NO REFERENCE BLOCK BASED BLUR DETECTION

Liu Debing[1], Chen Zhibo[1], Ma Huadong[2], Xu Feng[1], Gu Xiaodong[1]*

[1]Thomson Corporate Research, Beijing
de-bing.liu@thomson.net
[2]Beijing University of Posts and Telecommunications, Beijing

ABSTRACT

Blur is one of the most important features related to image quality. Accurately estimating the blur level of an image is of great help to estimate its quality. In this paper, a No Reference Block-based Blur Detection (NR-BBD) algorithm is proposed. It calculates the local blur at the boundaries of Macro Blocks (MBs) and then averages all of them to get the blur of the image. A content dependent weighting scheme is employed to reduce the influence from the texture. Compared with traditional edge based blur metrics, NR-BBD has a lower complexity, exhibits more stable for different image content, and results in a higher correlation with the perceived subjective visual quality (the resulting Pearson Correlation is 0.85 in the data set with 1176 images with different content type and different quality level.).

Index Terms— Blur, Blur Detection, Image/Video Quality Measurement, No Reference

1. INTRODUCTION

Video quality measurement is an important factor for video coding, processing, and distributing. It can be divided into two categories: subjective and objective. Subjective assessment of the video quality is considered to be more reasonable and accurate, but it is time consuming and cannot be used in some cases such as real time quality monitoring. Therefore, lots of effort has been put into the investigation of objective quality measurement.

Objective quality measurement can be divided into 3 categories according to the availability of the original information: Full-Reference (FR), Reduced-Reference (RR), and No-Reference (NR). FR scheme needs the whole original information as reference, RR scheme only needs part of the information from the original signal, and NR scheme needs no information from the original signal. NR quality measurement has got much attention since original reference is usually impossible to be obtained in real scenarios, and it is supposed to be more difficult and less accurate due to lack of source information.

The basic approach of NR quality measurement is extracting the features from decoded videos and then builds up the relationship between the extracted features and the decoded visual quality. Blur is one of the most important features related to video quality. Accurately estimating the blur level of a video is of great help to estimate the video quality. Various methods have been proposed in past years. In [1], Marziliano et al. proposed a blur metric based on detecting the edge width, where image blur is defined as the sum of the edge width divided by the number of edges. In [2], Ferzli et al. measured the blur level of an image by integrating the concept of just noticeable blur into a probability summation model, in which it took advantage of HVS (Human Visual System) information to improve its performance. Same as the scheme in [1], it also needs to detect the edges where the local blur is calculated. A block based weighting scheme is applied to remove the influence from low texture. Marichal et al. measured the blur level of an image based on the histogram computation of the DCT coefficients in [3], where the histogram is weighted by the matrix which gives higher weight to diagonal coefficients with the assumption that the diagonal coefficients better represent the global blur. The final blur is defined as the weighted histogram divided by the sum of the weights in the matrix. In [4], N.F. Zhang et al. proposed using kurtosis to measure the sharpness of an image in semi-automated scanning electron microscopes (SEM). For a selected SEM image, the two-dimensional spatial Fourier transform is computed firstly. Then the bivariate kurtosis of the Fourier transform is calculated. It found that the calculated kurtosis was sensitive to the presence of the necessary high spatial frequencies for the acceptable levels of image sharpness. J. Caviedes et al. introduced the kurtosis concept into image sharpness measurement in [5]. It measures the sharpness level of an image by comparison of its kurtosis with that of normal distribution. Firstly edge detection by canny operator is performed in pixel domain. Then 8x8 block of pixels centered at the edge is transformed by DCT. The kurtosis of the DCT coefficients is calculated as the local sharpness and all the local sharpness values in an image are averaged to get the final sharpness metric. In [6], H. Tong et al. proposed a blur metric based on the edge type and sharpness analysis using Haar wavelet transform. Shiqian

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Wu et al. proposed an out of focus blur metric in [7]. R. Liu et al. considered identifying the blur region and the blur type for a partially-blurred image in [8].

