A No Reference Quality Metric for Measuring Image Blur In Wavelet Domain

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ABSTRACT

In this paper, a no reference blur image quality metric based on wavelet transform is presented. As blur affects specially edges and image fine details, most blur estimation algorithms, are based primarily on an adequate edge detection methods. Here we propose a new approach by analyzing edges through a multi-resolution decomposition. The ability of wavelets to extract the high frequency component of an image has made them useful for edge analysis through different resolutions. Moreover, the multi-resolution analysis is performed on reduced images size, and this could lead to an execution time improvement. In addition, the edges persistence through resolutions may be involved in accuracy blur quality measure estimation. To prove the validity of the proposed method, blurred images from LIVE data base have been considered. Results show that the proposed method provides an accurate quality measure

KEYWORDS

Image quality measure, no reference, blur, wavelet transform.

1 INTRODUCTION

Nowadays one could consider blur as the most frequent factor affecting image quality. Indeed blur is a common problem in most applications, such as in visual art, remote sensing, medical and astronomical imaging, as well as in machine vision. Human vision and cognition easily evaluate image quality without the need for a reference image. Developing an objective image quality measure would require such a reference, which is rarely available. In developing a no-reference blur image quality measure, we seek to evaluate the image quality and to correlate it with the human vision system or with the effective introduced blur amount, without the need for an original image as a reference [1]. Because edges have usually high spatial frequency content, there are very sensitive to blur. Therefore, edge detection is a common step in most blur image quality measures. In literature, a number of blur metrics based on edge sharpness analysis have already been proposed. For example Marziliano et al. [2] develop a blur metric based on analyzing the edges width. The sharpness measurement index provides by Caviedes et al. [3] is based on local edge kurtosis. Chuang et al. [4] evaluate blur by fitting the image gradient magnitude to a normal distribution. L. Firestone et al. propose in [5], a frequency threshold metric based on computing the summation of all frequency component magnitudes above a fixed threshold. N. B. Nill et al. present in [6] an image quality metric (IQM) based upon calculate the
normalized image power spectra weighted by a modulation transfer function. In [7] R. Fezli et al. develop a noise immune metric (NIS), based on image sharpness. Here wavelet transform is used to separate signal from noise singularities. Ong et al propose in [17] to use canny edge detector to extract edge pixels and the blur metric is found by estimating the edges width average. L.J. Karam et al. [8, 9, and 10] introduced a series of perceptual blur metrics based on human vision system model (HVS).

In this paper, we aim to improve blur image quality by reducing the defocusing effects. In this case, we seek to propose a blur measure relative to the blurring source. As defocusing is often modeled by a Gaussian filter, a blur measure, which correlate well with the blur generating filter standard deviation, is suitable with our purpose. Hence, our study is primarily based on the image edges analysis.

This study is focused on edge detection with multi scale singularities analysis. The wavelet transform may be an effective tool for edge detection since it produces significant coefficients precisely where the image intensity varies greatly locally. Therefore, in this work, a novel algorithm for blur image quality measure without a reference is introduced. A wavelet transform is applied for blurred edges characterization through a multi resolution analysis. To evaluate the proposed quality measure, we will use sets of blurred images from the LIVE database (Gblur, JPEG 2000) [11, 12 and 13].

The paper is organized as follows. Metrics based on edge analysis are presented in section 2. Section 3 describes in details the proposed method. In section 4, we explain the experimental set-up and methodology. Section 5 presents an objective evaluation of the proposed approach. The last section provides with some conclusive remarks and gives some perspectives for future works.

2 Metrics based on edge analysis

This section presents methods for blur image quality estimation based upon the edge spread study. The first one operates directly in spatial domain using gradient method for edge detection. The second characterizes blur effect through the multi resolution analysis using wavelet transform. This study has been completed by performing a multi resolution blur quality measure.

The multi resolution analysis provides an accurate blur study. This is why, we propose a new quality measure which exploits the accuracy of blur quality measure developed in spatial domain and the efficiently of blur effect characterization provided in wavelet domain.

2.1 Min Goo Choi et al. method

This method proposes a no-reference metric based on gradient method for edge detection [14]. To explicit the blur quality assessment algorithm, let as consider a test image \( f(x, y) \), with \( M \) rows and \( N \) columns.

