Abstract—This work presents a perceptual-based no-reference objective metrics, the proposed no-reference metric is able to predict the relative amount of blur in images with different content. Reduced-reference objective metrics only require partial information about the original image. In many circumstances, the reference image is not available for the assessment task. Hence, objective metrics using the reference image impose a limitation on their applications. On the other hand, a no-reference metric scheme computes the perceived visual quality directly from a given image without referring to the reference image. It is much more useful than the other two categories. Image quality is governed by a variety of factors such as sharpness, naturalness, colorfulness, contrast, and noise etc. To develop a no-reference objective image quality metric by incorporating all attributes of images without referring to the original ones is a difficult task. Hence, we shall concentrate on the work of the no-reference image sharpness (or blurriness) metric. Note that the image sharpness metric can also be applied to measure blurriness since they are inversely related.

Image quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Image Quality Measure is use to find out amount of degradation in compressed image. The image quality measure having two categories: subjective and objective. Subjective quality measures are based on Psychophysical experiments involving human observers. They provide a most convincing gauge considered that human visual system (HVS) is the final receiver of almost all the image/video information. However, Subjective quality assessment is very expensive, many observers, careful setup, time consuming, images are required for good statistical accuracy and impractical in real applications. Objective quality measures are Computing suitable metrics directly from the digital image. It is quantitative measures which are developed to automatically predict the perceived quality of HVS. Objective image quality metrics can be classified according to the availability of an original (distortion-free) image, with which the distorted image is to be compared. Most existing approaches are known as full-reference (FR), meaning that a complete reference image is assumed to be known [4]. In a third type of method, the reference image is only partially available, in the form of a set of extracted features made available as side information to help evaluate the quality of the distorted image. This is

Keywords: probability, no-reference, blur detection, sharp images, noisy images.

I. INTRODUCTION

NOW that digital cameras and the Internet have both become popular media, millions of photos are taken daily and a substantial portion are posted online. They are stored on computers, web sites, cameras, even in cell phones, often through the intermediary of backend databases. Digital photos have large variance of quality as a result of the various distortions they undergo. The different distortions an image applied to include picture shooting, image compression, transmission, post-processing, etc. For example, when taking a photo using a digital camera, incorrect focus, low quality lens, or camera shake create blur image, even in a high quality camera.

The development of objective metrics that can precisely predict the perceived image quality is in great demand. Objective metrics can be categorized into full-reference, reduced reference, and no-reference [1]. A reference such as the original image is needed for comparison with the processed image in the full-reference scheme.

Manuscript Received on April 2013.

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Reduced-reference objective metrics only require partial information about the original image. In many circumstances, the reference image is not available for the assessment task. Hence, objective metrics using the reference image impose a limitation on their applications. On the other hand, a no-reference metric scheme computes the perceived visual quality directly from a given image without referring to the reference image. It is much more useful than the other two categories. Image quality is governed by a variety of factors such as sharpness, naturalness, colorfulness, contrast, and noise etc. To develop a no-reference objective image quality metric by incorporating all attributes of images without referring to the original ones is a difficult task. Hence, we shall concentrate on the work of the no-reference image sharpness (or blurriness) metric. Note that the image sharpness metric can also be applied to measure blurriness since they are inversely related.

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referred to as reduced-reference (RR) quality assessment. This paper focuses on no-reference image quality assessment.

This paper represents no-reference objective blurrriness metric based on the cumulative probability of blur detection (CPBD) [5] which utilizes the concept of just noticeable blur (JNB) [6] together with a cumulative probability of blur detection (CPBD). In this the probability of detecting blur at each edge in an image is estimated. 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 (CPBD). CPBD metric gives value in the range from 0.0 to 1.0. Thus as the probability of blur is increases CPBD decreases up to 0.0 and image having metric value 1.0 is sharper and less blur image [6]. It is mainly used in Telemedicine application. The paper is organized as follows: Section II describes no-reference image quality measures. A new no-reference image blur metric is presented in Section III and performance results are presented in Section IV. Conclusion is given in Section V.

II. NO-REFERENCE IMAGE QUALITY MEASURES

No reference image quality assessment targeted towards blur distortions, several objective no reference blurriness/sharpness metrics are developed. The sharpness/blurriness metric are combined with other metrics to assess the overall quality of images. In Just Noticeable Blur (JNB) [6] metric, it was shown that blur metrics cannot predict well the relative blurriness in images with different contents. No-reference (NR) is objective image quality measures based on the measurement of image distortion at the place of receipt without any knowledge about original image. No reference metric do not require any reference information and useful in applications where reference is not available. The LPC metric is based on the evaluation of local phase coherence across the scales of an over complete wavelet transform. We compare the performance of the proposed method with four state-of-the-art metrics using a large database containing both simulated and real blur [7].