Most of the existed spatial blur metrics [1][2][5] need to detect the edges at first and then calculate their local blur values at the detected edges, which is referred as edge based blur metric in this paper. Different from the edge based metrics, the proposed No Reference Block-based Blur Detection (NR-BBD) scheme does not need to detect any edges. In NR-BBD, the positions for local blur calculation are fixed at the boundaries of Macro Blocks (MBs). A content dependent weighting scheme is employed to reduce the influence from the texture. It excludes the regions with too complicated or too plain texture out of the final blur calculation. Compared with edge based blur metrics, NR-BBD has a lower complexity because of no edge detection process, exhibits more stable in dealing with different content because its position selection is more reasonable, and results in a higher correlation with the perceived subjective visual quality.

This paper is organized as below: Section 2 describes NR-BBD algorithm in detail, Section 3 makes an in-depth comparison between NR-BBD and edge based blur metrics, some experimental results and analysis are illuminated in Section 4, and a general conclusion is presented in Section 5.

2. No-Reference Block Based Blur Detection

NR-BBD focuses on measuring the blur generated by H.264/AVC. The blur in the video coded by H.264/AVC is mainly from two aspects: quantization and de-blocking filter. The quantization erases the high frequency information of an image, more or less. The high frequency information is related to the detail of an image and the loss of the detail makes the image look like blurred. The de-blocking filter in H.264/AVC is designed to decrease the blocking artifact. It can be looked as a low-pass filter at the block boundaries (block size may be 4x4, 8x8, or 16x16.). The de-blocking filter reduces the difference between the neighboring pixels, which results in a blur effect.

Since the quantization and de-blocking filter are both based on blocks, NR-BBD calculates its local blur values at the boundaries of MBs. After the experiments on lots of images with different content, it found that the local blur calculation may be highly inaccurate in the regions with too complicated or too plain texture. Therefore a weighting scheme is designed to select the suitable regions in an image. In NR-BBD, it calculates the blur in vertical and horizontal directions separately and then averages them to get the final blur value. The vertical and horizontal blur levels may be different in the images with lots of directional motion blur or directional texture. The average of them can help to get a more stable result.

Fig 1 shows the flow chart of vertical blur calculation in NR-BBD, in which the three steps marked in red are key steps to keep the performance of NR-BBD. (The horizontal blur can be calculated in the same way as the vertical blur.) It contains following steps:

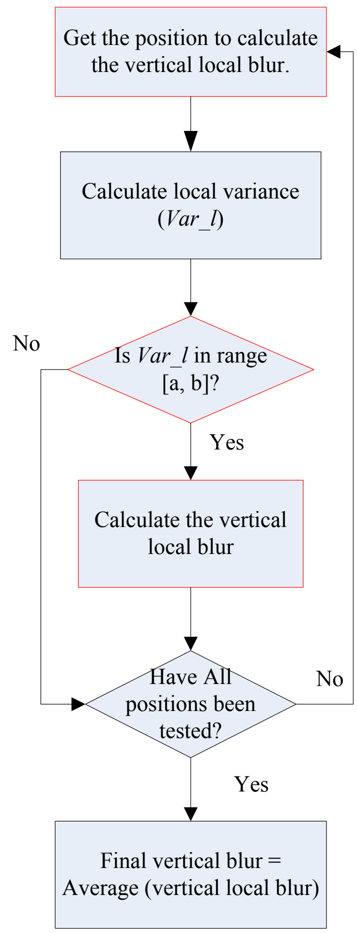


Fig 1 Flow char of vertical blur calculation in NR-BBD

Step-1: Get the position for local blur calculation

In NR-BBD, the positions for local blur calculation are set at the centers of MBs' boundaries. As shown in Fig 2, P_v1 and P_v2 are the positions for calculating the vertical blur; P_h1 and P_h2 are the positions for calculating the horizontal blur.

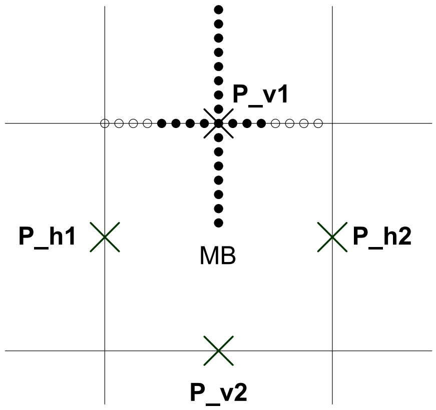


Fig 2 Positions for local blur calculation

Step-2: Calculate the local variance (*Var_l*)

NR-BBD calculates the local variance in the region around the position. As shown in Fig 2, the black cross region with 16 pixels in vertical direction and 8 pixels in horizontal direction around the position p_v1 is the region for the local variance calculation. (For horizontal local blur calculation, the local variance is calculated in the cross area with 16 pixels in horizontal direction and 8 pixels in vertical direction.)