The horizontal absolute difference value (HADV), of a pixel is defined as:

\[
D_h(x, y) = |f(x, y + 1) - f(x, y - 1)|
\]

(1)

The mean value of (1) for the whole image is given by:

\[
D_{h-mean} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} D_h(x, y)
\]

(2)

In the case that HADV value is larger than \( D_{h-mean} \), the corresponding pixel in (1) becomes an edge candidate \( C_h(x, y) \). If \( C_h(x, y) \) has a
HADV value larger than the horizontally adjacent pixels: \[ \{ C_h(x, y - 1), C_h(x, y + 1) \} \], the pixel is considered to be on the edge. The steps for detecting horizontally edge pixel \( E_h(x, y) \) are summarized as follows:

\[
C_h(x, y) = \begin{cases} 
D_h(x, y) & \text{if } D_h(x, y) > D_{h-mean} \\
0 & \text{elsewhere}
\end{cases} 
\]  
(3)

\[
E_h(x, y) = \begin{cases} 
1 & \text{if } C_h(x, y) > C_h(x, y - 1) \text{ and } C_h(x, y) > C_h(x, y + 1) \\
0 & \text{elsewhere}
\end{cases} 
\]  
(4)

Now, we examine whether the detected edge pixel correspond or not to a blurred edge. The ratio value for blur decision is obtained horizontally by equations (5) and (6).

\[
A_h(x, y) = \frac{1}{2} \times ((f(x, y + 1) + f(x, y - 1))  
\]  
(5)

\[
BR_h(x, y) = \frac{|f(x,y) - A_h(x,y)|}{A_h(x,y)}  
\]  
(6)

In the same way, \( BR_v \) could be estimated in the vertical direction using equations (1) to (6). The larger value between \( BR_h \) and \( BR_v \) is selected for final decision, which is called inverse blurriness.

\[
B(x, y) = \begin{cases} 
1 & \text{if } \max(BR_h, BR_v) > T_{HB} \\
0 & \text{elsewhere}
\end{cases} 
\]  
(7)

\( T_{HB} \) is a fixed threshold. (7) Means that the center pixel with inverse blurriness larger than \( T_{HB} \) could be considered as blurred. The authors have fixed the \( T_{HB} \) to 0.1 value. Finally, the blur ratio is estimated by:

\[
\text{Blur}_{ratio} = \frac{\text{Blur}_{cnt}}{\text{Edge}_{cnt}} 
\]  
(8)

Where \( \text{Blur}_{cnt} \), \( \text{Edge}_{cnt} \) are the number of blurred and edge pixels respectively.

The proposed blur image quality assessment (IQA) is defined as:

\[
IQA = 1 - \text{Blur}_{ratio} 
\]  
(9)

This approach analyzes all the image edge pixels and characterizes each one as blurred or not. Thus, the provided quality measure could be efficient but the needed process could consume much executing time.

2.1 Min Hong Hang et al. method

This method exploits the multi-resolution analysis provided by wavelet transform. An edge map is produced after combining the high frequency coefficients at each decomposition level. Thus, the blur quantity is estimated by analyzing the edge properties through resolutions \([15]\). This method provides a parameter which indicates whether the image is blurred or not. In addition, we propose to complete the analysis by a blur quality measure. Hence, the blur quality assessment approach consists of two steps (multi resolution edge detection, developing a quality measure). The detailed algorithm for edge detection is given as follows:

- Apply wavelet transform at three resolutions using Daubechies wavelet of order 1 (Db1).
- Construct the Contour map at each resolution: \( i \):

\[
\text{Cont}_i(k, l) = \sqrt{D_{hi}^2(k, l) + D_{vi}^2(k, l)} 
\]  
(10)

- At each resolution \( i \), divide the contour map into blocks of size \( 2^{4-i} \times 2^{4-i} \), and calculate the local maxima in each block. The result is denoted as \( \text{Cont}_{max}(k_i, l_i) \) with \( (i=1, 2, 3) \), \( k_i = \frac{k}{2^{4-i}} \) and \( l_i = \frac{l}{2^{4-i}} \).
A threshold is applied to refine the contours and keep them more intense.

From these obtained contours, one could now proceed to the evaluation of the blur level. Thus, four edges prototypes (Ridge-structure, Step-structure, Roof structure and Ramp-structure) have been considered. To evaluate the blur level, one could underline the effect of applying the Db2 wavelet on the considered edge prototypes at each resolution. Hence the quality measure could be proposed by study the wavelet transform effect on different edge prototypes. That is allows proposing the following algorithm:

- Calculate the number of edge pixels at each resolution level $i$: $N_{\text{edge}}$ is the number of pixels which verify the following condition:

$$\text{Cont}_{\text{max}1}(k_i, l_i) > \text{Thr}$$ (11)

- Calculate the total number of the Ridge-structure and Step-structure: $N_{\text{da}}$ is the number of pixels which verify the following condition:

$$\begin{cases} \text{Cont}_{\text{max}1}(k_i, l_i) > \text{Cont}_{\text{max}2}(k_i, l_i) \\ \text{Cont}_{\text{max}2}(k_i, l_i) > \text{Cont}_{\text{max}3}(k_i, l_i) \end{cases}$$ (12)

- Calculate the total number of Roof-structure and Ramp-structure: $N_{\text{rg}}$ is the number of pixels which verify the following condition:

$$\begin{cases} \text{Cont}_{\text{max}1}(k_i, l_i) < \text{Cont}_{\text{max}2}(k_i, l_i) \\ \text{Cont}_{\text{max}2}(k_i, l_i) < \text{Cont}_{\text{max}3}(k_i, l_i) \end{cases}$$ (13)

