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Blind image blur assessment by using valid reblur range and histogram shape difference

David Boon Liang Bong [a,b,*], Bee Ee Khoo [b]

[a] *Faculty of Engineering, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Malaysia*
[b] *School of Electrical & Electronic Engineering, Universiti Sains Malaysia, Penang, Malaysia*

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ABSTRACT

The presence of blur artifact is an annoyance to image viewers, and affects the perceived quality of the image. Telecommunication service providers and imaging product manufacturers are interested in this quality feedback for their process and product improvement. However, human-based quality feedback is tedious, expensive and has to be done in compliance with the standards for subjective evaluation such as the ITU-R BT. 500 standard. Thus, automatic assessment of images is proposed to overcome the difficulties in human-based evaluation. The automatic assessment is basically an objective estimation to predict the blur severity of an image. In this paper, a new model for blind estimation is proposed by using reblur algorithm to create reblur image and measure valid reblur range. Shape difference of local histograms is measured between the reblur and test images to produce the blur score. The proposed model is performed in the spatial domain without the need of data conversion or training. Experiment results show that the proposed model is highly correlated to human perception of blurriness, and performs better than other state-of-the-art blur metrics in the spatial domain.

1. Introduction

The presence of blur in digital images could give adverse quality perception to the viewers. The perceived quality for blur images is often thought to be in a linear relationship with the severity of distortion. However, in reality, this is not true because human vision system (HVS) judges the perceived blurriness based on many factors such as the image texture [1], saliency of the distortion [2] and visual content [3]. Thus, a non-linear relationship exists between the perception and the severity of blur.

Service providers have strong interest in knowing the final quality of the delivered visual data, and this quality information could serve as guideline for improvement on the data transmission services and systems [4]. Apart from this, product manufacturers are also interested in this quality information to improve the products for image acquisition and display. Conventionally, blur measurement focuses on comparing the original and distorted images by using methods such as the mean squared errors (MSE) and its equivalence, the peak signal-to-noise ratio (PSNR). These methods gauge the difference in pixel values of the original and distorted images, and are sometimes referred as the fidelity measures. Nevertheless, the difference scores from fidelity measures are found to have poor correlation with human-perceived quality, especially for blur images [5]. In other words, these conventional methods merely measure the signal fidelity instead of perceived quality of the images, and do not produce the intended quality feedback as needed by the communication service providers and product manufacturers.

Since human quality perception is the ultimate quality feedback which is sought after by some interested parties,

* Corresponding author at: Faculty of Engineering, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Malaysia. Tel.: +60 82 583313.
E-mail addresses: davidblbong@yahoo.com, bbldavid@feng.unimas.my (D.B.L. Bong).

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it is of no doubt that engaging human as quality evaluators would give the best and accurate result. However, quality evaluation by human observers is often tedious, expensive and has to be conducted according to specified standards such as the ITU-R BT.500 [6] recommendation for subjective evaluation. In addition, quality as perceived by human observers is often rated inconsistently among different individuals because of personal preferences, interest, experience and also due to the influence of contextual effects [7]. Thus, a more viable approach is to formulate theory or method which is able to estimate the perceived blur.

Objective blur estimation has two major categories – reference-based estimation and blind estimation. For the reference-based estimation, information from the original undistorted image is needed together with its corresponding blur image for the deduction of the blur metric while for the blind estimation, no information is needed at all from the original image. Reference-based estimation can be subdivided into two types – full-reference and reduced-reference estimations. Full-reference estimation requires the availability of the whole original image while reduced-reference estimation only uses some extracted features or information from the original image. The extracted features or information from reduced-reference could be in the form of quality score of the original image, which is being transmitted for comparison with the blur image; or image feature which are extracted or transformed from the original image, usually in a smaller memory size compare to the original image.

Fig. 1 depicts blur estimation for full-reference, reduced-reference and blind estimations respectively. Both the full-reference and reduced-reference estimations are known as "double-ended" approach due to the requirement for both the reference and the test signals, while blind estimation is known as "single-ended" approach for using only the test signal [8].

Numerous methods and theories have been proposed for the automatic estimation of blur images. Here, the scope of blur estimation is purely on blurriness, and excludes other distortions such as ringing and blocky effects. However, most of the proposed estimations either perform conversion or transformation of the image data to a transformed domain, or require training to tune some parameters in their proposed models. The data conversion ensures that additional image features could be obtained from the transformed data while the training could provide certain values for parameters that are critical or important to the estimation model. In spite of the advantages that could be garnered from performing data transformation and training, these two approaches increase the complexity of the model. Furthermore, conversion of the spatial data into another transformed domain creates redundancy as digital images are viewable only in the spatial domain. Also, the use of training samples often poses reliability issue, especially in cases where the training stage uses a

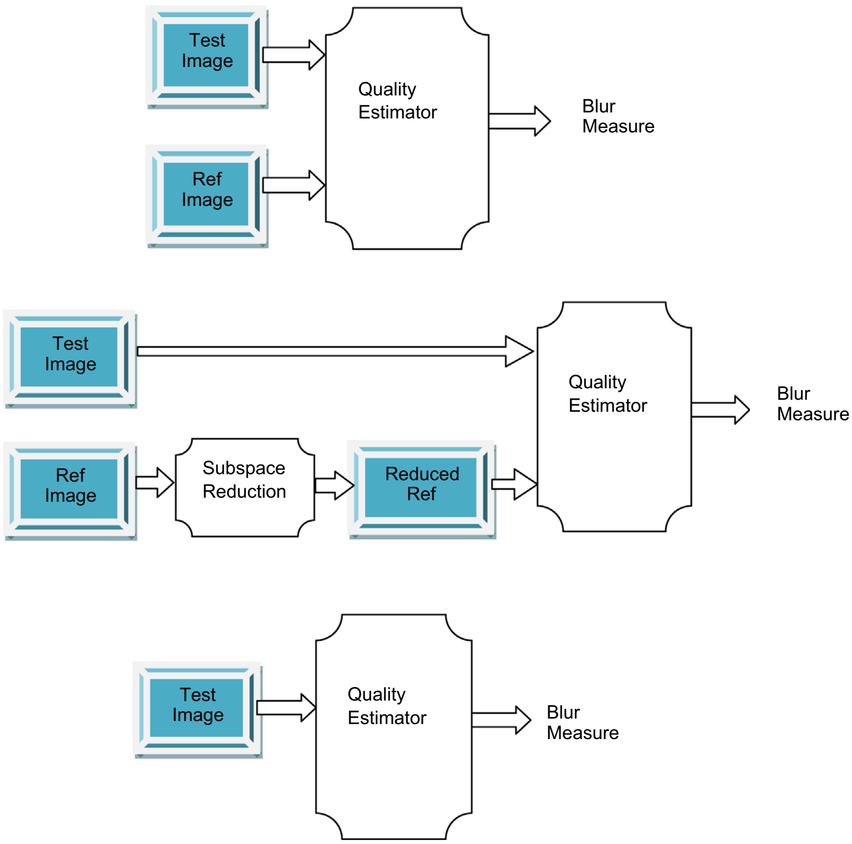

Fig. 1. (a) Blur measure with full-reference estimation (b) Blur measure with reduced-reference estimation (c) Blur measure with blind estimation.