A No-reference Image Blur Metric Based on Two-pass Edge Analysis

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Abstract—**This paper presents an efficient no-reference blur metric for images where image quality is quantified by the two pass edge analysis. The proposed method is based on the experimental result shown in section Ⅱ which demonstrates that not all the edges spread when the images become blurred. So in the proposed method the spread of the edges were measured two times, one for the test image and one for the blurred image, to find the edges whose width increment correlates well with the image blurred intensity. Experiments using the LIVE blur database demonstrate that the proposed algorithm correlates well with subjective quality evaluations.**

Keywords-No Reference; Image Blur Metric; Edge Width;

I. INTRODUCTION

Image quality assessment becomes more and more important with the increasing demand for image-based applications. Efficient Image quality assessments can help to improve the performance of the image processing system and other related systems. This section presents an overview of the classic no-reference blur metrics and then shows the advantages of the proposed metric.

Variance metric is the simplest blur metric. It reveals the statistical properties of images [1]. As the pixels in blurred image tends to be more similar with neighborhood pixels. This metric calculates the variance of images and assumes that the image gets more blurred when the variance becomes smaller. This method is easy but not efficient enough to be used alone as a metric for no-reference blur metric.

Neighborhood correlation metrics is proposed by [2]. They considered that the blur is actually a process of convolution, which will cause every pixels contain the information of neighboring pixels. This leads to the increase of the correlation [Wang et al. 2004]. So they calculate the neighborhood correlation of the pixels in the wavelet domain.

Derivative-based metrics includes the gradient metrics and Laplacian derivatives metrics. These metrics is based on the novel idea that high frequencies in transform domain often reflect large derivatives in spacial domain. These metrics have good accuracy and often be used as the first step of other metrics.

Edge width metric is very effective to assess the image blur and it is more accurate than metrics mentioned above [3]. The edge width metric contains two steps generally. The first step is edge detection and the second is to calculate the average edge width of all edges found in the first step.

Kurtosis metrics also reveals the statistical properties of images as Variance metric we mentioned above [4]. Kurtosis metric is more complex and more efficient than Variance metric.

No-Reference Structural Sharpness (NRSS) metric is proposed by Xiaofu Xie and Jian Zhou. The NRSS metric constructed a reference image by a low-pass filter, and assessed the image quality by computing the SSIM between the original image and the reference[5][6]. The NRSS combines the traditional image bluer assessment method with the SSIM and obtained good performance.

As main contribution of this paper, a perceptual-based no-reference metric is proposed. Our proposed method is based on the fact that not all edges spread when images become blurred, which means that it is inappropriate to find all edges and calculate their average width to assess image blur as Edge Width metric does. We should reject the edges whose widths have no contribution to the image blur. We thus proposed the two-pass edge analysis method to check out which edges should be rejected. Compared with existing metrics, our metric correlates well with subjective quality evaluations.

II. DISCUSSION ON EDGE WIDTH BLUR METRIC

As mentioned above, many blur metrics have been proposed. Edge width metric is one of the most popular metric among all these metrics.

A. *The Process of Original Edge Width Metric*

Edge width metric is proposed by Pina Marziliano. They think that an image appears blurred when the high spatial frequency components are attenuated and this will lead to the spreadability of the edges [3]. So the edge width can estimate the image blur to some extent. They attempted to measure the spread of the edges as follow. First they use an edge detection method to find edges in the image. Then they scan each row of the image. For each edge point, they get the edge width of each edge point by the difference of end position and start position. The start and end position of the edge point are defined as the local extrema locations closest to the edge point. The edge width metric is summarized as Fig.1.

