Reference Free Blur Metric for Measuring Image Blur and Classification of the Type of the Blur

REPORT FOR PROJECT ELECTIVE

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ABSTRACT

Image Blur is an important source of image degradation, which arises from different sources such as, atmospheric turbulence, camera's relative motion during exposure, object not being properly focused by the camera. There are several reference based approaches for determining the blur in image. Here we have used a reference free approach to determine the amount of blur in an image, thus assessing its quality by clustering images of different quality using k-means clustering. Also we have classified the type of blur introduced in the image by obtaining different patterns for different point spread functions (PSFs). The classification is done by using Support Vector Machine (SVM). The results shows that the implementation provides decent performance in measuring the blur metric, thus giving a qualitative measure of the image and also the type of blur present in the image, which leads us to the cause of the blur in the image.

1 INTRODUCTION

Nowadays, with the advent of technology digital images are everywhere. With cameras, smartphones and many other devices people capture digital image and they can share the images in the internet with others. But the main concern about digital images is the quality of the image. Blurriness in an image plays an important role in determining the quality of the image. The less blurry the image is, the sharper it is, and thus we can judge that the image is of good quality. Though technology in modern digital cameras are capable of removing significant amount of blur that can degrade the image, still blur can occur in images due to various factors, such as atmospheric impact or some mechanical error while capturing the image or sometimes blur can be introduced in the image in an artistic point of view[4]. In our project we have developed a method by which we determine the blurriness of the image and estimate its quality and also further classify the type of blur that is introduced in that particular blurred image. In Section 2 we have discussed about the background related to our problem for determining the blur metric; in Section 3 we explained the methodology upon which we did our implementation; in Section 4 we discussed about the results from our implementation.

2 BACKGROUND

There are various conventional metrics available, such as Mean Square Error (MSE), Peak-signal-to-noise ratio (PSNR) and Structural Symmetric Index (SSIM) [6]; but all of these are reference based approach. We know the original image quality. In our project we have used a non-referencing approach [1][2] to measure the amount of blur present in the image, i.e. we do not have any knowledge about the original image quality with respect to blur. We have to determine whether the image is blurry or not by looking at it only. Few previous approaches are there to estimate the amount of blur in without taking any reference image into consideration. Mostly they involve average edge width determination, cumulative probability of blur detection around the edges of the image, etc.

3 METHODOLOGY

We have followed a two step approach in this project. First, we used a non-referencing approach to measure the blurriness of the image and in the next step we are determining the cause of blur in the image; whether the blur occurred due to atmospheric turbulence (Gaussian Blur), camera's relative motion with exposure (Motion Blur) or Out-of-Focus Blur.

3.1 BLUR METRIC

In the Blur Metric that we are determining, we are initially applying a Laplacian of Gaussian (LoG) filter on the image and picking up the maximum value from that. The LoG filter highlights the edges of the image, from that we are selecting the brightest edge pixel. This gives a sharpness measure as sharp images will have prominent edges. So for our Blur Metric, we can use this LoG measure to determine the blurriness of image, the lower the value the more blurred the image is. Now to verify whether this measure is a good measure for blur determination, we applied an averaging disk filter on the image in increasing size of the radius of the filter. Then on those blurred image we apply LoG filter and compute the maximum value from them. So for this maximum LoG blur estimator we have plotted the values for 5 test images with respect to the radius of the averaging disk filter (Fig. 1). We have noticed that as we are increasing the blurriness in the image, the value of the maximum LoG blur estimator also decreases for all the sample images. So we can consider this measure for estimating the blur in an image.

