A No-Reference Image Blur Metric

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Abstract—This paper presents a no-reference image quality measure, targeted towards blur distortions based on the study of human blur perception for varying contrast values. Utilizing sensitivity of human blur perception at different contrasts, a probabilistic framework is developed. This framework is used to estimate the probability of detecting blur at each edge in an image. The blur perception information at each edge is then pooled over the entire image to obtain a final quality score by evaluating the cumulative probability of blur detection. Proposed metric is able to predict relative amount of blurriness in images. Higher metric value represents less blurred image. Results are provided to illustrate the performance of proposed metric. Performance of proposed metric is compared with existing no reference image quality metric for various publically available image databases.

Index Terms—Blur detection, no-reference, objective, sharpness metric.

I. INTRODUCTION

The development and use of multimedia technology in different and varied fields has led to use of compression in many applications. With increasing use of multimedia technologies image compression requires higher performance. To address needs and requirements of multimedia and internet applications, many efficient image compression techniques, with considerably different features, have developed. Compression reduces storage and transmission requirements. But due to compression quality of image decreases because compression introduces distortion in an image. Image quality measures are used to measure amount of degradation in compressed image [1].

Subjective quality measure gives most reliable results because in this human is judging quality of output image. Thus subjective measures offer high correlation with human vision system. In subjective quality measure, appropriate number of individuals gives their opinion on quality of output image. Subjective methods are costly, time consuming and impractical for real time implementation [12]. Based on amount of reference information available about original image, objective image quality measures can be classified into full-reference, reduced-reference, no-reference metrics [1]. In full-reference original image is available which is compared with the compressed image to give amount of distortion in compressed image [5]. Reduced-reference uses some available features extracted from original reference image to compare with compressed image. In no-reference, image quality of compressed image is predicted without any information about original image. So no-reference image quality measures are useful in application where original reference image is not available [2].

In this paper no-reference image quality measure targeted towards blur distortion is proposed. Loss of high frequency information because of compression, results into blur in an image. In Just Noticeable Blur (JNB) metric [3], it was shown that the existing blur metrics cannot predict well the relative blurriness in images with different contents. Just Noticeable Blur metric [3] does not correlate with images having non-uniform saliency content. Then Multi-scale sharpness metric based on the Local Phase Coherence (LPC) [8] of complex wavelet coefficients is proposed. The computed LPC values are sorted and a weighted averaging method is used to obtain a single sharpness index. The weights are selected such that higher weight is assigned to the higher LPC values which correspond to sharper image regions [8]. This is done to give emphasis to the sharpest region in the image in order to consider the situations when the foreground is sharp and the background is blurred.

In this paper modification on JNB has done and proposes an improved no-reference image quality metric using probabilistic framework based on sensitivity of human blur perception at different contrasts. This framework is used to estimate the probability of detecting blur at each edge in an image. The blur perception information at each edge is then pooled over the entire image to obtain a final quality score by evaluating the cumulative probability of blur detection.

The paper is organized as follows. Section II describes proposed no-reference image quality metric. Section III presents performance result. Conclusion is given in Section IV.

II. NO-REFERENCE IMAGE BLUR METRIC

This section describes proposed no-reference image quality measure based on the cumulative probability of blur detection. In section III it is shown that CPBD metric gives good performance across different blur types and across databases when compared with existing no-reference blur metric.

Blur in an image is due to attenuation of the high spatial frequency [3], which commonly occurs during filtering or data compression. For contrast C [3], the probability of detecting blur takes the form of a psychometric function [3] which is modelled as an exponential given by

\[ P_{\text{BIAN}} = P_{\text{BIAN}}(g_i) = 1 - \exp \left( -\frac{w(g_i)}{\text{JNB}(g_i)} \right) \] ...

(1)

where \( w(g_i) \) is the measured width of the edge \( g_i \) and \( \text{JNB}(g_i) \) is the just noticeable blur (JNB) width, which depends on the local contrast C in the neighbourhood of the edge \( g_i \), and \( \beta \) is the parameter whose value is obtain by
means of least squares fitting. The JNB width \( w_{\text{JNB}} \) at various contrasts can be given as [3]:

\[
\begin{align*}
\text{JNB} = & \begin{cases} 
5 & \text{if } C \leq 50 \\
3 & \text{if } C \geq 81
\end{cases} \quad \text{(2)}
\end{align*}
\]

In equation (1), at JNB, \( w(\theta) = w_{\text{JNB}}(\theta) \) which corresponds to the probability of blur detection \( P_{\text{BLUR}} = P_{\text{JNB}} = 63\% \).