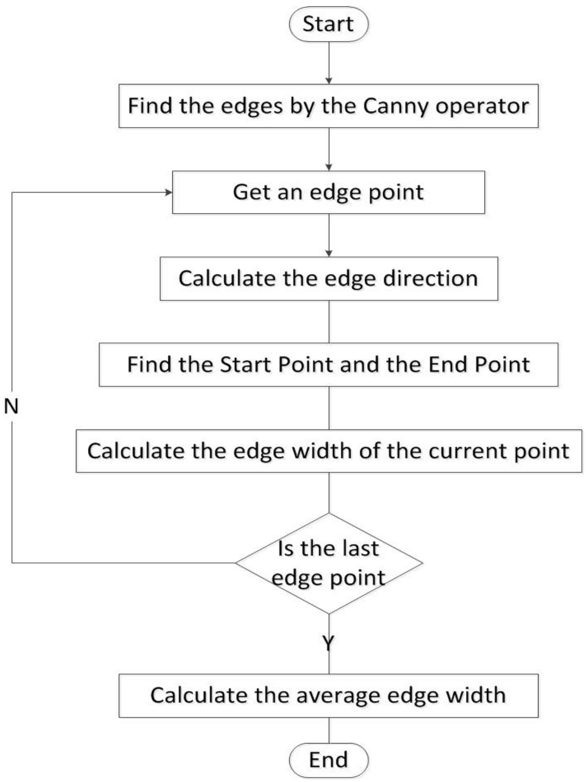

Figure 1. The process of original edge width metric

B. The Relationship Between Image Blur and Edge Width Increment

As mentioned in section A, Pina Marziliano proposed that edge width is corresponding to image blur. When image become blurred, the edges will spread [3]. So they calculate the average edge width to estimate the image blur.

But we think that just calculate width of all the edge points and get their average value as the blur index is not so appropriate. Because not all edges spread when images become blurred. We validate this hypothesis by an experiment, the process of which is shown in Fig.1. First we use an edge detection method to get the edge map of original image and calculate the width of all the edge points in original image according to the edge map. Then we blur the image using a Gaussian template and calculate the width of edge points in blurred image according to the same edge map (the edge map of original image). The size of Gaussian template is 20 and the standard deviation is 10. The Symbol W in Fig.1 means the calculation of edge width, proposed by Pina Marziliano, which is mention above. The edge width increment is calculated by edge width in blurred image minus edge width of the same edge point in original image. Fig.2 Shows the histogram of the edge width increment.

