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Image Sharpness Measure for Blurred Images in Frequency Domain

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Abstract

One of the most challenging problems for researchers in the field of image processing is image quality assessment. A very important factor in image quality assessment is image sharpness/blurriness. The goal of researchers in the field of image quality assessment is to design and develop algorithms and measures for detecting sharpness and blurriness in an image. In this paper a new technique is proposed to calculate image sharpness/blurriness measure in frequency domain.

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Keywords: Image Quality, Image Sharpness, Frequency Domain Image processing, No-reference image Quality, Blurring.

1. Introduction

Blur in an image is caused by a lot of factors like defocus, camera shake, motion etc. One of the challenging tasks is to design an algorithm to compute an image quality measure blindly. In certain image processing applications it is very important to quantify the quality of blurred images. Image quality algorithm design can be done subjectively by considering human opinion score or objectively. There are three different strategies to design objective image quality assessment algorithms: 1) Full Reference Image Quality Assessment (FR-IQA) 2) Reduced Reference Image Quality Assessment (RR-IQA) 3) No-reference Image Quality assessment (NR-IQA) [1]. In this paper a NR-IQA technique in frequency domain is proposed which will help in identifying which image is blurred

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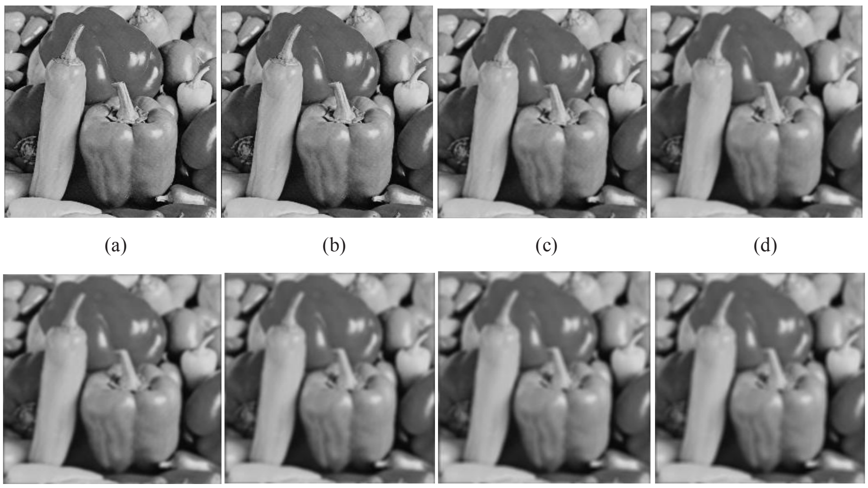
or sharp and will give us the extent of blurring in the image. Various design strategies has been used by different researchers to develop image quality measures for blurred images. Kurtosis based[2][3], derivative based[4], approaches involving calculation of edge-width[5][6], variance based[7], histogram based [8][9][10], power spectrum based measures[11] and wavelet based techniques[12]. Two of the popular image sharpness/blurriness image quality measures are A) Image sharpness technique based on cumulative probability of blur detection (CPBD)[13] and B) No-reference Objective image sharpness metric based on Just Noticeable Blur (JNB) [14]. A detailed analysis of techniques described in [2]-[12] is also available in [14]. In section 2 the preliminaries are discussed, then in section 3 the image quality measure is proposed, followed by presentation of results in section 4 and finally conclusion in section 5.