Natural images consist of flat regions with uniform intensity values as well as regions containing edges and texture information [1]. When humans view an image, the information present in the image is pooled in a certain manner such that they can come up with an overall perception of its quality [4]. Equation (1) provides the probability of blur detection for single edge. But natural images consist of large number of edges, so there is need to find a method for predicting how the information obtained from single edge can be pooled together over entire image to get final single quality score [2]. In JNB [3], pooling over edge pixels in individual blocks with significant edge content and then over all the considered edge blocks, is accomplished using metric based on a probability summation model.

Metric used in JNB [3] based on assumption that the blur increases when \( P_{\text{BLUR}} \) increases. But in JNB metric, blur below JNB is not perceived. So there is need of improved metric that detect blur below JNB also. In the proposed metric, the pooling is based on the cumulative probability of blur detection (CPBD), which is obtained from the normalized histogram of probability of blur detection of the processed edges in the entire image. The CPBD corresponds to the percentage of edges at which the probability of blur detection is below the just noticeable blur detection probability [3]. If image is increasingly blurred, the spread of blur in the edges is increases and hence higher probability of blur detection is use at considered edges. The proposed CPBD blur metric corresponds to the percentages of edges at which the probability of blur detection is below JNB [3].

A block diagram summarizing the computation of the proposed CPBD metric is shown in Fig 1. Edge detection is first performing on the image. Here only horizontal edges are detected because results obtain from detecting both horizontal and vertical edges [13] did not provide any improvement in results for Gaussian-blurred and JPEG-2000 compressed images. Then image is divided into 64x64 blocks. Depending on the edge information in each block, the blocks are then classified as edge blocks or non-edge blocks. The condition to be classified as edge block 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. The blocks classified as non-edge blocks are not processed further. For each edge pixel \( e_i \) in the edge block, the corresponding edge width \( w_{\text{edge}}(e_i) \) is determined as in [10] and JNB edge width \( w_{\text{JNB}}(e_i) \) is obtained depending on the local contrast \( C \) [3] of the block using equation (2). The probability of detecting blur at the edge pixel \( e_i \) is then computed by using equation (1). A normalized histogram of the blur detection probabilities is obtained, which gives probability density function of \( P_{\text{BLUR}} \).

Finally form probability density function of \( P_{\text{BLUR}} \), the cumulative probability of blur detection is calculated as,

\[
\text{CPBD} = P\left(P_{\text{BLUR}} \leq P_{\text{JNB}}\right) = \int_{P_{\text{BLUR}}}^{P_{\text{JNB}}} P_{\text{BLUR}} \, dP_{\text{BLUR}} \quad \text{(3)}
\]

Where \( P(P_{\text{BLUR}}) \) denotes the value of probability distribution function at a given \( P_{\text{BLUR}} \).

The above metric is based on fact that, at JNB, \( w(\theta) = w_{\text{JNB}}(\theta) \), which corresponds to probability of blur detection \( P_{\text{BLUR}} = P_{\text{JNB}} = 63\% \) [3]. Thus for given edge \( \theta_i \), when \( P_{\text{BLUR}} = P_{\text{JNB}} \), the blur is considered to be not detected at the edge [2]. As an image is increasingly blurred, the spread of the edges increase, which result in higher value of \( w(\theta) \) and hence higher probability of blur detection at the considered edge.

Thus proposed CPBD blur metric, given by equation (3), corresponds to the percentage of edges at which the probability of blur detection is below \( P_{\text{JNB}} \). Hence, a higher metric value represents a sharper image.
III. PERFORMANCE RESULTS

In this section, performance results for CPBD blur metric are presented. Test sets are taken from various publically available databases. Then the performance of the proposed metric is tested using test sets which consist of various Gaussian blurred and JPEG2000- compressed images. Results are presented to illustrate how well the performance of the proposed no-reference image blur metric based on cumulative probability of blur detection metric correlates with the subjective scores as compared to the existing no-reference image blur metric.