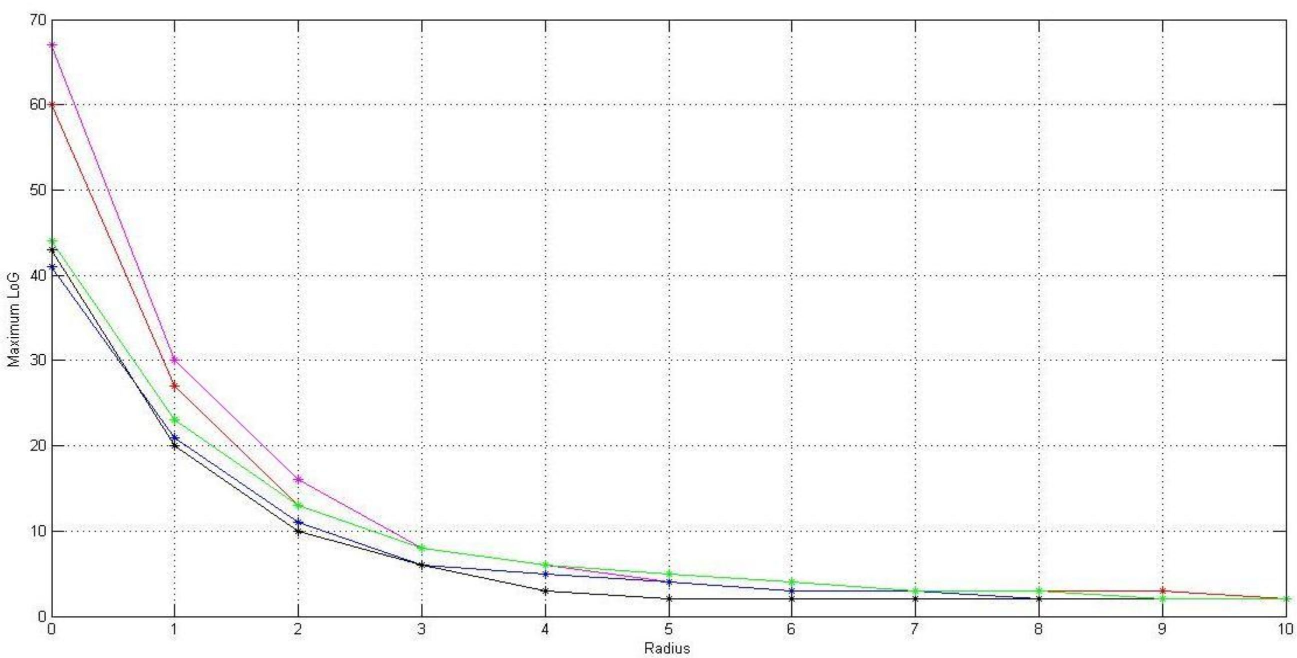

Fig. 1: Maximum LoG Blur Estimator vs. Radius of different averaging filter

Also from this graph we can visualize that after a certain time the maximum LoG value does not change. This means that the image is already blurred enough, blurring it more would have very less impact on it compared to blurring a sharp image. So we are obtaining another metric from this, i.e. the standard deviation of the maximum LoG values obtained after degrading the actual image by further blurring it. The concept that we use here is that when we blur a sharp image and then we re-blur the blurred image, in the first case we can perceive the drastic changes in the removal of the high frequency components from the image, but in the latter case we just observe slight differences in the details of the corresponding images [3].

3.2 BLUR CLASSIFICATION

3.2.1 BLUR FEATURES

Blur can be caused in image due to various reasons. There are different types of blurs that are observed, namely - Gaussian Blur, caused by atmospheric turbulence, Motion Blur, caused by the camera's relative motion with respect to exposure and finally if the entire image is not focused properly then Out-of-Focus or Defocus Blur is present in an image. Here we distinguished out different types of Blur in the image.

The image blurring can be modeled as the following degradation process from the high exposed image to the observed image [5][7]:

$$g(x) = q(x) * f(x) + n(x) , \qquad (1)$$

where x={x1,x2} denotes the coordinates of an image pixel, g represents the blurred image, f is the intensity of the original high quality image, q denotes the PSF (point spread function) of a certain blur type, * indicates the convolution, and *n* is the additive noise.

In the process of Blind De-convolution it is very difficult to recover the point spread function from the image, due to loss of imformation due to the process of blurring. Our main objective is to classify the blur present in the images into their respective degradation functions. We have considered several blurring functions.

In applications such as satellite imaging Gaussian Blur is used to model the point spread function atmospheric turbulence.

$$q(x, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{{x_1}^2 + {x_2}^2}{2\sigma^2}\right), \qquad x \epsilon R \qquad (2)$$

where σ is the blur radius to be estimated, and R is the region of support. R is usually set as [-3σ, 3 σ], because it contains 99.7% of the energy in a Gaussian function.

Motion Blur is caused by the linear motion of the camera during exposure. It can be modeled as:

$$q(x) = \begin{cases} \frac{1}{M}, & if\ (x_1, x_2)\begin{pmatrix}\sin(\omega)\\ \cos(\omega)\end{pmatrix} = 0\ \ and\ \ x_{1^2} + x_{2^2} \le \frac{M^2}{4} \\ 0, & otherwise \end{cases} \qquad (3)$$

Where M denotes the length of translation of the pixels and ω is the angle of the motion.