2. Preliminaries

When an image is degraded by excess quantity of blur, identification and classification of elements in the image becomes very difficult. Primary goal of this paper is quantification of the quality of blurred images. The quality score thus obtained can be used for a variety of image processing applications. In this paper we design an image quality measure for blurred images which will denote the quality of image based on the amount of blurriness in the image. The proposed technique is designed in frequency domain. Figure 1 shows Peppers image with varying amount of blur. Uniform blurring in the images is simulated by convolution of the image with Gaussian blur kernel. The standard deviation of the Gaussian blur kernel is varied to obtain different images in figure 1(b)-(c). Figure 3shows the cantered Fourier spectrum for the corresponding images. An important observation from figure 2 is that when the blur in an image increases the number of high frequency component in the images decreases. As it is observed from figure 2(a) more number of white spots are around the centre for the original good quality peppers image and the number of white spots reduce around the centre as the standard deviation of Gaussian blur signal increases which we observe from figure 2(b)-(h). This concept is used to design the proposed image quality measure for blurred images. A threshold value is fixed for high frequency components and then the number of high frequency components above the threshold value is calculated and finally this is used to calculate the image quality score. A sharper good quality image will have higher number of high frequency components compared to a blurred image.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 1. Peppers image blurred with Gaussian Blur with different standard deviation (a) Original Image (b) sigma =0.4 (c) sigma = 0.8 (d) sigma = 1.2 (e) sigma =1.6 (f) sigma = 2.0 (g) sigma = 2.4 and (h) sigma = 2.8.

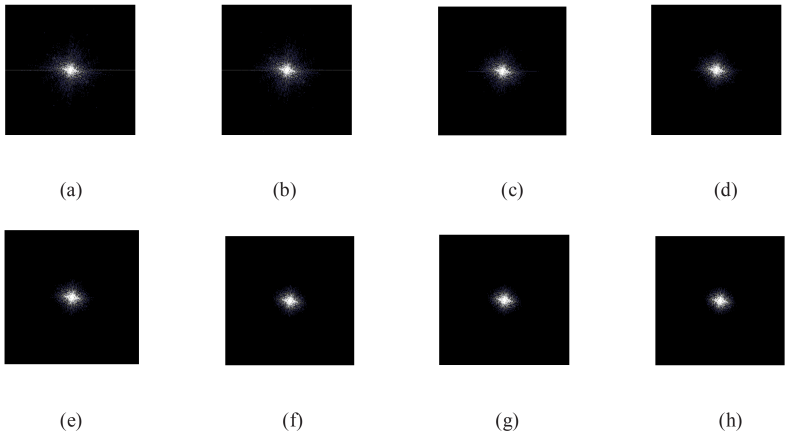


Fig. 2. Centered Fourier spectrum of Peppers image blurred with Gaussian Blur of different standard deviation
(a) Original Image (b) sigma =0.4 (c) sigma = 0.8 (d) sigma = 1.2 (e) sigma =1.6 (f) sigma = 2.0 (g) sigma = 2.4 (h) sigma = 2.8

3. Proposed Algorithm for calculating Image Quality measure

3.1 Algorithm for image quality measure

Input: Image I of size $M \times N$.

Output: Image Quality measure (FM) where *FM* stands for Frequency Domain Image Blur Measure

Step 1: Compute F which is the Fourier Transform representation of image I

Step 2: Find Fc which is obtained by shifting the origin of F to centre.

Step 3: Calculate $AF = abs(Fc)$ where AF is the absolute value of the centered Fourier transform of image I.

Step 4: Calculate $M = max(AF)$ where M is the maximum value of the frequency component in F.

Step 5: Calculate T_H = the total number of pixels in F whose pixel value > *thres,* where $thres = M/1000$.

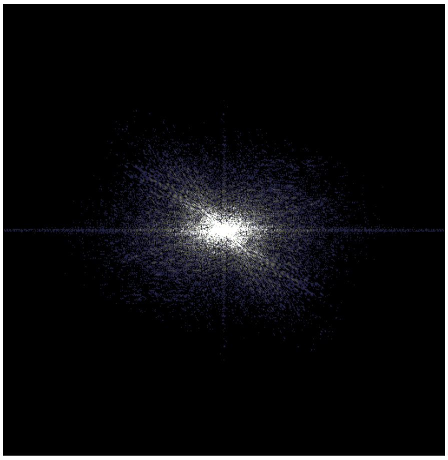
Step 6: Calculate Image Quality measure (FM) from equation (1).