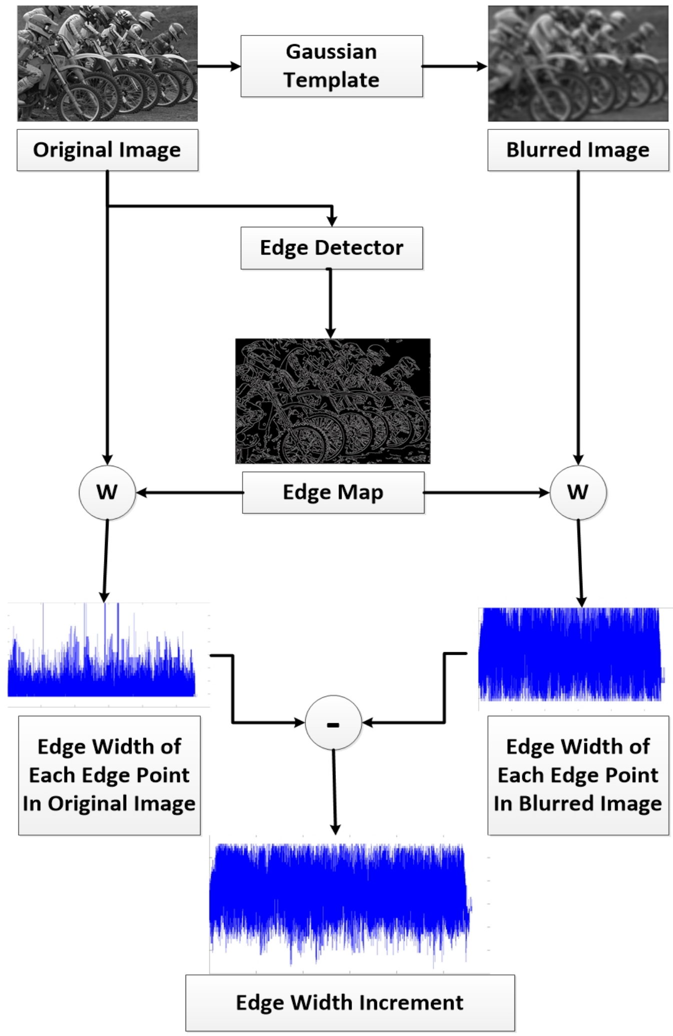

Figure 2. Flow chart of the experiment

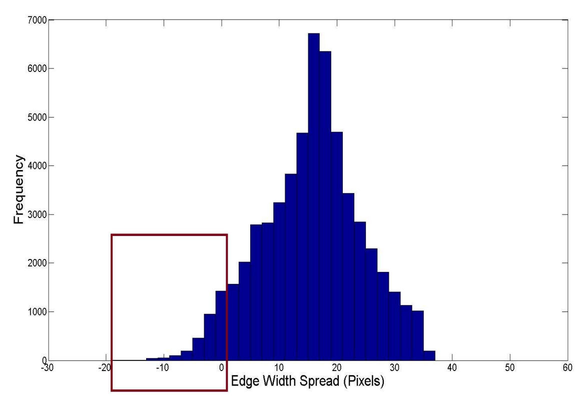

Figure 3. Statistical chart of edge width spread

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From Fig.2 we can find that the increment of some edges width are smaller than 0. That means not all the edges spread when image become blurred, some of the edge width even get smaller. Only part of the edge width get bigger when images become blurred. What's more, the distribution of edge width increment is regular and symmetrical. In order to draw an universal conclusion, we use different Gaussian templates and 4 images (shown as Fig.4) to find the relation between image blur and edge width increment. All the four images come from the LIVE database. The size of Gaussian templates are 10, 15, 20, 25 respectively. The standard deviation of Gaussian templates is 10. The histogram of the edge width increment in the 4 images using different Gaussian templates are shown as Fig.5.

Figure 4. Test Images: (left-up) bikes; (right-up) buildings; (left-down) caps; (right-down) plane.

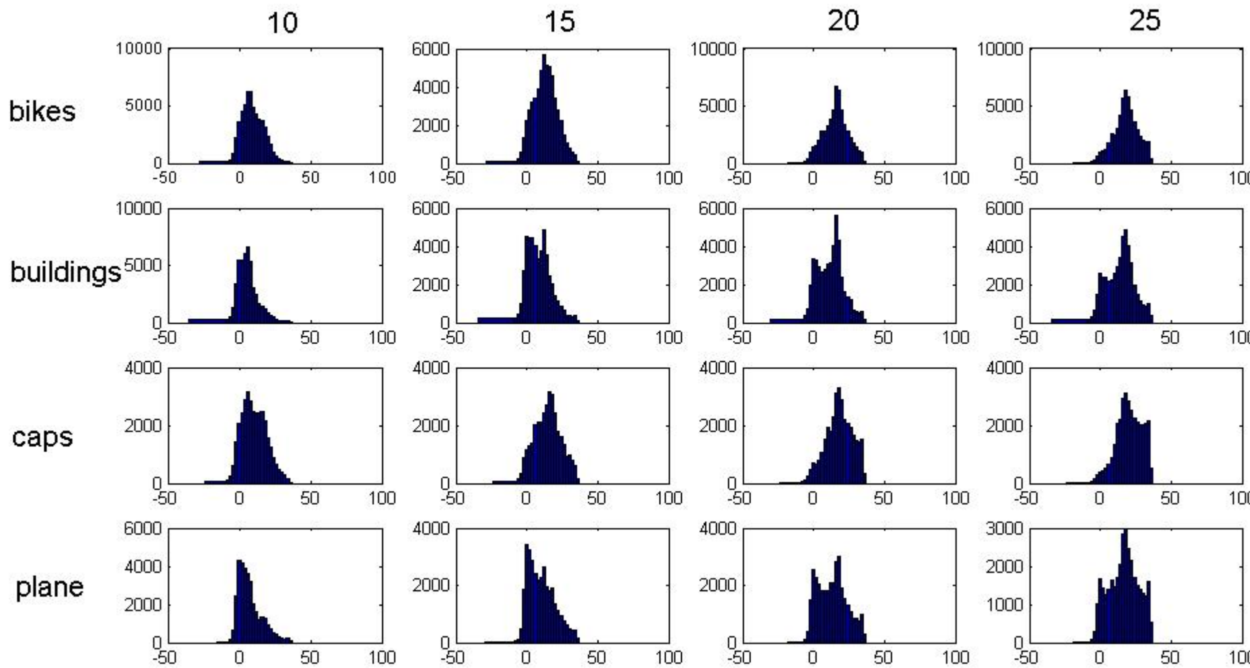

Figure 5. Histograms of the edge width increment using different Gaussian template, the vertical label indicate the image and the horizontal label indicate the size of Gaussian template.