The final blur that we have considered is Out-of-Focus Blur or Defocus Blur. It is modeled as,

$$q(x) = \begin{cases} \frac{1}{\pi R^2} & , \sqrt{x_{y^2} + x_{y^2}} \le R \\ & 0,\ otherwise \end{cases}, \qquad (4)$$

Now if we apply Fourier transform to both sides of equation (1), we get

$$G(u) = F(u)Q(u) + \ N(u), \qquad (5)$$

where $u = \{u_1, u_2\}$.

For Motion Blur, the Fourier Transform of q(x) comes out to be: $Q(u) = \frac{\sin(\pi M\omega)}{\pi M\omega}, \omega = \pm\frac{1}{M}, \pm\frac{2}{M}, \ldots$

For Defocus Blur, the Fourier Transform of q(x) comes out to be: $Q(u) = \frac{J_1(\pi Rr)}{\pi Rr}, r = \sqrt{u_{1^2} + u_{2^2}}$

J_1 is the first order Bessel equation of the first kind. Its amplitude is characterized by almost periodic circles of radius R along which Fourier magnitude takes zero value.

For Gaussian Blur, the Fourier Transform of the point spread function returns a Gaussian function again. So there is no significant change in the pattern obtained in the Frequency domain.

In order to know the PSF, Q(u), we attempted to obtain the parameter of Q from the image G(u) only. We used a normalized logarithm of Q in our implementation to find out the pattern for the respective types of blur in the image.

$$\log(|Q(u)|)_{norm} = \frac{\log(|Q(u)|) - \log(|Q_{\min}|)}{\log(|Q_{max}|) - \log(|Q_{min}|)}, \qquad (6)$$

Where Q_{max} and Q_{min} are the maximum and minimum values of Q(u) respectively.
In Fig. 2 we have shown how different pattern are obtained by introducing different type of blur in a particular image.

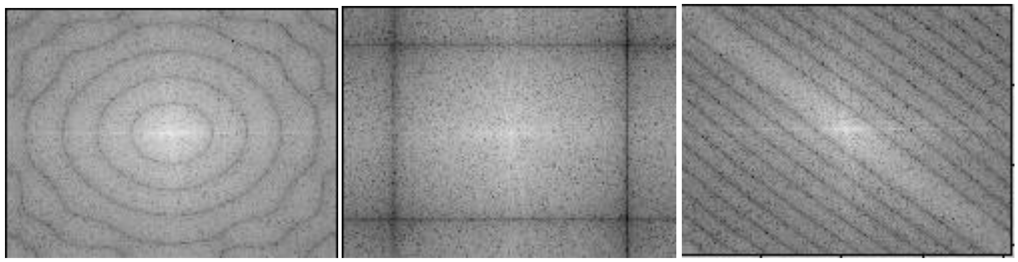

Fig. 2: (Top Row L-R) Image of Defocus Blur with R=5, Image of Gaussian Blur with σ=2, Image of Motion Blur with M=15 and ω=45
(Bottom Row L-R) Normalized Logarithmic Spectrum for Defocus Blur, Gaussian Blur and Motion Blur.

3.2.1 CLASSIFICATION METHOD

We obtain specific patterns from the normalized logarithmic spectrum for different type of blurs. For Out-of-Focus or Defocus Blur we obtain a concentric ring like pattern. In case of Gaussian Blur more or less no change in pattern is obtained from the logarithmic spectrum of a blur free image. Also no noticeable changes are found for $\sigma>2$. Whereas for Motion blurred image the normalized logarithmic spectrum more or less comes out to be streaks of lines, which are found to be approximately perpendicular to the direction of the motion in the blurred image. We apply a modified canny edge detector, by adjusting the threshold values and standard deviation of the Gaussian filter on these normalized logarithmic spectra. This is done to extract the blur features from the images. If we do automatic thresholding then it is difficult to isolate the blur features. In Fig. 3 we have shown how the blur features are isolated from the normalized logarithmic spectra.