$$Image\ Quality\ Measure\ (FM) = \frac{T_H}{M \times N} \tag{1}$$

3.2 Algorithm Demonstration

Centered Fourier Spectrum of both good quality Lena image and blurred Lena image is shown in Figure 3. Then M which is the maximum value of centered Fourier spectrum of the images is computed and a threshold thres = M/1000 is fixed. Experimentally it is observed that this particular threshold value gives a fairly accurate sense of image quality. The experiments are conducted on all the images of the Berkeley Segmentation Dataset (BSD) [15]. The number of pixels which have greater value than the threshold in both Lena images shown in figure 3(a) and (c) are calculated - for good quality Lena image the count is 4780 and blurred Lena image is 1176. Finally Image quality measure FM using equation (1) is computed for both images. FM (Lena Image) = 0.0182 and FM (Blurred Lena Image) = 0.0045.


(a)


(b)


(c)

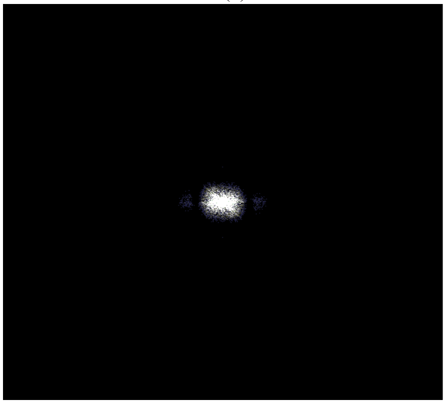

(d)

Fig. 3: (a) Lena Image (b) Centered Fourier Spectrum of Lena Image
(c) Blurred Lena Image and (d) Centered Fourier Spectrum of blurred Lena Image.

3.3 Time Complexity

Time complexity for computation of Fast Fourier Transform = O(nlogn) where n= M×N which is the total number of pixels in image *I*. The time complexity for all other steps is O(n). Thus the time complexity of our proposed algorithm is O(nlogn).

4. Results

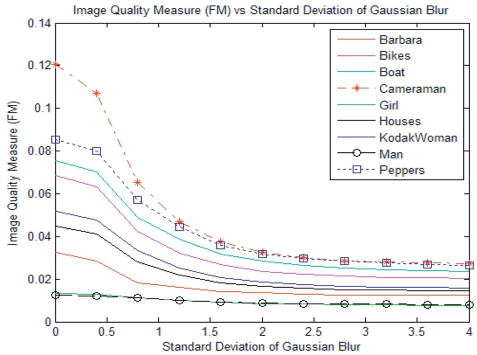
4.1 Analysis with Gaussian Blur

The blurring is simulated by convolution of the image with the Gaussian Blur kernel. We observe the trend and compare the trends with JNB metric and CPBD measure. The proposed technique is tested on standard image processing test images and images of the Berkeley Segmentation Dataset (BSD). In figure 4 some of the standard images which are used for the analysis are shown. Figure 5(a)-(c) shows the trends of the proposed image quality measure FM and the CPBD and JNB measure values. The main observation is that as the standard deviation of the Gaussian blur kernel increases the image quality decreases. As it is observed from figure 5(a) the image quality measure decreases. The proposed approach is better than JNB metric and CPBD measure as these measures fail after a certain point where with increase in the value of standard deviation of Gaussian blur kernel the image quality measure gives a higher value as we can observe from figures 5(b) and (c).

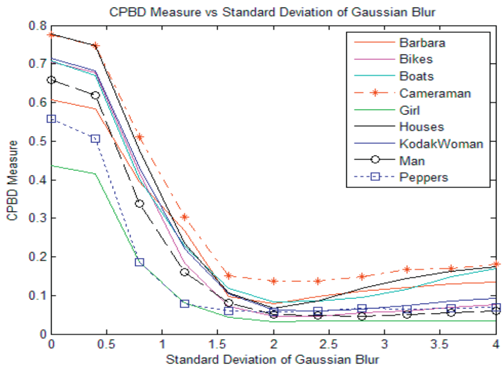
(a) (b) (c) (d)

(e) (f) (g) (h)

