A NO-REFERENCE PERCEPTUAL IMAGE SHARPNESS METRIC BASED ON A CUMULATIVE PROBABILITY OF BLUR DETECTION

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ABSTRACT

In this paper, a no-reference objective sharpness metric based on a cumulative probability of blur detection is proposed. The metric is evaluated by taking into account the Human Visual System (HVS) response to blur distortions. The perceptual significance of the metric is validated through subjective experiments. It is shown that the proposed metric results in a very good correlation with subjective scores especially for images with varying foreground and background perceived blur qualities. This is accomplished with a significantly lower computational complexity as compared to existing methods that take into account the visual attention information.

***Index Terms*—** Perceptual, no-reference, objective, sharpness metric, image quality, Human Visual System, Visual Attention, Just Noticeable Blur

1. INTRODUCTION

Image acquisition, processing, and compression systems can introduce various types of visual distortions including blurring, ringing, ghosting, and noise, to name a few [1,2]. These distortions degrade the perceived visual quality of the images/video and can be very annoying to the consumers. Hence, in order to effectively improve the perceived quality of visual media, it is important to be able to measure the amount of perceived distortion. Potential applications include image/video compression, transmission, enhancement, display, restoration and registration [3].

In recent years, the ability to accurately assess the perceived visual quality using objective metrics has gained a lot of interest. This has mainly come about because of various factors, such as the complex nature of the time-consuming subjective assessment experiments and applications that demand real-time online visual quality monitoring. Many of the earlier objective visual quality metrics required a reference together with the processed image or video sequence [4]. These metrics belong to the category of full-reference objective metrics. Reduced reference objective metrics which only require partial information about the original image have also been proposed. Obviously, requiring knowledge of the reference image imposes a limitation on the applications in which these metrics can be used. A more powerful category of metrics are the no-reference objective metrics which can predict the perceived visual quality without any prior knowledge of the original undistorted image/video [1, 5-7].

Of particular interest here, is the no-reference objective assessment of perceived blur distortions. Blur distortions occur due to the loss of high frequency information in images and videos. Many objective metrics have been proposed to estimate the amount of sharpness/blurriness in visual media, several of which have been evaluated and compared in [8]. The results in [8] indicate that metrics that exploit the perceptual characteristics of the HVS, result in a more accurate prediction of the perceived blurriness/sharpness. The metric proposed in [8] takes into account the human perception of blur over various localized regions with varying contrasts and pools the localized perceived blur distortions together using a probability summation model in order to obtain a quality score. It was shown in [9] that the metric proposed in [8] does not correlate well with subjective scores for images with non-uniform saliency content including images having different background and foreground blur qualities. To get around this problem, a saliency-based no-reference sharpness metric was proposed in [9]. The metric of [9] makes use of a visual attention model [10, 11, 12] and saliency maps that are used in computing a no-reference saliency-weighted blur/sharpness metric. The metric of [9] considers the salient information in a scene and gives more importance to foveated regions in the conspicuous areas and penalizes the less salient regions.

In this paper, a novel no-reference sharpness metric based on a cumulative probability of blur detection is proposed. It is shown that the proposed metric correlates very well with the subjective test scores especially for images with different background and foreground blur contents and images with non-uniform different saliency content. Furthermore, the proposed metric does not require any additional information such as visual attention or saliency maps, and hence it has a significantly lower computational complexity than the method proposed in [9], which incorporates visual attention information.

This paper is organized as follows. Section 2 presents the proposed perceptual based no-reference objective

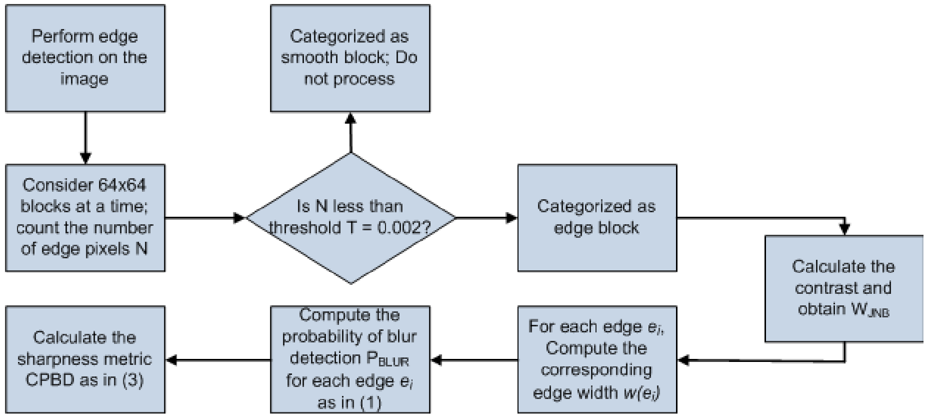

Fig. 1. Block diagram summarizing the computation of the proposed CPBD sharpness metric.

sharpness metric. Simulation results are presented in Section 3. A conclusion is given in Section 4.