The first row of Fig.5 show histograms of edge width increment in image 'bikes' using different sizes of Gaussian template. The histograms reach peak at 8, 12, 16, 18 when the size of template is 10, 15, 20, 25 respectively.

The second row of Fig.5 show histograms of edge width increment in image 'buildings'. The histograms get maximum value at 8, 12, 16, 18 when the size of template is 10, 15, 20, 25 respectively, which is the same as first row. However, the overall shape of the second row is unlike the first row. When the size of Gaussian template is greater than 10, the histograms in second row have 2 extreme values while the histograms in first row only have 1.

The third row of Fig.5 show histograms of edge width increment in image 'caps' using different sizes of Gaussian template. The characteristic of the histograms are similar with the second row.

The fourth row of Fig.5 show histograms of edge width increment in image 'plane' using different sizes of Gaussian template. The histograms reach peak at 0, 1, 18, 18 when the size of template is 10, 15, 20, 25 respectively. The overall shape of the fourth row is not similar as any row above. The histograms have more proportion when the edge width increment is about 0.

From Fig.5 we can draw some conclusions as follow: (a) No matter which template and image is used, there always exists some edges whose width increment are smaller than 0; (b) When the size of Gaussian template become larger, the peak of the histogram will move right; (c) In different images, the overall shape of the histograms are not similar.

III. THE IMAGE BLUR METRIC BASED ON TWO-PASS EDGE ANALYSIS

In section II, we use an experiment to prove that when image become blurred, not all width spread. Our proposed metric is based on this fact. It will find the edges whose width will increase when the image become blurred and use these points to calculate the blur index. The proposed method need analyze the edge for two times, one for the test image and the other for the blurred image (blur the test image using a Gaussian template). So we call it the image blur metric based on two-pass edge analysis.

A. The Process of Our Proposed Metric

The process of our proposed metric is as follow. First we blur the test image by a Gaussian template and then get the blurred image. Secondly we use an edge detector to get the edge map of the test image. Then we can calculate the edge width of each edge point in test image by the test image and the edge map according to the method proposed by Pina Marziliano. By the same way we can calculate the edge width of each edge width in blurred image by the blurred image and the edge map. We use the edge map of the test image to calculate the edge width in blurred image. That's because if we want to figure out the edge width increment, the edges in Test image and the edges in Blurred image must be corresponding. So the edge map should be unchanged. Then we can find whether the width of each edge point increase when the image become blurred by comparing the edge width of each edge in test image and the edge width of each edge in blurred image. For each edge, if the edge width increment is smaller than 0, it will be excluded. At last we calculate the average width of the edges whose width increase when image become blurred and apply the average width as the blur metric index.

The flowchart of our proposed method is as follow. It's easy to see that our proposed metric is more complex and time-consuming than the original edge width blur metric. But in one hand, the blur width metric is very fast, in the other hand, our proposed method calculate the edge width two times but only calculate the edge map one time. So the increase of the computation time is not so obvious.