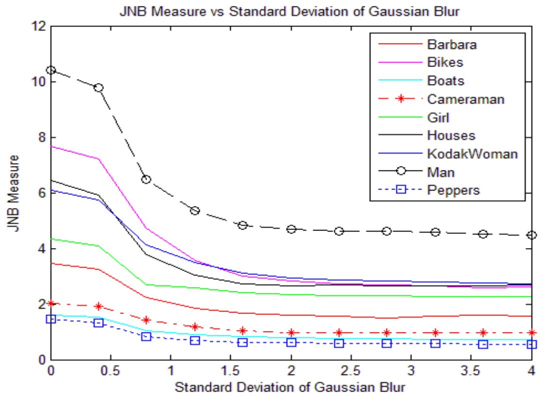
Fig. 4. Examples of Test images used for our analysis (a) Bikes (b) Boats (c) Cameraman (d) Girl (e) Kodak Woman (f) Man (g) Barbara and (h) Houses



(a)



(b)

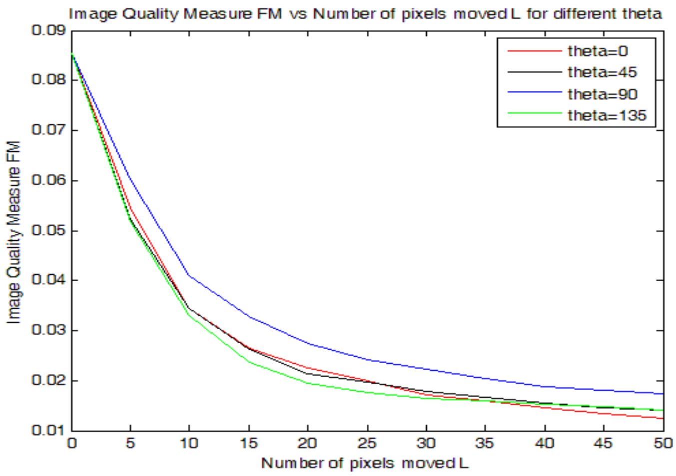


(c)

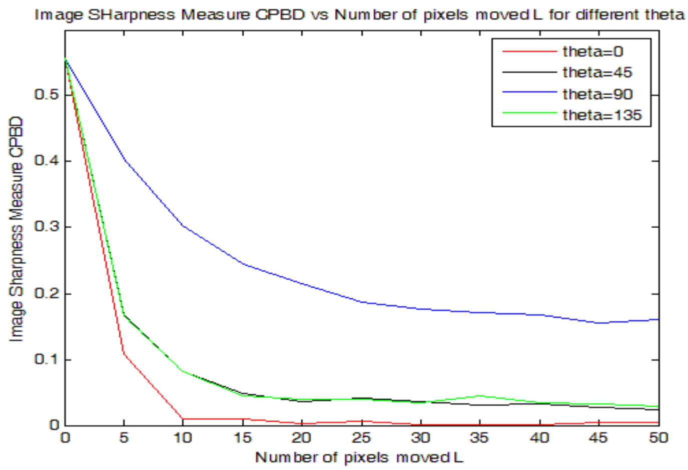
Fig. 5 Comparison of different image quality measures for images blurred by Gaussian Blur (a) Image Quality Measure (FM) vs Standard Deviation of Gaussian Blur (b) CPBD Measure vs Standard Deviation of Gaussian Blur and (c) JNB Measure vs Standard Deviation of Gaussian Blur.