The formula of the local variance calculation is as below:

$$Var\_l = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}},$$

where N is the number of pixels (I.e. 24 in our scheme), x_i are the pixels in the black cross region around p_v1 in Fig 2, and $\bar{x}$ is the average value of all x_i.

Step-3: Judge if *Var_l* is in the range of [a, b].

It has been found that the local blur calculation may be highly inaccurate in the regions with too complicated or too plain texture. The range limitation of *Var_l* can help to exclude those regions.

The range of [a, b] may be adjusted in different scenarios. In our experiments, it is set experientially as [2, 30].

Step-4: Calculate the vertical local blur

For the local blur calculation, the idea is from the scheme in reference [1]. It detects the two pixels with local minimum or maximum luminance values along vertical direction. The distance between the two pixels is the vertical local blur. Fig 3 illustrates the process, where P0 is the position for the local blur calculation, P1 is the pixel with local minimum luminance value, P2 is the pixel with local maximum luminance value, and the local blur value is the distance between P1 and P2 (i.e. 6).

Different from the scheme in reference [1], a pixel with same luminance value with the former detected pixel won't stop the detection. This is important because the coding process tends to make the neighbor pixels have same luminance value. From the experience of subjective assessment, the perceptual blur level is increased as its Quantization Parameter (QP) increased. To match the perceptual blur, the calculated blur should have good monotonicity with QP. The including of pixels with same luminance value helps to keep the monotonicity between the calculated blur and QP.

Step-5: Calculate the final vertical blur

All the vertical local blur whose related *Var_l* is in the range of [a, b] are averaged to get the final vertical blur.

The features of NR-BBD can be summarized as below:

- Calculate the local blur at the centers of MB boundaries.
- Design a content dependent weighting scheme to reduce the influence from the texture
- Define the local blur value as the distance between the two pixels with local minimum and maximum luminance value.

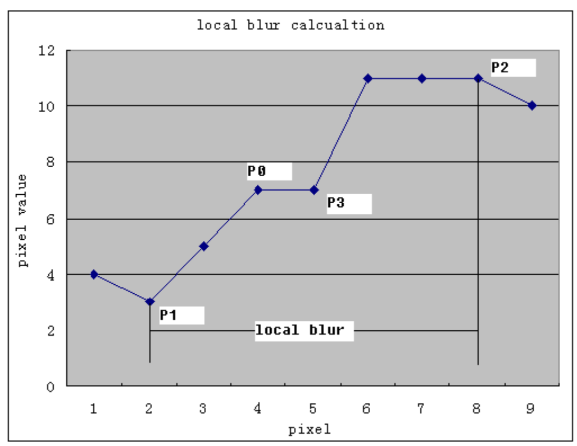


Fig 3 Local blur calculation in NR-BBD

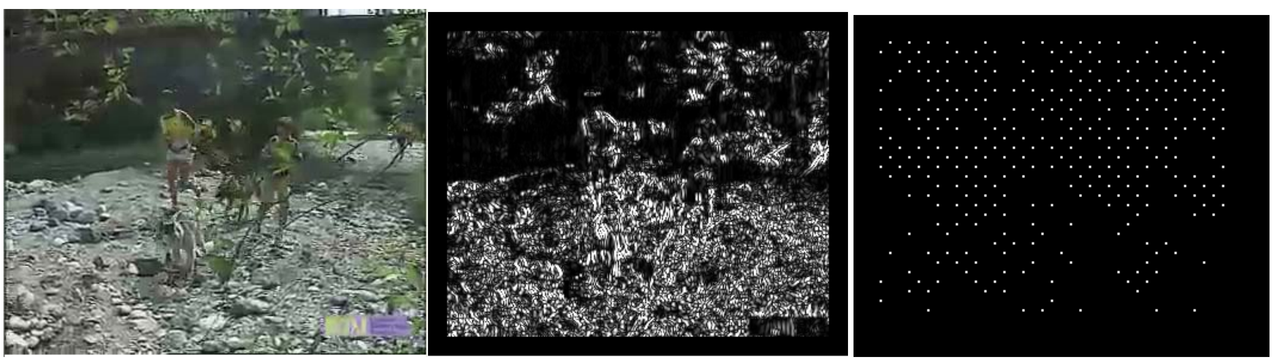
3. Comparison between NR-BBD and texture edge based blur metrics

