A New No-Reference Image Quality Measure for Blurred Images in Spatial Domain

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Abstract—**Determination of quality of an image is a very challenging task and is very important for modern image processing applications. One of the most common distortions in images is blurring. For a human visual system excessive blurring in an image is not visually pleasing and creates difficulty in identifying objects. In this paper we propose a quality measure which is calculated in spatial domain to determine the quality of blurred images.**

Index Terms—**image quality assessment, blurring, no-reference, sharpness, human visual system.**

I. Introduction

In image processing applications one of the most common distortions encountered is blurring. Blurring in images can be caused by lot of reasons like motion, camera shake, defocus etc. Thus it is very important to quantify the quality of blurred images for certain image processing algorithms. Objective image quality analysis can be done in three ways: 1) Full- Reference Image Quality Assessment algorithm (FR-IQA) 2) Reduced Reference Image Quality Assessment algorithm (RR-IQA) and finally 3) No-Reference Image Quality Assessment algorithm (NR-IQA) [1]. In this paper we will be proposing an NR-IQA technique in spatial domain which will help us in identifying which image is blurred or sharp and will give us the extent of blurring in the image. Human eyes can detect the quality of an image without the need of reference images and when image is heavily blurred our visual system fails to identify different objects present in the image. We will validate our results against human perception by comparing it against Mean Opinion Scores obtained by conducting experiments on human subjects. Different approaches for image blur/sharpness measure are there. Some examples are Kurtosis based [2][3], derivative based[4], edge-width [5][6], variance[7], histogram based [8][9][10], power spectrum based[11] and wavelet based[12]. Image sharpness technique based on cumulative probability of blur detection (CBPD) [13] and No-reference Objective image sharpness metric based on Just Noticeable Blur (JNB) [14] are most commonly used techniques. The comparison of techniques [2]-[12] is available in [14]. In section II we will discuss preliminaries, then in section III we will propose our image quality measure and finally we report our results in section IV.

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II. Preliminaries

Excess blur in an image is a distortion and causes difficulty for user to identify and classify objects in an image. Our goal in this paper is to quantify the quality of an image which is distorted by blur and this score can be used for a variety of image processing applications. Human eyes are sensitive to sharper changes in intensity levels on edges so for a good quality image the intensity difference between adjacent regions must be very high and in case of blurry images the intensity difference between adjacent regions will be lower in comparison to sharper images. We use this concept to model our proposed image quality measure – Blur measure (**BM**). Lower value of **BM** denotes higher blurring which means that visibility of objects in the image is very poor and higher value of **BM** denotes sharper images. A good image quality measure is one where the difference between the score of a good quality image and highly blurred image must be high so that images can be easily distinguishable and classifiable according to amount of blur by looking at the score. Experimentally it has been found that when we find edge pixels using sobel operator the difference between **BM** score of a good image and heavily blurred image is highest compared to other techniques like Canny, Prewitt, Laplacian of Gaussian (LoG).

III. Proposed Image Quality Measure

Given an image *I*, first step is to find the edge of the image using Sobel operator. Let *E* be a set containing all edge pixels in the image computed using Sobel operator. We define N_{xy} a set of 8-neighbors of a pixel $I(x, y)$ where $I(x, y) \in E$.

Our model is based on the concept that for good quality image sharpness will be more and amount of blur will be less. For a sharper image the intensity changes near the edge will be very high and for blurred images the change in intensity values will be smaller. We define

$$BM = \frac{\sum_{I(x,y)\in E} \sqrt{\sum_{I(x',y')\in N_{xy}} \{\mathrm{I(x,y)} - \mathrm{I(x',y')}\}^2 \Big/ |\mathrm{N}_{xy}|}}{\sum_{I(x,y)\in E} I(\mathrm{x,y})} \quad (1)$$

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where $|N_{xy}|$=total number of pixels in the set N_{xy}.

Higher value of BM score means that there is higher change in intensity along the edges which in turn means that image has higher sharpness, where as a lower value of BM score means smaller changes in intensity along the edges and means that blurriness in the image is very high.

IV. RESULTS

In this section we present our results to demonstrate the performance and applications of our proposed image quality measure for blurred images ***BM.*** We have tested our technique on blurred images of three standard image quality datasets and also standard images like peppers, cameraman, boats etc. We do three types of analysis – firstly we calculate our proposed measure BM on three standard databases of image quality and compare our measure with Difference Mean Opinion score (DMOS) which gives the correlation of our measure with human visual system as DMOS score is obtained by conducting experiments on human subjects. For second analysis we find the trend of our image quality score with increase in blur. We increase the standard deviation of the blur in the image and then we observe the trend. Finally we take blurred images and we try to remove the blur in the images using one of the best known algorithm BM3D [15][16] and we find our image quality scores before and after de-blurring to analyze the performance of the de-blurring algorithm.

A. Database Independence

We test our quality measure ***BM*** on three different image quality datasets a) LIVE Image Quality database [17][18][19], b) CSIQ Image Database[20] c) TID 2008[21] image quality database. We do not use all the images in these databases; we are interested only in the set of images in these databases which are distorted by blurring. The LIVE database has images from 29 different scenes and distorted images were derived from this dataset. Images were evaluated by different human subjects in seven experiments and DMOS score calculated during these experiments are made available in the database. The images in LIVE database were blurred using a circular-symmetric 2-D Gaussian Kernels. Total number of images in LIVE database with Gaussian blur is 174 and we calculate our image quality measure ***BM*** for each image in the database. The CSIQ image database has images from 30 different scenes and from these images a set of distorted images is derived with different levels of blur. The total number of images distorted with blurring in this database is database is 150. Experiments were conducted with 35 human subjects in the ages 21-35 and DMOS were obtained and made available in the database. The TID2008 image quality database has images from 25 different scenes and 125 images with different levels of blur distortion are present in this database and we compute our image quality measure for each of these images. Each of these databases is available with Difference Mean Opinion Scores (DMOS) for each image. DMOS scores are computed by conducting experiments on human subjects and give the idea of human opinion on image quality. We find Spearman Rank Correlation Coefficient (SROCC) of our image quality measure ***BM*** with the DMOS scores. We compare results with one of the most popular image sharpness/blur metric based on JNB (Just Noticeable Blur). The results are presented in Table I.