As the blurriness of the images increases, the metric is expected to decrease. So, the multiplicative inverse of these metrics is calculated and used for assessing the image sharpness. Blurring occurs in an image due to the loss of high frequency information as shown in Section IV, it shows a good performance across blur types (Gaussian blur and JPEG2000 blur) and across databases as compared to existing sharpness/blurriness metrics [6].

The probability of detecting blur takes the form of a psychometric function [6] which is modelled as an exponential given by

\[ P_{BLUR} = P_{BLUR}(e_i) = 1 - \exp\left( -\frac{w(e_i)}{W_{NB}(e_i)} \right)^{\beta} \]

Where \( w(e_i) \) is the measured width of the edge and \( \beta \) is the JNB width which depends on the local contrast in the neighbourhood of edge \( e_i \) and \( \beta \) is the parameter whose value is obtained by means of least squares fitting.

\[ W_{NB} = \begin{cases} 5, & \text{if } C \leq 50 \\ 3, & \text{if } C \geq 51 \end{cases} \]

Equation (2) will calculate width of JNB. For given contrast if contrast value is less than or equal to 50 then width of JNB is considered as 5 otherwise it will considered as 3. [6]

The JNB, which corresponds to the probability of blur detection

Probability of blur detection for single edge is calculated (1). But, since natural images consist of large number of edges [8], it is important to devise a method for predicting how the information obtained from single edge can be pooled together to get a single quality score [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 is used to detect blur which is below just noticeable blur (JNB) [6] which is 63% and hence to this percentage of edges blur is not likely to be detected using just noticeable blur. 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. If image is increasingly

III. A NEW NO-REFERENCE IMAGE BLUR METRIC

This section describes the propose an improved no-reference blur metric which utilizes the concept of just noticeable blur (JNB) [6] together with a cumulative probability of blur detection (CPBD).
A No Reference Image Blur Detection Using Cumulative probability Blur Detection (CPBD) Metric

blurred the spread of 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 just noticeable blur (JNB)[6]. A higher metric value represents a sharper image.

Fig.(1) is block diagram which is shows the computation of the proposed CPBD metric. It is targeted towards blur distortions in received image. First perform the edge detection on the image. The image is then divided into 64x64 blocks. Smooth blocks are excluded as they do not contribute to blur eperception. For this purpose, a particular edge detector is run first on each block, and each block is categorized as a smooth block or an edge block. The decision is made based on the number of edge pixels in the block; if the number is higher than a threshold, the block is considered an edge block; otherwise it is considered a smooth block. The threshold is chosen to be a percentage of the block. For a 64 X 64 block, the threshold is chosen to be 0.2% of the total number of pixels in the block. For each edge block, edge pixels are located and the corresponding width is computed, such as \( w(ei) \) and \( wJNB(ei) \).

In the current implementation, only horizontal edges are detected. The metric was also tested by including both horizontal and vertical edges. From the obtained results [9], it was established that including both vertical and horizontal edges in the calculations did not provide any significant improvement in the results for Gaussian-blurred and JPEG2000-compressed images. Hence, only horizontal edges are considered. The probability of detecting blur at the edge pixel \( P_{BLUR}(ei) = P_{BLUR} \), is then computed by using (1)

\[
P_{BLUR}(ei) = \frac{\text{count of edge pixels}}{\text{total number of pixels}}
\]

A normalized histogram of blur detection probabilities (histogram of \( P_{BLUR} \) /Total number of processed edge pixels) is obtained, which gives the probability density function of \( P_{BLUR} \). Finally, from the probability density function of \( P_{BLUR} \), the cumulative probability of blur detection, which is the proposed metric, is calculated as

\[
CPBD = P(P_{BLUR} \leq P_{JNB}) = \sum_{P_{BLUR}=0}^{P_{BLUR}=P_{JNB}} P(P_{BLUR}) \quad \ldots (3)
\]

Where \( P(P_{BLUR}) \) is the value of probability distribution function at a given edge pixel \( ei \). The above metric is based on the fact at JNB, \( w(ei) = wJNB(ei) \), which corresponds to probability \( P_{BLUR} = 63\% \) of blur detection [6]. Thus for given edge \( (ei) \), when the blur is considered to be not detected...
at the edge [3]. As an image is increasingly blurred, the spread of the edges increase, which result in higher value of \( w(e) \) and hence higher probability of blur detection at the considered edge. The proposed CPBD blur metric, given by (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 (in a probabilistic sense). Hence, a higher metric value represents a sharper image.

