = 1 - \exp\left(-\left|\frac{w(e_i)}{w_{JNB}(e_i)}\right|^{\beta}\right), \tag{1}$$

where $w(e_i)$ denotes the edge width detected around the ith edge pixel e_i. $w_{JNB}(e_i)$ denotes the JNB width corresponding to the maximum amount of blurriness around the edge pixel e_i without being perceived by human at its contrast. The value of β is obtained by means of least squares fitting and normally set to 3.6. Apparently, P_{BLUR} increases as the edge blurriness increases. When $w_{JNB}(e_i) = w(e_i)$, the corresponding probability of detecting blur is 63%, i.e., $P_{JNB} = 63\%$. However, JNBM misses the fact that the blur is unlikely to be perceived when it is below JNB. Therefore, based on the assumption that the blur below JNB cannot be detected, CPBD is presented in [24] to only correspond to the percentage of edges where blur cannot be detected. As shown in (2), the metric is calculated by cumulating the probability of blur detection P_{BLUR} below P_{JNB}, and a higher value indicates a sharper image.

$$\text{Metric} = P(P_{BLUR} \leqslant P_{JNB}) = \sum_{P_{BLUR}=0}^{P_{BLUR}=P_{JNB}} P(P_{BLUR}). \tag{2}$$

However, CPBD and JNBM share some common limitations on edge computation. First, the edge width can only achieve pixel-level accuracy and is obtained by counting the numbers of pixels with increasing and decreasing grayscale around an edge pixel. Second, the quality assessment has to be performed block by block, and thus contrast is fixed for all edge pixels within one block. Not only is it inconvenient for the metric to operate, but the fixed block-based contrast is inappropriate for the quality assessment of each pixel. Because each block consists of edge pixels with different blurriness, and a contrast adaptive to each edge pixel is more promising to measure the unique blur distortion. Moreover, since contrast is fixed for all pixels within one block, CPBD and JNBM cannot pick out the salient edges that grab most attention from human perception for blur assessment. Also, removing the smooth blocks from metric computation by hardly thresholding the number of the edge pixels is thoughtless. Finally, it is found that they failed to detect the horizontal edges as illustrated in Fig. 1.

2.2. Edge model

To well utilize the edge information for blur assessment, a parametric edge model [30,31] is incorporated for edge description and detection in this work. Since edges in 2-D images can be characterized by sharp intensity changes in one direction, 1-D notation is used to explain the edge model as follows. A step edge at x_0 can be represented by $e(x; b, c, x_0) = cU(x - x_0) + b$ where $U(\bullet)$ is the unit step function. b denotes the edge basis. c represents the edge contrast. As shown in Fig. 2(a), a typical edge $s(x; b, c, w, x_0)$ can be regarded as a smoothed step edge which is obtained by convolving $e(x; b, c, w, x_0)$ with a 1-D Gaussian filter $g(x; w) = \frac{1}{\sqrt{2\pi w^2}} \exp\left(\frac{-x^2}{2w^2}\right)$ and so

$$s(x; b, c, w, x_0) = b + \frac{c}{2}\left(1 + erf\left(\frac{x - x_0}{w\sqrt{2}}\right)\right), \tag{3}$$

where $erf(\bullet)$ is the error function. w originates from the standard deviation of the blurring kernel and can be referred as the edge width parameter. With this model, the width and contrast estimation of an edge can be conducted pixel by pixel along the edge. That is, each pixel on the edge will have a unique width estimate and contrast estimate. Hence, we define $w(e_i)$ and $c(e_i)$ to represent