https://doi.org/10.2352/ISSN.2470-1173.2018.12.IQSP-368
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Quality Assessment of Out-of-Focus Blurred Images Based on Objects Depth Ordering and Saliency

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Abstract

Blur is one of the most encountered visual distortions in images. It can be either deliberately introduced to highlight some objects, or caused by acquisition/processing. Both cases usually induce spatially-varying blur or out-of-focus blur. Despite its wide occurrence, only a few dedicated image quality metrics can be found in the literature. Most of the proposed metrics are based on the assumption of uniformly blurred images. Consequently, in this paper, we propose a quality assessment framework handling both types of blur and predicting their inherent level of annoyance. To achieve this aim, a local perceptual blurriness map providing the level of blur at each location in an image is first generated. Then, depth ordering is obtained from the image in order to characterize the placement of the image objects in the scene. Next, the visual saliency information is computed to take into account the visual importance of each object. Finally, the local perceptual blurriness map is weighted using both objects depth ordering and saliency maps to provide final scores of blur. Experimental results show that the proposed metric achieves good prediction performance compared to state-of-the-art metrics.

Introduction

Nowadays, more and more people use hand-held cameras to share their everyday life by taking pictures anywhere and anytime. However, most of the acquired images are often subject to distortions, such as noise, blockiness and blur, negatively affecting the perceptual image quality. The different distortions can be caused by various issues during image acquisition or processing. Among the most encountered distortions, we can cite the blur. The latter can occur due to different reasons, such as defocus, camera shaking, compression or object motion... However, blur is not necessarily considered as an annoying distortion since it can be used to highlight some objects or to create artistic effects such as shallow depth of field and bokeh effects. This can be done by bringing the foreground into focus and blurring the background using for instance SLR (single-lens reflex) cameras.

In general, out-of-focus blur is perceived as spatially-varying blur/sharpness, as illustrated in Figures 1b and 1c. Thus, providing a quality assessment method for spatially-varying blur or out-of-focus blur can be useful to monitor the acquisition step, to guide the user in background blur magnification or in iterations of deblurring [1–4].

In the last decade, great efforts have been dedicated to the development of objective quality assessment metrics. The aim of these metrics is to predict a quality score of an image/video as close as possible to the visual experience of the user *i.e.* the human observer [5]. In general, depending on the amount of information extracted from the reference image, which is exploited by the metric to compute the quality score, objective quality metrics can be divided into three categories: *Full-reference* (FR) metrics are supplied with the original undistorted image along with the test image. *Reduced-reference* (RR) metrics are provided with only some features from the reference image in addition to the test image. Finally, *No-reference* (NR) metrics do not require any information about the reference image, instead, the assessment is performed based only on the tested image.

In recent decades, a considerable number of objective image blur/sharpness metrics belonging to the above three categories (FR, RR and NR) have been proposed. A comprehensive overview can be found in [6–8]. Most attempts for quantifying the amount of blur visual impairment focused on image edges, especially the edge width. For instance, in [9, 10], the authors proposed to first detect the edges, followed by the estimation of edge widths along horizontal and vertical directions [9] or local gradient direction [10]. Finally, the blurriness score is computed as an average of edge width of all extracted edges. In the same vein, Ferzli and Karam [11] proposed to combine edge width approach with the just noticeable blur (JNB) model. The JNB is a perceptual model indicating the minimum amount of blurriness that can be noticed relative to a given local contrast. Based on this approach, several extensions have been proposed [12,13]. In [13], the probability of detecting blur at each edge was pooled by a cumulative probability of blur detection (CPBD) algorithm. In [14], blur index is obtained by computing local sample statistics in the vicinity of detected edges of the original and re-blurred images.

From another point of view, some works exploited the fact that the blur is usually caused by the reduction of high frequencies of an image. Following this idea, in [1], the ratio between high and low frequency energy has been used as a blur measure. In [16], the high frequency discrete cosine transform (DCT) coefficients that are close to zero were exploited in blur determination.

Moreover, statistics on the distribution of pixel intensities or transform coefficients have been exploited as a blur measure, such as entropy, kurtosis of DCT coefficients [17] and log-energies of the DWT subbands [18]. Finally, other works proposed hybrid approach combining both spatial and transform features of the image, such as S3 (spectral and spatial sharpness) measure [8].