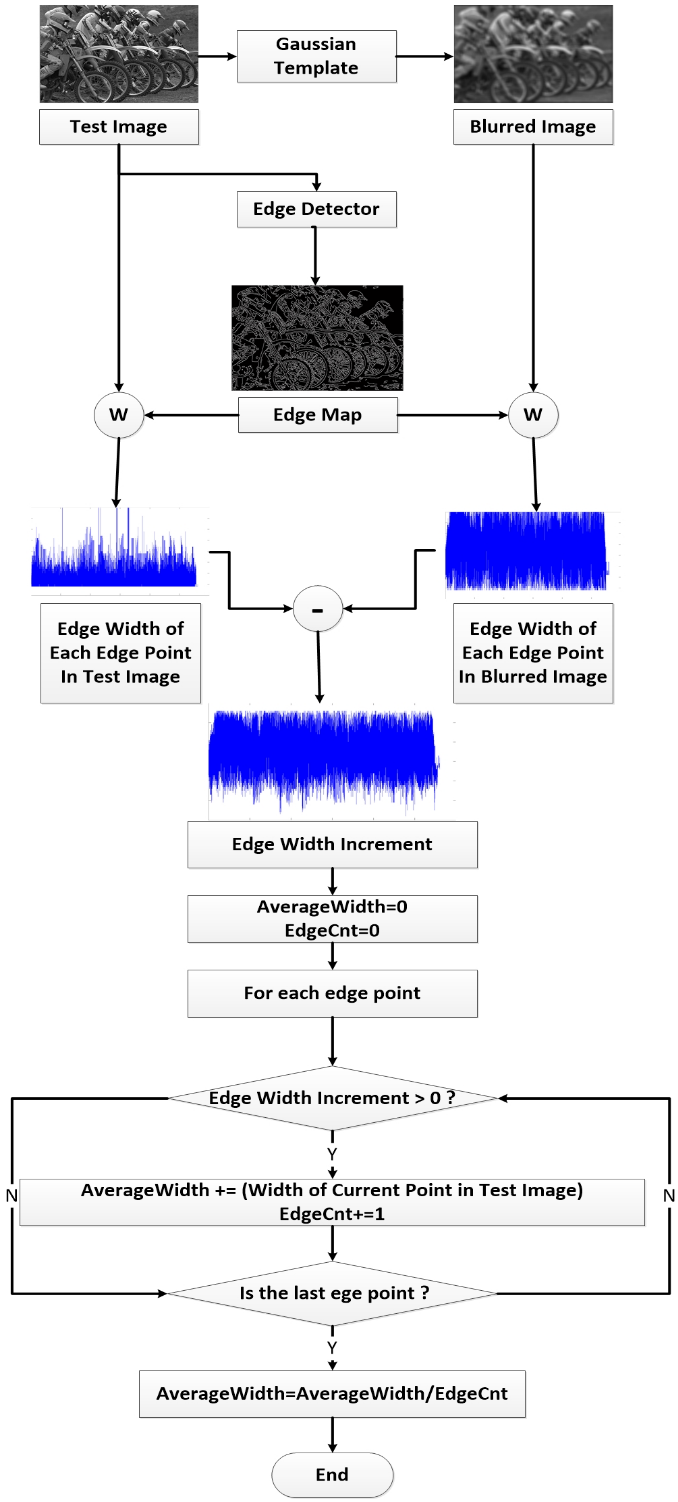

Figure 6. Flow chart of our proposed metric

B. *The Selection of Gaussian Template*

The last section introduced the process of our proposed method based on two-pass edge width analysis. But in the last section we did not specify the size and the standard deviation of the Gaussian template. Actually if we use different Gaussian template, the efficiency of our proposed metric is also different. That is because when we using different sizes of Gaussian template, the histograms of the edge width increment are also different (as shown in Fig.5). That means the edge points whose edge width increment greater than 0 are also different. This will lead to different results of our metric.

In order to find the specific size and standard deviation of the Gaussian template to help the metric get the best performance. We apply our metric with different sizes (10, 20, 30) and standard deviation (5, 10 ,15) of Gaussian template to assess all the images in LIVE blur database. For each Gaussian templates, we will get the metric index of all the images in the LIVE blur database. Then we apply a non-linear regression analysis to the metric index to get an linear relationship between the Mean Opinion Score (MOS) and the metric index. At last we calculate the Correlation Coefficient (CC) and Rank Order Correlation Coefficient (ROCC) between the MOS and metric index. For different Gaussian templates, the CC and ROCC are different.

The experimental results (CC and ROCC) of different Gaussian template are shown as Table 1. In Table 1, the G_a_b means we use the Gaussian template whose size is a and standard deviation is b. And the 'Original' means the result of the metric proposed by Pina Marziliano.