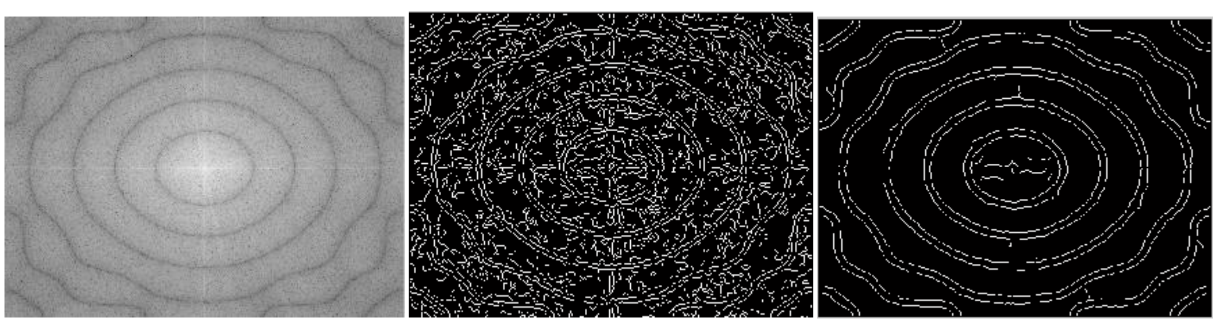

Fig. 3: (L-R) Normalized logarithmic spectrum for Defocus Blur with R=5, Applying Canny Edge detector on the previous with automatic thresholding, Applying Canny Edge detector with adjusted thresholding values and standard deviation

After obtaining the pattern for different type of Blur we have stored them as image files. Then using those images as a training set, we classified the different kind of blur present in images. For the classification of different type of blurred image we used Support Vector Machine in our implementation [8].

4 IMPLEMENTATION AND RESULTS

The implementation was performed using MATLAB 2010a. The measurement of the Blur Metric and Classification of the Type of Blur were done separately. We created our data set for testing from 250 images of resolution 400X300 and generated blurred image of different magnitude and types (250 each for Motion Blur, Defocus Blur and Gaussian Blur). For Gaussian Blur we chose $\sigma = \{1.5, 2.0, 2.5, 3.0, 3.5, 4.0\}$. For Motion Blur we had, $M = \{5, 9, 15\}$ and $\omega = \{0, 45, 90, 135\}$. For Defocus Blur we had $R = \{2, 5, 8, 11, 14, 17, 20, 23\}$

4.1 RESULTS FOR MAXIMUM LoG MEASURE

Out of those 1000 images we picked out 175 such images randomly and stored their Maximum LoG Measure and the corresponding standard deviation of the Maximum LoG Measure, when we gradually degrade the image by further blurring the original image into an array. We apply k-means clustering algorithm for this array into 5 different clusters to classify the quality of image as 5 different classes; 'Excellent', 'Good', 'Fair', 'Not Good' and 'Poor'. The graph for k-means clustering is shown in Fig. 4.