In addition to these NR IQA metrics specifically developed for blur distortion, the general-purpose NR-IQA algorithms, such as BRISQUE [19], DIIVINE [20] and NIQE [21], can also be used to assess the amount of blur.

Most of the existing metrics dedicated to blur consider its uniformly distribution, which is not always the case, as stated before. Exploiting the already proposed blur quality metrics to

(a) (b) (c)

Figure 1: Examples of blurred images. (a) uniformly blurred image, (b) and (c) out-of-focus blurred images [22].

assess the quality of out-of-focus blurred images can be unsuitable. The latter have been developed and evaluated by targeting only uniformly blurred images. In addition, blur intensity varies spatially across the image, making the task difficult and the perceptual quality depending on several factors. To the best of our knowledge, with the exception of the work described in [22], there is no image quality metric specifically developed for blur impairment produced by out-of-focus.

Consequently, providing an image quality metric for out-of-focus blur capable to identify the usefulness/annoyance of blur is of paramount importance. The aim of this works is to develop such a quality metric identifying the importance or the annoyance of blur in the image and accounting for it when pooling final quality scores. This is done by weighting the local blurriness scores using depth ordering obtained based on monocular depth cue and saliency information, thus allowing fine tuning of local perceptual blurriness map.

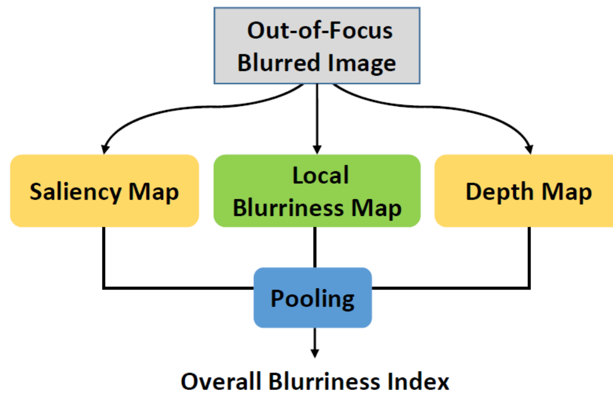

Figure 2: The framework of the proposed metric.

Proposed Approach

The flowchart of the proposed metric is shown in Figure 2. The proposed method considers three features: (1) a local perceptual blurriness map that provides the level of blur at each location in the image, (2) depth ordering extracted from the image to characterize the placement of the objects in the scene, and (3) saliency information to take into account the visual importance of each object. A weighting strategy is applied to the local perceptual blurriness map using depth and saliency information to provide adapted scores. In the following, we describe in detail each step of the proposed method.

To be able to consider both features, i.e., depth and saliency information, in quantifying the overall blurriness of an image, the intermediate blur information should be in the form of local blurriness map. Consequently, as a first step, the local perceptual blurriness map is computed. To reach this goal, we have considered no-reference blurriness/sharpness metrics, because, most of state-of-the-art NR blur quality metrics do not provide such a blurriness map. Specifically, we tested the one proposed by Ryu *et al.* [15], and those of Narvekar *et al.* and Vu *et al.* described in [13] and [8], respectively.

We conducted a deep experimentation and our choice was for the method proposed by Vu *et al.* [15] (referred to as S3), which provided the best performance. S3 metric assesses the sharpness of image, and it is used here to provide local blurriness map. Because, sharpness is generally considered as the antonym of blurriness and being inversely proportional to it.

Once the local blurriness map has been computed, denoted *BM*, the second step consists of using saliency and depth information to adjust the derived local blurriness map.

The use of depth information is justified by the fact that blur visibility at different depth levels is different. Different psychovisual studies showed that the perception of blur of the object is highly dependent on the objects distance (position in the scene) [23]. The viewer tolerates blur in the background of the scene (deeper objects) more than in the foreground (closer objects). Since the perceived blur in the background is considered by HVS as a monocular depth cue, and used to establish depth ordering of different objects/regions [24]. In other words, blurring the background is a useful addition to increase depth impression and consequently the viewing experience. In contrast, blurring the foreground can be interpreted as visual impairment (annoying) rather than pictorial cue. For instance, the blur of the image in Figure 1c is more accepted than the one of Figure 1b.