2. PROPOSED NO-REFERENCE SHARPNESS METRIC

2.1. Just Noticeable Blur concept

The proposed no-reference sharpness metric utilizes the concept of "Just Noticeable Blur" (JNB) as proposed in [8, 13]. JNB can be defined as the minimum amount of perceived blurriness around an edge given a contrast higher than the "Just Noticeable Difference" (JND). According to the subjective tests performed in [13] the probability of blur detection at an edge, for a given contrast C, takes the form of a psychometric function which can be modeled as an exponential as follows:

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

where $w(\mathrm{e_i})$ is the measured width of the edge $\mathrm{e_i}$ and $w_{JNB}(\mathrm{e_i})$ is the JNB edge width which depends on the local contrast around the edge. The parameter β is obtained after applying curve fitting using a least squares estimator for different contrasts C. This is done to increase the correspondence of (1) with the experimentally determined psychometric function for blur distortions. From the experimental results in [13] it was found that β has a median value of 3.6 and the JNB edge widths at various contrasts can be modeled as:

$$w_{JNB} = \begin{cases} 5 & C \leq 50 \\ 3 & C \geq 51 \end{cases} \qquad (2)$$

where C is the contrast which is defined as the magnitude of the difference between the maximum and minimum intensities in the localized region near the edge.

2.2. Proposed metric based on a cumulative probability of blur detection (CPBD metric)

A block diagram summarizing the computation of the proposed metric is shown in Fig. 1. The image is first divided into 64x64 blocks, approximating the size of foveal regions. Depending on the edge information in each block, the blocks are then classified as edge blocks or non-edge blocks. The criterion to be classified as edge blocks is that, the number of edges detected in the block should at least be 0.2% of the total number of pixels in the block [13]. The blocks classified as non-edge blocks are not processed further. For each edge pixel $\mathrm{e_i}$ in an edge block, the corresponding edge width $w(\mathrm{e_i})$ is determined as in [13] and the JNB edge width $w_{JNB}(\mathrm{e_i})$ is obtained depending on the local contrast C of the block using (2). The P_{BLUR} at the edge pixel $\mathrm{e_i}$ is then computed by using (1). It should be noted that, at the JNB, $w(\mathrm{e_i}) = w_{JNB}(\mathrm{e_i})$, which corresponds to a probability of blur detection $P_{BLUR} = P_{JNB} = 63\%$. Thus, for a given edge $\mathrm{e_i}$,when $P_{BLUR} \leq P_{JNB}$, the blur is considered to be not detected at that edge. As an image is increasingly blurred, the spread of the edges increases, which results in a higher value of $w(\mathrm{e_i})$ and in a higher probability of blur detection at the considered edge.

In order to take into account the fact that the HVS scans a visual scene and that the overall perceived blur distortion depends on the scanned localized blur distortions over the entire scene, the proposed no-reference sharpness metric pools the localized probabilities of blur detection by means of a cumulative probability of blur detection (CPBD) and is given by:

$$CPBD = P(P_{BLUR} \leq P_{JNB}) = \sum_{P_{BLUR}=0}^{P_{BLUR}=P_{JNB}} P(P_{BLUR}) \qquad (3)$$