CPBD metric gives value in the range from 0.0 to 1.0. Thus as the probability of blur is increases CPBD decreases up to 0.0 and image having metric value 1.0 is sharper and less blur image.

IV. PERFORMANCE RESULT

In this section, results are presented to illustrate the performance of the proposed CPBD blur metric. The performance of the proposed metric is tested for publically available database using a variety of Gaussian-blurred and JPEG2000 compressed images. Database used are LIVE [8] and IVC [9]. The LIVE database consists of 29 RGB colour images [8]. The images are distorted using different distortion types: JPEG2000, JPEG, blurring. Results are presented to illustrate the performance of the proposed CPBD metric Fig. 3 illustrates the behaviour of the proposed CPBD blur metric for the 512×768 hats image which was obtained from the UT Austin LIVE database [8]. Fig 3(a)-(c) shows blurred version of hats image using 2-D Gaussian kernel having standard deviation of 0.1, 1.2 and 2.1 respectively. Fig 3(d)-(f) shows probability distribution function (PDFs) corresponding to Fig 3(a)-(c). The corresponding cumulative distribution functions are shown in Fig 3(g)-(i). From Fig 3(g)-(i), it can be seen that as amount of blur increases, proposed CPBD metric decreases.

(174 images) and all of the JPEG2000-compressed images (227 images) from the LIVE database are used in our experiments. The images are distorted using different distortion types: JPEG2000, JPEG, blurring. Results are presented to illustrate the performance of the proposed CPBD metric Fig. 3 illustrates the behaviour of the proposed CPBD blur metric for the 512×768 hats image which was obtained from the UT Austin LIVE database [8]. Fig 3(a)-(c) shows blurred version of hats image using 2-D Gaussian kernel having standard deviation of 0.1, 1.2 and 2.1 respectively. Fig 3(d)-(f) shows probability distribution function (PDFs) corresponding to Fig 3(a)-(c). The corresponding cumulative distribution functions are shown in Fig 3(g)-(i). From Fig 3(g)-(i), it can be seen that as amount of blur increases, proposed CPBD metric decreases.

Obtained CPBD values for Fig 3(a)-(c) i.e., for blurred version of lighthouse images are for Fig 3(a) CPBD = 0.7487, for Fig 3(b) CPBD = 0.4253 and for Fig 3(c) CPBD = 0.0236.

Fig 4 shows the behaviour of the proposed metric for blur version of 512×768 Bikes image and it also shows as blurriness in the image increases, proposed CPBD metric decreases.
To measure how well proposed metric correlates with the subjective scores for various data base, VQEG report[10] was followed. To account for the quality rating compression at test range, a four parameter logistic function given in[10], is used. Logistic function is given by:

\[
MOS_P = \frac{\beta_1 - \beta_2}{1 + e^{(M - \beta_3)/\beta_4}} + \beta_2
\]

Where MOSPi is the proposed MOS and Mi is the proposed metric for image i. The values of \(\beta_1, \beta_2, \beta_3, \beta_4\) are the model parameters [10] 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 1 Performance of CPBD metric w.r.t. DMOS score for LIVE database

<table>
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<tr>
<th>Distortion</th>
<th>Metrics</th>
<th>Pearson</th>
<th>Spearman</th>
<th>RMSE</th>
<th>MAE</th>
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<td>CPBD</td>
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<td>0.8942</td>
<td>0.6342</td>
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<tr>
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<td>0.9111</td>
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</tbody>
</table>

V. CONCLUSION

This paper presented a blur metric proposed is based on the CPBD metric. First perform the 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 CPBD metric gives value in the range from 0.0 to 1.0. Thus as the probability of blur is increases CPBD decreases upto 0.0 and image having metric value 1.0 is sharper and less blur image.[6]. It is mainly used in Telemedicine application.

VI ACKNOWLEDGEMENT

We would like to express our sincere regards to PROF. K. P. PATIL (Head of E&TC. Department) & PROF. DR. V. K. Bairagi for their for constant encouragement and precious suggestions throughout the paper writing.

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