Thus, to get the depth information from a single 2D image, we opted for the monocular depth estimation methods. It is important to note, that our aim is not to derive a perfect depth map, but only to obtain a map providing global ordering of the different objects in the scene. For that, we opted for the method proposed by Palou *et al.* [25], where the occlusion cues, namely, *T-junctions* and *convexities* are exploited for this purpose.

In addition, to make our proposed metric more reliable and to consider HVS-related components, we included visual saliency in the proposed method. Because, if blur distortion occurs in a region attracting the viewers attention this will be more annoying than other regions with low perceptual significance [26]. To generate the saliency map *SM*, we used the graph based visual saliency (GBVS) model described in [27] for its efficiency and good results.

Accordingly, in order to derive the overall perceptual blurriness score of the out-of-focus blurred image, the computed local blurriness map (*BM*) is weighted using the saliency (*SM*) and depth (*DM*) maps as follows:

$$Q = \log_{10}\left(\frac{\sum_{i,j} SM(i,j)\cdot DM(i,j)\cdot(1-BM(i,j))}{\sum_{i,j} SM(i,j)\cdot DM(i,j)}\right) \quad (1)$$

where i and j are the pixel coordinates and Q is the overall blurriness index. The Logarithmic is used in order to take into account the non-linearity of the HVS. The three maps (*SM*, *DM* and *BM*) have been normalized in the range of [0,1], where a value close to 0, indicates a low saliency pixel, a deeper pixel and a blurred pixel. In contrast, a value close to 1, indicates a high saliency value, a closer pixel and a sharper pixel. Consequently, Q rises with increasing blurriness. Examples of the three maps are depicted in Figure 3.

Experimental Results

In order to evaluate the performance of the proposed metric, we used an out-of-focus blurred image dataset presented in [22]. This dataset contains 150 images with different levels of blur and their respective subjective scores. 30 original (distortion-free) images with a resolution of 720×480 have been out-of-focus blurred with five different levels. The images have been blurred by manually adjusting the camera focal length.

To assess the performance of our metric, we used the three common performance measures: the linear Pearson's correlation coefficient (LCC), Spearman's rank order correlation coefficient (SROCC), and the root mean squared error (RMSE). The metric is considered as having good performance, if the values of PCC and SROCC are high (close to ± 1), and the value of RMSE is low (close to 0). All these measures are computed between DMOS and the score provided by the proposed metric (DMOS_p) after a non-linear regression. This regression is performed using a 5-parameter logistic function as recommended in [28] and defined as follows:

$$DMOS_p(x) = \beta_1\left(\frac{1}{2} - \frac{1}{1+\exp^{\beta_2(x-\beta_3)}}\right) + \beta_4 x + \beta_5 \quad (2)$$

Table 1: Performance evaluation (LCC, SROCC, RMSE) on out-of-focus blurred image dataset.

Methods	LCC	SROCC	RMSE
BRISQUE [19]	0.725	0.742	0.905
DIIVINE [20]	0.636	0.592	1.015
NIQE [21]	0.789	0.828	0.808
CPBD [13]	0.733	0.788	0.908
S3 [8]	0.804	0.864	0.781
LISM [15]	0.740	0.773	0.885
Q_out [22]	0.901	0.889	**0.570**
Proposed	**0.913**	**0.895**	0.608

We compared the proposed metric with a total of seven metrics from the literature. The set of considered metrics can be classified into three categories: the first category consists in three general-purpose NR-IQA algorithms, which are BRISQUE [19], DIIVINE [20] and NIQE [21]. The second category of metrics are those that are specifically developed for blur distortion, we selected the CPBD [13], LISM [15] and S3 [8] (without our contribution) metrics. Finally, the third category contains the only one metric developed specifically for out-of-focus blurred images, which is proposed in [22] and denoted here as Q_out.

The LCC, SRCC and RMSE results are provided in Table 1, where the top performing metric is given in boldface. First, one can observe from this table that blur IQA metrics provide better results than the general-purpose NR-IQA metrics, with exception of NIQE metric that is competitive with regards to the remaining general-purpose NR-IQA metrics. Moreover, the metrics specifically developed for out-of-focus blurred images (our and Q_out metrics) are the ones providing the best results and outperform all evaluated metrics. Finally, thanks to the the introduction of the depth and saliency features, the proposed metric exceeds the performance of the all considered metrics in the evaluation. The added value brought by depth and saliency information can be noticed by comparing the performance of our metric with those of S3 metric without our proposal. Thus showing, the proposed method is reliable and consistent with subjective scores.