To estimate the blur level of an image, usually three steps are conducted: firstly selecting some regions in the image, secondly calculating the local blur in the selected regions, and finally combining all local blur to get the blur level of the image. The key point of this kind of approaches is that the combined calculated blur values of the selected regions can represent the blur value of the whole image.

Fig 4 shows the comparison between NR-BBD and edge based blur metrics. The test image is chosen from the sequence *husky* which has been encoded by JM10.1 with QP = 44. It is obvious in Fig 4(a) that blur artifact is visible all over the image (including the area with no strong edges). As indicated in Fig 4, there are two main disadvantages in the local blur calculation at the edges.

- The edges are too concentrated in a limited region.
  From Fig 4(b), we can see that 90 percent of the edges locate in the lower part of the test image, which results in that the final blur value of the image is mainly determined by the local blur calculation in the lower part. While in Fig 4(c), NR-BBD covers more regions with the same weight.
  Since the local blur calculation may be influenced by many factors such as texture gradient, texture direction, and texture complexity, it is hard to guarantee the high accuracy of one specific local blur. An effective approach is to include plenty of local blur values and average them to get a stable result. If the local blur values are mostly obtained from a same region, the error in that region will be magnified.
- The edges may locate in the region hard to accurately estimate the local blur.
  The local blur calculation is influenced by surrounding texture, especially in the area with too complicated or too plain texture.
  As shown in Fig 4, the lower part of the test image has highly complicated texture, where the calculated local blur value will be much different from the real value, but the edges are mostly located there.
  In NR-BBD, it uses the local variance to select the suitable regions for local blur calculation.

The blur generated by compression is distributed all over the image, not only around the edges. From the above comparison, we can get the conclusion that when measuring the blur generated by compression, the region selection of NR-BBD is more reasonable than edge based region selection. Moreover, the fluctuation of blur value for different image content is mainly from the fluctuation of the local blur in the regions with too complicated or too plain texture. NR-BBD excludes those regions out of the final blur calculation, which helps it less influenced by image content than edge based blur metrics.



(a) test image (b) edges obtained by Sobel filter (c) positions in NR-BBD

Fig 4 Comparison between NR-BBD and edge based blur metrics

4. Experiments

In the experiments, three approaches are compared to show the importance of the three features of NR-BBD listed in section 2:

- **NR-BBD**: the proposed method.
- **Ref-1**: the scheme in reference [1].
  Ref-1 detects the edges by Sobel operator at first and then calculates the local blur at the detected edges. It has no weighting scheme and its local blur calculation is different from that of NR-BBD. When detecting the pixels with local minimum or maximum luminance values, the detection will be stopped by a pixel with same luminance value as the former detected pixel. I.e. in Fig 3, the local blur value by Ref-1 is the distance between P1 and P0 because P3 has same luminance value as P0.
- **Ref-1_R**: Refined version based on Ref-1.
  The only difference between Ref_1_R and Ref-1 is in the local blur calculation. The local blur calculation of Ref_1_R is in the same way as that of NR-BBD.

The ranges of the calculated blur values of the three approaches are different. For the convenience of comparison, they are scaled to [0, 100].

The first experiment is on the videos. 24 original 720P sequences in different content types (movie, news, sports, etc.) are selected. Every original sequence is encoded to 6 distorted sequences with QP = 24, 29, 34, 37, 40, and 45, separately. The blur of all the frames in a sequence are calculated and then averaged to be its final blur. Fig 5 shows the result, in which every 7 points are from the same video content, the first one is the original sequence and the next 6 points are the distorted sequences with QP = 24, 29, 34, 37, 40, and 45, separately.