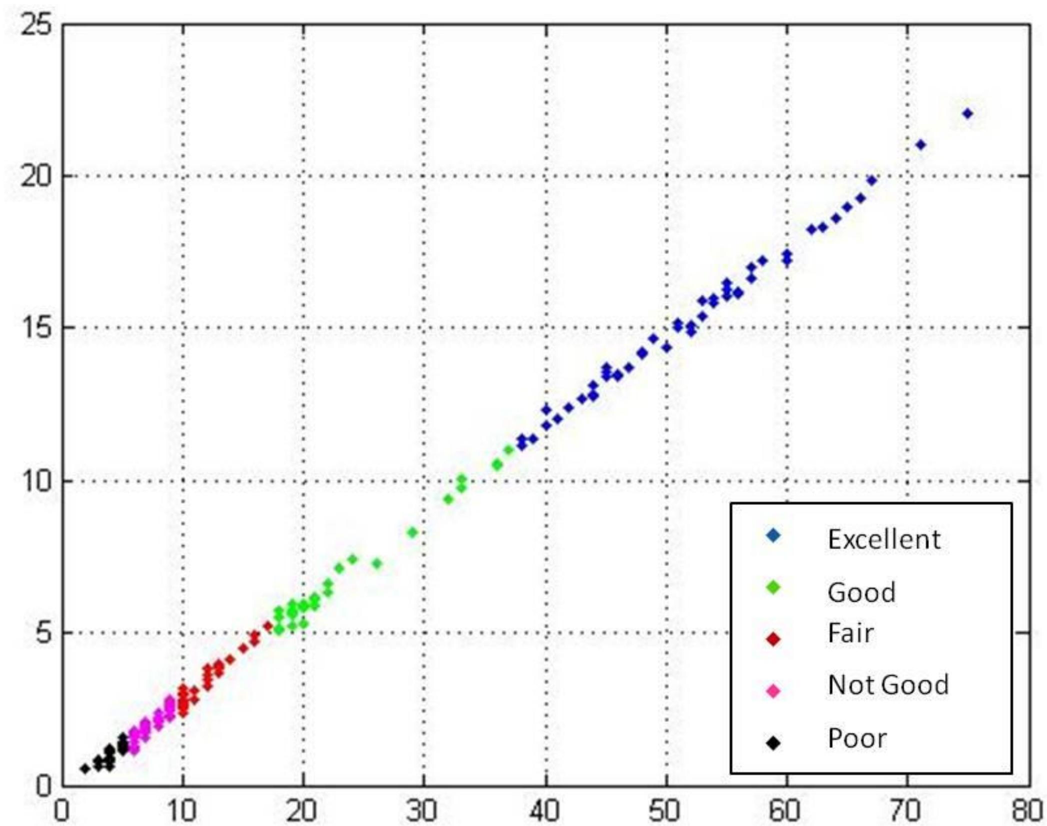

Fig. 4: k-means clustering applied on Maximum LoG Measure (k=5)

From Fig. 4 we see that we obtain a linear relationship between the Maximum LoG Measure and the standard deviation of the Maximum LoG by blurring it further. This is obvious fact as it is based on the principle that if an image is already blurred (low value of Maximum LoG measure), on further blurring it we will perceive less changes in the image i.e. the standard deviation will be also low. Similarly for sharp images we will have high Maximum LoG Measure and on further blurring we will perceive a significant change in the Maximum LoG Measure, thus the standard deviation is also high.

4.2 RESULTS FOR THE BLUR CLASSIFICATION

For the training set we used 750 blurred images (250 each for 3 types). We obtained the normalized logarithmic spectrum of the Fourier Transform of the images. On that we applied modified canny edge detection. The resultant of the edge detector is stored as an array in form of a feature vector. We randomly chose around 40 images for each class of blur to test our performance. We tested separately for Defocus/Out-of-Focus Blur, Motion Blur and Gaussian Blur to analyze the performance of our classification. Around 90% (approximately) of the test samples were properly classified for all the 3 type of blurs by using Support Vector Machine (SVM) for classification. There were few misclassifications present. This occurred due to pattern in few samples having similarity with patterns of other classes or acquiring some different pattern altogether from its own class. In Fig. 5 we have shown few cases which led to the misclassification of the type of blur present in the image.

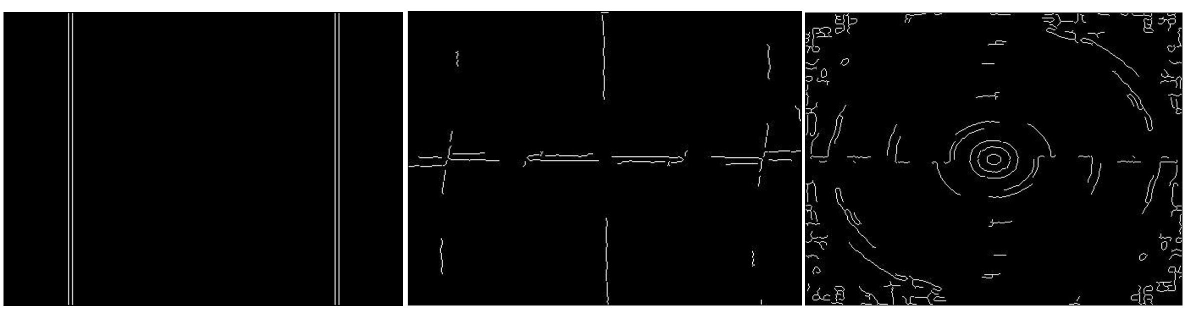

Fig. 5 (L-R): Gaussian Blur misclassified as Motion Blur, Motion Blur misclassified as Gaussian Blur, Pattern from Defocus Blur somewhat different from standard patterns obtained for Defocus Blur.

5 CONCLUSIONS

From the results obtained for the Blur Metric and for classification of the type of Blur, we obtain a quite decent performance. We have used a reference free approach to determine the quality of an image with respect to the amount of blur present in it. Also by using a machine learning approach, i.e. by using SVM we are able to classify the type of blur that is introduced in the image.

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