Conclusion

In this paper, we proposed a quality metric dedicated to out-of-focus blurred images. The proposed approach first characterizes the blurriness using local perceptual blurriness map. The latter is fine tuning using depth and saliency information to provide adapted scores. The depth ordering is considered as a monocular cue for depth, and saliency information to emphasis on the visually important regions. Thanks to the inclusion of these perceptual features our method achieves high correlation with human judgment. In addition, the proposed metric is competitive with regards to the most general/blur-specific -purpose NR-IQA metrics.

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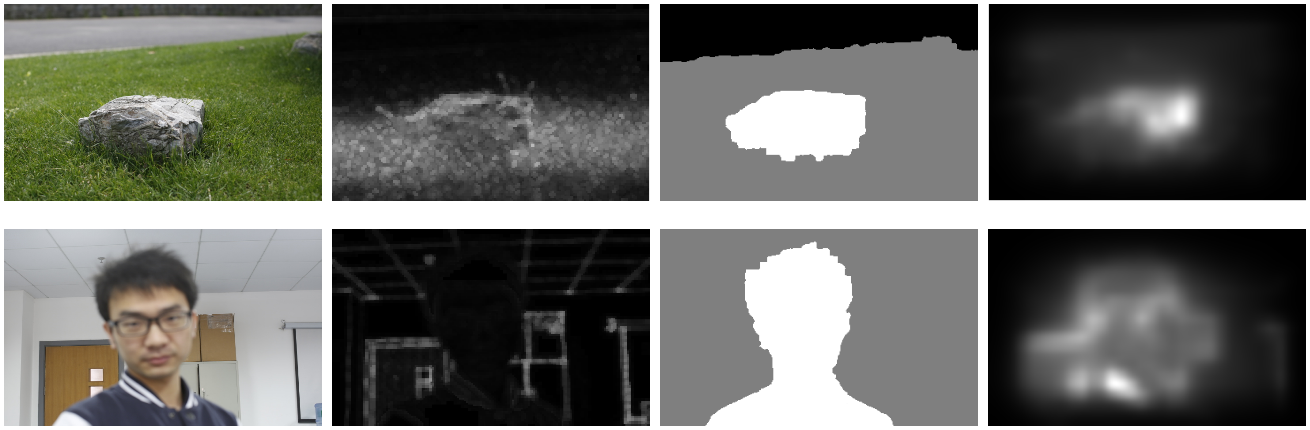

(a) Input Image (b) Blurriness map (S3) (c) Depth map (d) Saliency map

Figure 3: Examples of the input image, blurriness map, depth map and saliency map.

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Author Biography

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Chaker Larabi received his PhD from the University of Poitiers in 2002. He is currently Associate Professor at the same university. His actual scientific interests deal with quality of experience and, bio-inspired processing/coding/optimization of images and videos, 2D, 3D, HDR and 360. He is a member MPEG and JPEG committees. He served as the chair of the JPEG Advanced Image Coding (AIC) and the Test & Quality subgroup. He acted as the French head of delegation (HoD) for several years. Chaker Larabi played several roles in different conferences. He was Program Chair of EUVIP 2011, Plenary Chair for EUVIP 2013, Chair of the EI Image Quality and System Performance (2014, 2015 and 2016), Short courses co-Chair of EI 2016 2017 2018. He was special sessions co-chair for ICIP 2016 and Publicity chair for ICIP 2017. He is regular reviewer for many international conferences and journals. He serves as associate editor for the Springer journal of Signal, Image and Video Processing (SIVP), the SPIE/IS&T Journal of Electronic Imaging (JEI), IEEE ACCESS and Elsevier Journal of Visual Communication and Image Representation (JVCI). He is senior member of IEEE, member of the CIE and IS&T. He participated to several national and international projects. He supervised more than 14 PhD theses and he published over 150 papers. He is currently head of the Electrical and Computing engineering at the University Institute of Technology of Poitiers.