TABLE I. COMPARISON BETWEEN BM AND JNB MEASURES

Database	Proposed BM (SROCC with DMOS)	JNB (SROCC with DMOS)
LIVE	0.8335	0.8253
CBIQ	0.8413	0.7801
TID2008	0.8554	0.7254

Thus we can infer from Table I that our measure is very close to how a human being would analyze the quality of blurred images with naked eye and performs better than JNB.

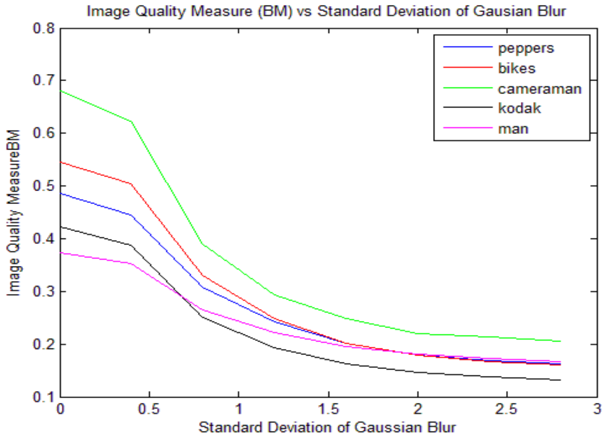
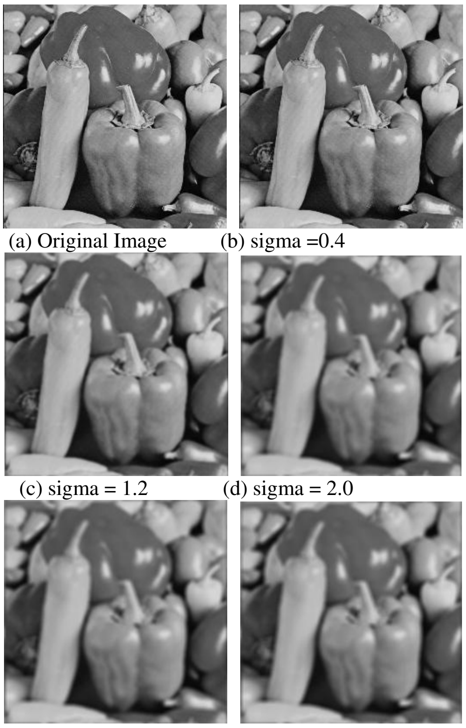


Figure 1. Image Quality measure (BM) vs. Standard Deviation of Gaussian Blur examples

(a) Man (b)Bikes

(c) Cameraman (d) Kodak_woman

Figure 2. Examples of some of the images used in our analysis



(a) Original Image (b) sigma =0.4

(c) sigma = 1.2 (d) sigma = 2.0

(e) sigma = 2.4 (f) sigma = 2.8

Figure 3. Peppers image blurred with different standard deviation

(a) BM = 0.1442 (b) BM = 0.5617

(c) BM = 0.1507 (d) BM = 0.4281

(e) BM = 0.2018 (f) BM = 0.2785

(g) BM = 0.1465 (h) BM = 0.2894

Figure 4. Analysis of images after removing of blurs using BM3D technique.

B. *Analysis with Gaussian Blur*

The blurring is simulated by convolution of the image with the Gaussian Blur kernel. We vary the standard deviation from 0.4 to 2.8 and observe the trend in Fig. 1. The examples of images used in our study are shown in Fig. 2. In Fig. 3 we observe the pepper image blurred by a Gaussian kernel with varying standard deviations. In the proposed image quality measure a lower value suggests that the image is more blurred compared to a higher score. We observe that for all images when we increase the standard deviation of the Gaussian blur kernel the score decreases non-linearly.

C. *Application–Analysis of Blur Removal Algorithm*

One of the applications of our proposed image quality measure for blurred images is that we can assess the performance of de-blurring techniques and we can use our image quality score to analyze the extent of blur removed from the image. For analysis we have used one of the state of the art de-blurring techniques BM3D. Blur in images were removed using BM3D technique and our proposed quality measure is calculated on images before and after blur removal. Some of the examples of de-blurred images are demonstrated in Fig. 4, the left side images are blurry images which is the input to the BM3D algorithm and the right side images are de-blurred by the BM3D algorithm, we can see that the images in the right side have a higher value of **BM** compared to the image in the left side which means that image is more sharper and more visually pleasing to human visual system.

V. CONCLUSION

In this paper we proposed a new no-reference image quality measure for blurred images in spatial domain and we compared our results with one of the best known image sharpness/blur metric JNB. The proposed image quality measure is closer to human perception as it has higher correlation with DMOS scores obtained by conducting experiments on human subjects. The proposed algorithm is very fast since the time complexity of edge detection using sobel operator is linear with respect to 2-D array and our image quality measure computation time complexity is sub-linear with respect to 2-D array as the computation is occurring only along edge pixels.

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