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A noise-immune no-reference metric for estimating blurriness value of an image

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ABSTRACT

Blur is a type of distortion that may happen in digital images. Blur estimation is an important issue in image processing applications such as image deblurring and depth estimation. Several blur metrics exist in the literature, but they are mostly sensitive to the presence of noise. In this paper, a simple yet accurate no-reference blur metric with low computational cost is proposed, which is robust against noise. The proposed blur metric is based on the observation that there is a considerable difference between the DCT of a sharp image and the one associated with its blurred version. The effect of noise is mainly reflected in the higher order DCT coefficients. Hence, the noise effect is mitigated in this paper via discarding the higher order DCT coefficients. The experiments, performed on four databases (including CSIQ, TID2008, IVC, and LIVE), indicate the capability of the proposed metric in measuring image blurriness. Comparative results with other existing approaches show the superiority of the proposed blur metric, especially at the presence of noise.

1. Introduction

Blurriness is a phenomenon that may disturb the entire or part of an image. In both entire and partial blurriness, the amount of blurriness in an image may be variant from pixel to pixel. In both types of blurriness, an accurate estimation is very important. Several blur metrics exist in literature, but they may not be robust against noise.

Existing image blur metrics can be classified into five categories. In the first category, the energy of the image is used for the blur estimation [1]. Since the blur smoothens the image and reduces the energy of high frequency coefficients, the energy can be used to estimate the amount of blurriness [2]. In [3] the number of high frequency DCT coefficients above a threshold is counted for blur estimation. In another study, the energy ratio of the high frequency coefficients to the low ones has been used for the blur estimation [4].

The second category of blur metrics considers edges in the image. The edges and their width can be extracted by vertical/horizontal gradients [5] or local gradients [6]. In [7], the edge detection is associated with the concept of Just Noticeable Blur (JNB). The JNB is a perceptual model which specifies the probability of blur detection by human eye. The JNB was improved by the Cumulative Probability of Blur Detection, namely CPBD, which is based on a probability framework on blur perception sensed by human eye in different illumination conditions [8].

The third category of blur metrics is the statistical methods that are based on the distribution of pixel intensities or transform coefficients. Some of these statistical methods suppose that the sharper images have a greater variance or entropy in their pixel intensities [9,10]. The stretch of DCT coefficients distribution has been used as a measure for the blur detection [11]. The Local Phase Coherence (LPC) was used to estimate the amount of blur in a given image [12]. The local phase has coherence in image discriminating features. These features can be extracted from the complex wavelet transform domain. The coherence is preserved only in sharp images. Therefore, the image sharpness can be measured using the coherence feature. To compute LPC, the image is passed through a set of Gabor filters in M scales and N directions. Then, the LPC is computed from these $M \times N$ sub-bands [12]. In [13], the differences between local histograms in a given test image and the ones in the blurred version have been used to estimate the blurriness value. The statistics such as tail weights in the upper and lower parts of the histogram in spatial domain have been used as shape features to provide the shape difference.

The local gradient measures are used in the fourth category of blur metrics. In [14], the Singular Value Decomposition (SVD) was

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used to estimate the amount of blurriness. The two greatest singular values are appropriate to measure the image gradient intensity. In [15], the relative gradient intensity corresponding to the two greatest singular values has been used for the sharpness estimation. In another study, a measure based on a statistical analysis of local edge gradients was presented [16]. In this method, first, the edge map is extracted from the local gradients of the image. Then, the blurriness value is estimated using the edge width within the image blocks.

The blurriness metrics in the fifth category are provided from a combination of the other four categories. For example, in [17] the authors proposed a measure which is based on the total variation in spatial space and the slope of the magnitude spectrum in frequency space. The total variation of an image is the sum of absolute difference between an image and a spatially shifted version of the image. In fact, this difference represents the gradient of image in a specific direction, e.g. vertical or horizontal, hence, it is a feature under the forth category. Meanwhile, the slope of the magnitude spectrum in frequency space is a statistical measure which is based on the distribution of the image transform in frequency domain. This feature is in the third category of blur metrics. Indeed, the blur metric proposed in [17] is a combination of the third and the forth categories. As another example in this category, the method proposed in [18] is based on both multiscale gradients and wavelet decomposition of the images. The distance between the gradient statistics of the input image and a statistical model of natural scenes is computed for measuring blurriness value of the image. The gradient statistics and the statistical model of natural scenes are constructed from multiscale wavelet decomposition of images. Consequently, the blurriness metric proposed in [18] is a combination of the third and the forth categories.