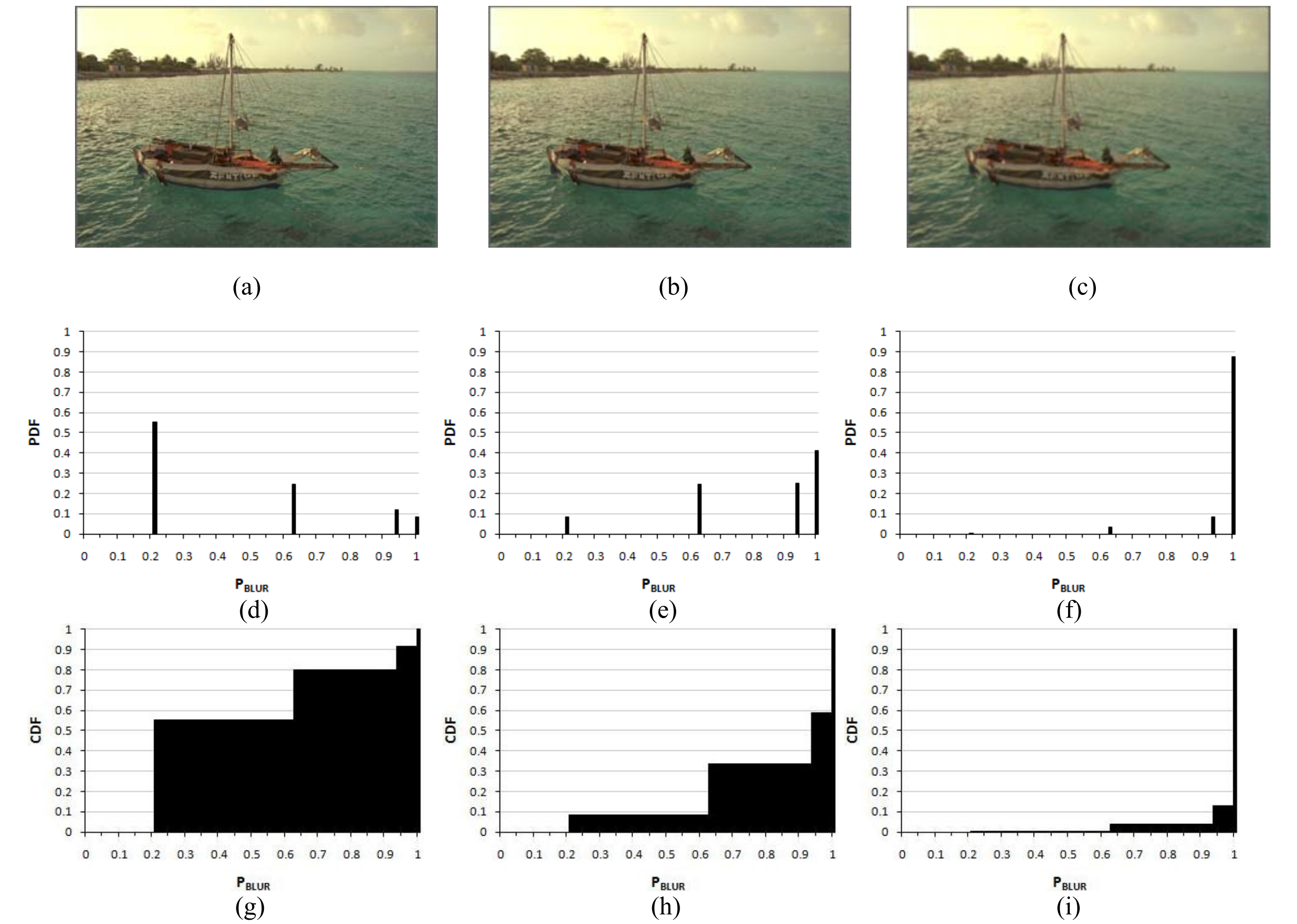

Fig. 2. Effect of blurring on the probability distribution function and the cumulative probability distribution function (CDF) of the localized blur detection probabilities P_{BLUR}. **(a)** Original Sailing1image [14]. **(b)** Image blurred using a 2-D Gaussian kernel having σ = 0.9. **(c)** Image blurred using a 2-D Gaussian kernel having σ = 1.7. **(d)** $P(P_{BLUR})$ of the image in (a). **(e)** $P(P_{BLUR})$ of the image in (b). **(f)** $P(P_{BLUR})$ of the image in (c). **(g)** CDF of P_{BLUR} for the image in (a). **(h)** CDF of P_{BLUR} for the image in (b). **(i)** CDF of P_{BLUR} for the image in (c).

where $P(P_{BLUR})$ denotes the value of the probability distribution function at a given P_{BLUR}.

The proposed CPBD sharpness metric (3) corresponds to the percentage of edges at which the probability of blur detection is below P_{JNB} and, hence, to the percentage of edges at which blur cannot be detected.