From Fig 5, we can get following results:

1) NR-BBD and Ref_1_R are better on the monotonicity with QP.
   From the experience of subjective assessment, for the same video content, its perceptual blur level is increased as QP increased. So we can evaluate the performance of a blur metric by the monotonicity between its calculated blur and QP.
   In Fig 5, NR-BBD and Ref_1_R show good monotonicity with QP in every 7 points. Ref-1 is bad for some of the sequence such as samples 22-27. It shows that including pixels with same luminance value in local blur calculation is important to keep the monotonicity with QP.

2) NR-BBD is the best in dealing with different video content.
   The blur level in different original sequences is different, which results in that the start points of every 7 points in Fig 5 are also different. That is reasonable. However from the experience of subjective assessment, observers are much more sensitive to the compression blur than the original blur, especially when the QP is high enough. That is, for most of sequences, the blur values of different original sequences should not be different too much and the blur values of the distorted sequences with same QP should also not be different two much.
   From Fig 5, NR-BBD has no much difference between different video content. Ref_1_R is not so good. For example, the blur value of the sample at 99 (original sequence) is close to the blur value of the sample at 140(distorted sequence with QP = 45). That does not match the result from the subjective test. Ref-1 is extremely influenced by video content. Its calculated blur values of some original sequences are much higher than the blur values of other distorted sequences with QP = 45. That surely is unreasonable.

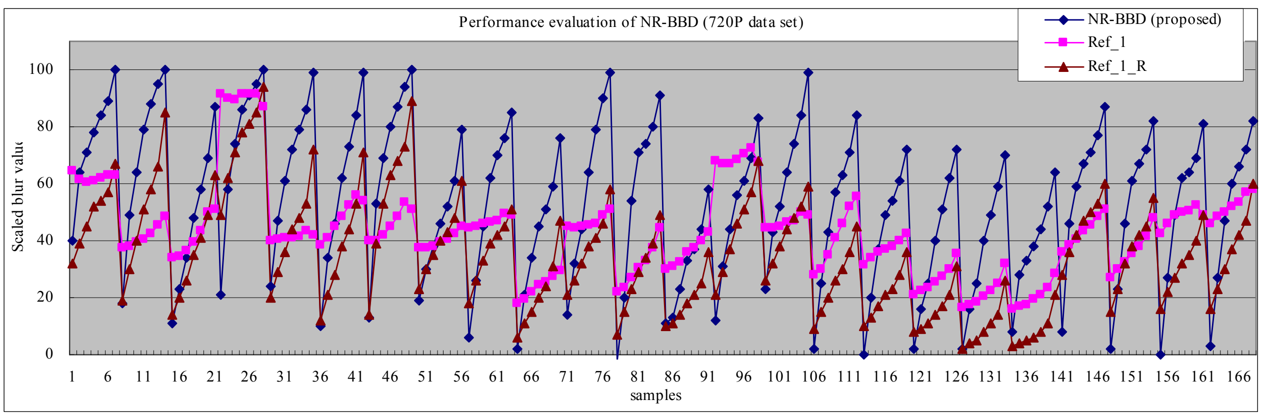


Fig 5 Performance evaluation of NR-BBD

The second experiment is done on images. 1176 images are random selected from the above 720P sequences. A subjective test is organized to give the perceived subjective visual quality level of every image and then the three approaches are used to calculate the blur values. The resulting Pearson Correlation between the perceived subjective visual quality and the calculated blur value is listed in Table 1. It shows that the calculated blur value by NR-BBD well matches the perceived subjective visual quality. It is much better than other two approaches.

Table 1 Pearson Correlation between the perceived subjective visual quality and the calculated blur values

Approaches	NR-BBD (proposed)	Ref_1	Ref_1_R
Pearson Correlation	0.85	0.35	0.73

5. CONCLUSION

A no-reference block based blur detection (NR-BBD) algorithm is proposed in this paper. Compared with traditional edge based blur metrics, it does not need to detect edges. The positions for local blur calculation are fixed at the MB boundaries, so it is in a lower complexity and easier to be parallelized. Moreover, with the help of a content dependent weighting scheme, NR-BBD is better on the selection of the suitable regions for local blur calculation, which help NR-BBD to be less influenced by image content and get higher correlation with the perceived subjective visual quality (Pearson Correlation is 0.85 in the data set with 1176 images with different content type and different quality level.).

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