4.2 Analysis with Motion Blur

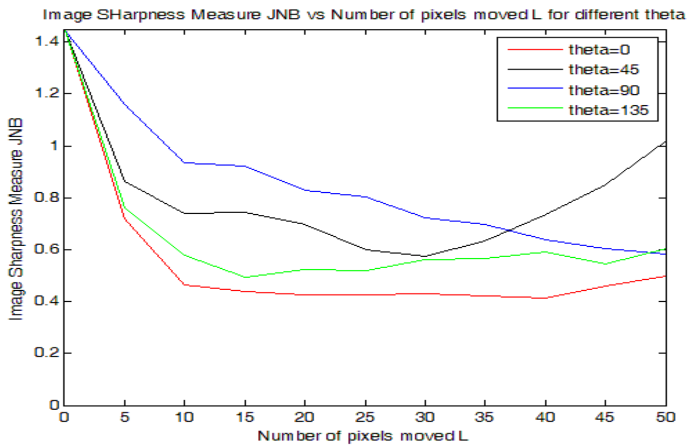
Blur in an image is also caused by motion of the camera. Motion blur is characterized by two parameters *L* and theta where *L is* the number of pixels by which the camera has linear motion and *theta* is the angle in counter-clockwise direction by which the camera moves. Motion blur is modelled by convolution of image *I(x,y)* with a Point Spread Function(PSF) *H(x,y)*. H(x,y) is obtained by the following process:- a) an ideal line segment with the desired length and angle, centred at the centre coefficient of *H* is drawn, b) then for each coefficient location (i,j), the nearest distance between that location and the ideal line segment is computed c) *H* is calculated as *H=maximum(1 – nearest distance, 0)* d) *H* is normalized. Inbuilt MATLAB function is used to obtain *H* using the above mentioned steps. It is observed from figure 6(a) that for different values of *theta* [0, 45, 90 135 degrees], the relationship between number of pixels *L* and the proposed image quality measure for peppers image is shown. It is observed that in all cases as the value of *L* increases the quality of image degrades. This trend is followed for different *theta* values.



(a)



(b)



(c)

Fig. 6 Comparison of different image quality measures for images blurred by Motion Blur (a) Image Quality Measure (FM) vs Number of Pixels by which camera has linear motion L at different directions theta for peppers image (b) CPBD measure vs Number of Pixels by which camera has linear motion L at different directions theta for peppers image and (c) JNB measure vs Number of Pixels by which camera has linear motion L at different directions theta for peppers image.

It is observed from figure 6(b), the CPBD measure also follows the same trend but in certain cases with high L value we see that image quality score increases, which is not accurate depiction of image quality. Similarly from figure 6(c) we infer that JNB measure also fails for certain cases.

4.3 Application – Analysis using Blur removal algorithm

An important application of the proposed image quality measure is the analysis of image de-blurring algorithms. One of the state of the art image de-blurring technique BM3D [16][17] developed by Tampere University of technology is used for conducting experiments. Blurring in the images was removed using BM3D technique and our proposed quality measure was calculated on images before and after blur removal. Figure 7 demonstrates some of the examples where 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, it is observed that the images in the right side have a higher value of the proposed image quality measure **FM** compared to the image in the left side which means that image is more sharper and more visually pleasing to the human observer.

(a)

(b)

(c)

(d)

(e)

(f)

(g)

(h)

(i) (j)

Fig. 7. Before and after removing blur from images using BM3D technique (a) FM = 0.0231 (b) FM =0.0927 (c) FM= 0.0142 (d) FM = 0.0554 (e) FM= 0.0284 (f) FM= 0.0311 (g) FM = 0.0301 (h) FM = 0.0626 (i) FM = 0.0286 (j) FM = 0.0414

5. Conclusion

In this paper a new no-reference image quality measure for blurred images in frequency domain is proposed and the results are compared with two of the best known image sharpness/blur measures JNB and CPBD. The inference from figure 5(a) is that when blur in an image increases the quality of image decreases. Lower the value of image quality scores in the image means higher the amount of degradation in the image, poorer the quality of the image. The time complexity of our proposed algorithm is *O(nlogn)* where *n* is the total number of pixels in the image. The advantage of the proposed approach over CPBD and JNB approaches is that the image quality score is always decreasing with increase in blur in the image but for CPBD and JNB approaches in certain cases with increase in blur the image quality score increases as seen from figures 5(b) and 5(c) respectively. The proposed method gives a better understanding of image quality based on figures 6(b) and 6(c) where the CPBD and JNB measure fails to accurately predict the image quality in case of motion blur. We observe clearly from figure 6(a) that when blur in an image increases the image quality score decreases for all cases.

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