Fig. 2 illustrates the behavior of the proposed CPBD sharpness metric for the Sailing1 image which was obtained from the UT Austin LIVE database [14]. Figs. 2 (a), (b) and (c) show the blurred versions of the Sailing1 image using a circularly symmetric 2-D Gaussian kernel having a standard deviation of 0, 0.9 and 1.7, respectively. Figs. 2 (d), (e) and (f) show the probability distribution functions (PDFs) $P(P_{BLUR})$ corresponding to Figs. 2(a), (b), and (c), respectively. The corresponding cumulative distribution functions are shown in Figs. 2 (g), (h), and (i), respectively. From Figs. 2(g), (h) and (i), it can be seen that, as the amount of blur increases, the proposed CPDB metric, which is equal to $P(P_{BLUR} \leq P_{JNB})$, decreases as expected. In our implementation, the computed P_{BLUR} values are first quantized using a scalar quantizer with a step size of 0.01 and the quantized values are used for computing the PDFs $P(P_{BLUR})$ and the proposed CPBD metric (3).

3. SIMULATION RESULTS

In this section, simulation results are provided to illustrate the performance of the proposed no-reference perceptual CPBD sharpness metric. The proposed metric was tested with various images obtained from the LIVE database [14] with different contents. As the blurriness in an image increases the sharpness metric is expected to decrease. Fig. 4 shows the behavior of the proposed metric for varying amounts of Gaussian blur for the Sailing1 image. From Fig. 4, it can be clearly seen that the proposed metric is behaving as expected. A similar behavior was observed for all the tested images

Sailing1 parrots monarch ocean womanhat

Fig.3. Test images having varying levels of blurriness between the objects and the surrounding areas.

In order to further validate the performance of the proposed metric, subjective tests were performed to assess the perceived blurriness in different images. Ten subjects, with normal or corrected-to-normal vision, participated in the subjective tests. Fig. 3 shows the five test images which were chosen from the LIVE database [14] because of the varying level of blurriness between the object and the surrounding areas. These images were blurred using a 2D Gaussian filter with standard deviations of 0, 0.9, 1.7, 1.8, 2.3, and 3.85 as in [9] to obtain a set of 30 images. Each image was presented 4 times giving a total of 120 images which were randomly displayed to a subject. A 19” Dell UltraSharp 1905P LCD screen with a resolution of 1280x1024 was used to display the images, one at a time. For each displayed image the subject was asked to rate the quality of the image in terms of the perceived blurriness on a scale of 1 to 5 corresponding to “Very annoying”, “Annoying”, “Slightly annoying”, “Perceptible but not annoying”, and “Imperceptible”, respectively. For each rated image, the Mean-Opinion-Score (MOS) was obtained by averaging the subjects’ score for each case. To find out how well the proposed metric values match with the subjective test results, the Pearson and Spearman coefficients were calculated as proposed by VQEG [15]. The Pearson coefficient indicates the degree of correlation whereas the Spearman coefficient indicates the degree of monotonicity between the objective and the subjective scores. Table 1 summarizes the values of the Pearson and Spearman coefficients for the proposed CPBD metric along with the metrics proposed in [9] and [13]. From these results, it is clear that the proposed sharpness metric correlates much better with the subjective scores for the tested images as compared to the metrics proposed in [9] and [13].

4. CONCLUSION

A no-reference perceptual blur metric based on the cumulative probability of blur detection was proposed. Simulation results indicate that the proposed metric achieves a superior performance as compared to existing metrics, especially for images that have different background and foreground blur distortions or non-uniform saliency content.

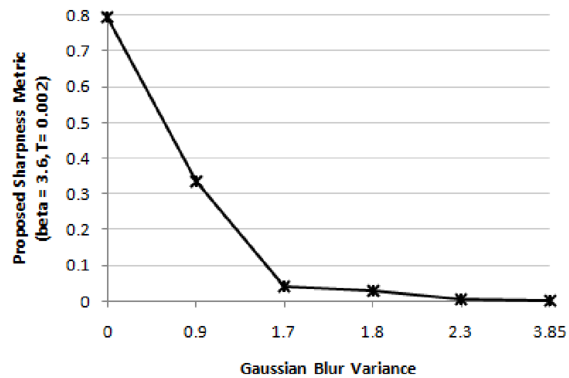

Fig.4. Performance of the proposed sharpness metric.

Table 1. Performance comparison of the quality metrics.

	Pearson	Spearman
Metric proposed in [13]	0.6251	0.5974
Metric proposed in [9]	0.6932	0.7010
Proposed CPBD Metric	0.9071	0.8862

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