Although several blur metrics exist in literature, they have some limitations or deficiencies, as stated below:

1. Some of the existing blur metrics are appropriate to estimate a specific type of blur, whereas, there are various types of blur, including motion, defocus or atmospheric turbulence blur. As an example, the authors in [19] proposed an algorithm for estimating the intensity of defocus blur in a single image. As another example, a method has been proposed in [20] to identify the motion blur.
2. Some of the existing approaches cannot quantify the severity of blurriness in various types of images. These approaches are often invalidated by the complication of the images, especially for natural scene images. For example, the overall gradient strength of an image, which has been used to quantify the severity of blurriness in [17], not only depends on the degree of blur, but also is largely affected by the amount of existing sharp details in the image.
3. Most importantly, our investigations indicate that the existing blur estimation methods are not robust against noise. The measures that use the energy of the image to estimate the amount of blurriness cannot operate correctly at the presence of noise [2]. In addition, the measures that employ the high frequency coefficients are not immune against noise, as noise can strengthen the high frequency coefficients [3,4].

To explain the importance of noise robustness for a blur metric, let to clarify the blurring process. In the case of entire and spatially-invariant blur, the blurring process can be modeled as the convolution of the true latent image $\mathbf{I}$ and a blur kernel $\mathbf{K}$ with additive noise denoted by $\mathbf{n}$:

$$\mathbf{B} = \mathbf{I} \otimes \mathbf{K} + \mathbf{n}, \tag{1}$$

where $\mathbf{B}$ is the blurred image and $\otimes$ denotes the convolution operator. As it can be conceived from Eq. (1), the latent image after convolving with the blur kernel is affected by noise. The blur kernel is generally unknown and should be estimated. To successfully estimate the blur kernel, a blur metric should be robust against noise. The noise robustness of a blur metric can be illustrated in such a way that the output of a blur metric for a noisy-blurry image should be, as close as possible, to the one associated with the non-noisy blurry image. As a future work, one can use the proposed blur metrik to estimate the blur kernel.

In this paper, a simple yet accurate blur metric with low computational cost is proposed which is robust against noise. The proposed blur metric is a no-reference one. A no-reference metric computes the perceived blurriness directly from a given image without referring to the reference image. We show that there is a considerable difference between the DCT of a sharp image and that of the blurred version. The proposed blur metric is based on this difference. The noise effect is mitigated in this paper via discarding the higher order DCT coefficients, because the effect of noise is mainly reflected in these coefficients. The proposed blur metric is capable of estimating the amount of blurriness for various types of blur. In addition, it can quantify the amount of blurriness in images with different complexities. We called this metric Noise-Immune DCT-based (NI-DCT) blur metric. The experimental results show that the proposed blur metric performs considerably well in measuring perceived blurriness in images, even at the presence of noise.

The rest of the paper is organized as follows. In Section 2 the proposed blur metric is presented. The efficiency of the proposed blur metric is compared with some other existing blur metrics in Section 3. The conclusions are drawn in Section 4.

2. The proposed method

Generally, the blurring process damages the image details. It is observed that once an image is blurred twice by the same blurring function, the image details are moderately damaged in the second

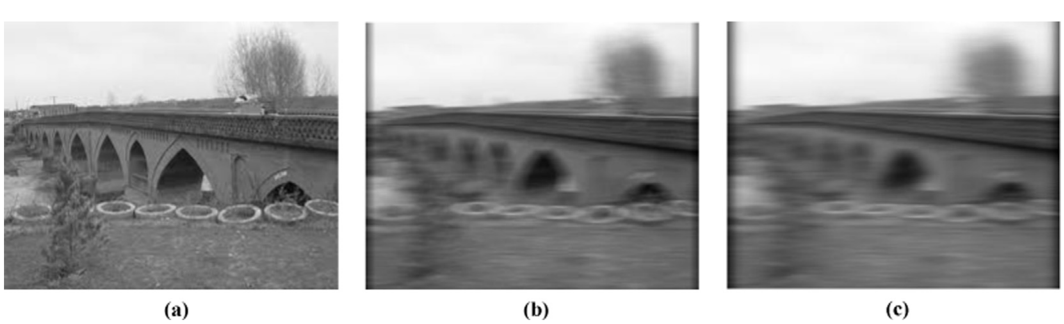

Fig. 1. The difference between the original image and the blurred one: (a) The original sharp image; (b) the blurred image using a low-pass filter (an average filter with a 1×15 window size); (c) the re-blurred image using the same filter.