The LIVE database [6] consists of 29 RGB colour images. The images are distorted using different distortion types: JPEG2000, JPEG, Gaussian blur in RGB components, white noise in RGB components and bit errors in the JPEG2000 bitstream when transmitted. In subjective experiment, subjects were asked to rate images in grade scale of 1 to 5 where 1-bad, 2-poor, 3-fair, 4-good, 5-excellent. In subjective experiment 15 to 20 subjects were participated. For each subject, score was converted into difference score. Then difference mean opinion score (DMOS) for each image was calculated.

The IVC database [7] consists of 10 reference images and 235 distorted images. The images are distorted using different distortion types: JPEG2000, JPEG and blurring. Fifteen subjects are taken for subjective tests. During the test both original and distorted images were shown sequentially. The subjects were asked to rate the distortion they noticed in the distorted image with respect to the original image on 5 point scale where 5-imperceptible, 4-perceptible but not annoying, 3-slightly annoying, 2-annoying, 1-very annoying. Then the mean opinion score for image was calculated.

Results are presented to illustrate the performance of the proposed CPBD metric. Fig 2 illustrates the behaviour of the proposed CPBD blur metric for the 512×768 lighthouse image which was obtained from the UT Austin LIVE database [6]. Fig 2(a)-(c) shows blurred version of lighthouse image using 2-D Gaussian kernel having standard deviation of 0.1, 1.2 and 2.1 respectively. Then probability distribution function (PDFs) corresponding to Fig 2(a)-(c) is computed. The cumulative distribution functions corresponding to PDFs is estimated which is CPBD value. It can be seen that as amount of blur increases, proposed CPBD metric decreases.

CPBD metric values for Fig. 2(a)-(c) are 0.7487, 0.4253 and 0.0 respectively. Fig 3 shows the behaviour of the proposed metric for blur version of 512×768 sailing image and it also shows as blurriness in the image increases, proposed CPBD metric decreases. These images are obtained from LIVE database [6]. CPBD value for different blur version of sailing image is obtained and plotted against Gaussian Blur variance. It shows as blurriness increases, CPBD metric value decreases.

To measure how well proposed metric correlates with the subjective scores for various database, VQEG report [9] was followed. To account for the quality rating compression at test range, a four parameter logistic function given in [9], is used. Logistic function is given by:

\[ MOS_{pi} = \frac{\beta_1 - \beta_2}{1 + e^{\beta_3 - \beta_4}} + \beta_2 \]

Where \( MOS_{pi} \) is the predicted Mean Opinion Score (MOS) and \( MOS_i \) is the proposed metric for image i. The values of \( \beta_1, \beta_2, \beta_3, \beta_4 \) are the model parameters [9] and are obtained using best fit to the corresponding subjective MOS scores and then used to find out predicted MOS. The predicted MOS values are then used in calculating the performance measures including PCC (Pearson correlation coefficient, indicates the prediction accuracy), SROCC (Spearman rank-order correlation coefficient, indicates the prediction monotonicity), RMSE (Root Mean Squared prediction error), MAE (Mean absolute prediction error). For good metric, the values of the Pearson and Spearman correlation coefficient should be high and values of RMSE, MAE should be low.

Table I and II summarizes result of proposed metric [1], along with the JNB metric [3] and LPC metric [8], for Gaussian blurred and JPEG2000 compressed images obtained from LIVE database [6] and IVC database [7] respectively. From Table I and II it can be observed that, the proposed CPBD metric has a good performance across Gaussian blur and JPEG2000 compressed images for LIVE and IVC databases as compared to existing no reference blur metrics.
IV. CONCLUSIONS

A blur metric is proposed based on the Cumulative Probability of Blur Detection. CPBD metric gives amount of blur detected in an image. As amount of blur increases, proposed CPBD metric decreases. So image having metric value close to 1.0 indicates image is sharp. Calculation of CPBD metric involves edge detection followed by estimating the probability of detecting blur at the detected edges. Then a probability density function for the obtained probabilities is calculated from which the final cumulative probability of blur detection is obtained. It is shown that the proposed metric exhibits a good performance across Gaussian blur and JPEG2000 compressed images for different databases as compared to existing no reference blur metrics. This can be used in telemedicine, CCTV, traffic cameras to detect blur from images and videos.

REFERENCES