TABLE I. THE CC AND ROCC OF DIFFERENT GAUSSIAN TEMPLATES

Gaussian Template	***CC***	***ROCC***
G_10_5	0.8901	0.8661
G_10_10	0.8898	0.8664
G_10_15	0.8897	0.8646
G_20_5	0.8964	0.8759
G_20_10	**0.9070**	**0.8860**
G_20_15	0.9066	0.8844
G_30_5	0.8974	0.8757
G_30_10	0.8983	0.8798
G_30_15	0.8975	0.8792
Original	**0.8842**	**0.8704**

As shown in Table 1, our proposed method gain the best efficiency when we use the Gaussian template whose size is 20 and standard deviation is 10. Therefore, we apply this Gaussian template for our proposed metric.

The scatter plot of subjective mean opinion score (MOS) versus the prediction result of our metric with G_20_10 is shown as Fig.7 and the scatter plot of MOS versus the prediction result of original edge width blur metric proposed by Pina Marziliano is show as Fig.8.

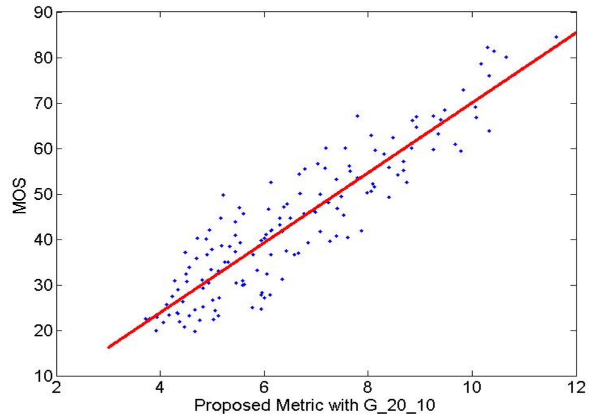

Figure 7. The scatter plot of MOS versus the prediction result of our proposed metric with G_20_10

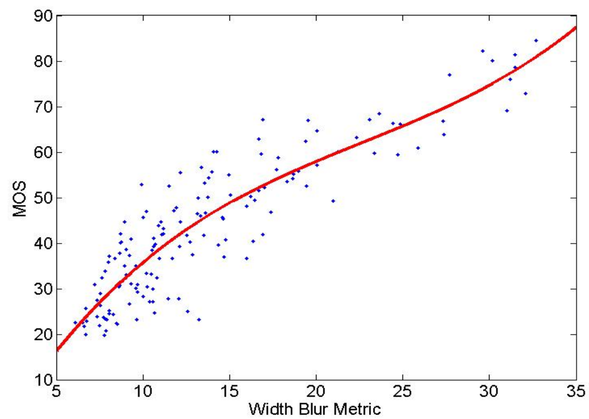

Figure 8. The scatter plot of MOS versus the Width Blur Metric proposed by Pina Marziliano

IV. RESULT ANALYSIS AND CONCLUSION

In last section we introduced our proposed image blur metric, The image blur metric based on two-pass edge analysis. And then we apply a suitable Gaussian template for our metric, the size of which is 20 and the standard deviation of which is 10.

From Fig.7 and Fig.8 we can find that our proposed method have an better efficiency than the original edge width blur metric. The CC of our proposed metric is 2.28% higher than the original metric and the ROCC of our proposed metric is 1.54% higher than the original metric. That means our proposed metric correlates well with subjective quality evaluations.

What's more, our proposed metric can be easily combined with other improvement for the edge width metric. That is because our metric is loose coupling, each component, such as Edge Detector and the edge width calculation, can be replaced by corresponding improvement metric[7].

However, there are still some problems need further research. In Table 1, the ROCC of our metric with G_10_5, G_10_10 and G_10_15 are 0.8661, 0.8664 and 0.8646 respectively. And all the three of them are smaller than the ROCC of original metric, which should not happen. We will find the reason in our next work.

Currently, our work just exclude the edge points whose edge width increment is too small when image become blurred. Actually, as shown in Fig.5, most edge width increments are concentrated in a certain range. So we can also try to exclude the edge points whose edge width increment is too large.

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