- Calculate the total number of Roof-structure and Ramp-structure which suffers from a loss of sharpness. $N_{\text{brg}}$ represents the number of pixels which verify the following conditions:

$$\text{Cont}_{\text{max}2}(k_i, l_i) > \text{Cont}_{\text{max}1}(k_i, l_i) \text{ and } \text{Cont}_{\text{max}2}(k_i, l_i) > \text{Cont}_{\text{max}3}(k_i, l_i) \text{ or } \text{Cont}_{\text{max}1}(k_i, l_i) < \text{Thr}$$ (14)

Using those parameters, one could define two quantities. The first ($BR$) informs us whether the image is blurred or not, the second ($QB$) informs us about the blur quantity of in images:

$$BR = \frac{N_{\text{da}}}{N_{\text{edge}}} \quad \text{and} \quad QB = \frac{N_{\text{brg}}}{N_{\text{rg}}}$$ (15)

Having an information whether the image is blurred or not and the possibly introduced blur quantity, we propose a quality measure which depends on these two parameters. It is equal to 1, if almost all edge pixels are sharp and $1-QB$ whether the loss of sharpness is considered. The proposed image quality assessment ($IQA$) is defined as:

$$IQA = \begin{cases} 1 & \text{if } BR > \xi \\ 1 - QB & \text{elsewhere} \end{cases}$$ (16)

$\xi$ is a positive parameter close to zero, we set it to be 0.05. $Thr=35$, since human vision systems are not sensible to intensity below intensity 30.

This method provides global information in terms of blur. Since it considers blocks of sizes $2^{n-1} \times 2^{n-1}$ at each resolution $i$, so it could not be as accurate as the first considered method.

## 3 PROPOSED METHOD

The proposed blur image quality measure exploits the edge width through a multi resolution analysis. Indeed, the multi resolution analysis reduces the analyzed image size and could improve the blur characterization. The proposed algorithm involves the following steps:

- Construct the contour map $\text{Cont}_i(k, l)$ by thresholding that obtained in the step 1 and 2 of the Hong Hang et al. Method.
While investigating the blur effect at different resolutions using wavelet transform, we conclude that for a fixed threshold, the edge detection is less efficient while going down in resolutions. This is due to smoothing introduced by the wavelet transform filters. Then for a better edges detection we found that, it is useful to propose a threshold value depending on the resolution \( i \) as follows:

\[
Th_i = 2^{i-1} \times \text{mean}(Cont_i(k, l))
\]  

(18)

- In the wavelet transform domain for each details image, the detected edge pixel should be considered as blurred whether the difference between it and the mean of its neighbors is less than a fixed threshold \( \xi_i \) depending of resolution \( i \). For good blur effect quantification, we exploit the fact that it has persistence of the edge pixels through resolutions. Indeed if one schematizes the local maxima found in the image details provided by wavelet transform (see Figure 1), one notice that the singularities spread becomes increasingly reduced through resolutions.

As the singularities values depend on resolutions, it is judicious to consider a set of threshold depending on the resolution \( i \). \( \xi_i = 0.5 \times 2^{i-1} \).

Hence, at each resolution level \( i \), one could estimate the number of edge pixels \( NE_i \) and the blurred ones \( NB_i \). Here in, a quality ratio \( Q_i \) could represent the blur quantity in edges at each resolution level \( i \):

\[
Q_i = \frac{NB_i}{NE_i}, \quad (i = 1, 2, 3)
\]  

(19)

As mentioned above, the relative edge pixels number becomes less important while increasing in resolution. This is why one could consider the \( Q_i \) factor more significant at the high resolution. Finally, the proposed blurred image quality measure (IQQA) is given by:

\[
\text{IQQA} = 1 - \frac{\sum_{i=1}^{3} 2^{3-i} \times Q_i}{\sum_{i=1}^{3} 2^{3-i}}
\]  

(20)

Expresses the image quality measure by considering the quantity of blur in each resolution level. The proposed method, takes into account all edge pixels detected by wavelet transform at each resolution.

4 EXPERIMENTAL RESULTS

The proposed method performances are evaluated on Live database images from Texas University [11, 12 and 13]. This database comprises a set of twenty-nine high-resolution images (24 pixels /bit) in RGB colors (Figure 2). All these original images are distorted using different distortions types: JPEG 2000, JPEG, white noise, Gaussian blur and bits errors in the GPEG 2000 bit stream when transmitted over a simulated fast fading Rayleigh channel. The Gaussian blurred images are generated using a circular-symmetric 2-D Gaussian kernel of standard deviation ranging from 0.42 to 15 pixels, while the JPEG 2000 compressed images are generated by
JPEG 2000 software with a compression rate ranging loss less to 0.05 bits/pixels.

In order to validate the proposed method, two tests were conducted. One using Gaussian blurred versions and the other using JPEG 2000 compressed images. Figures 3, 4 and 5 illustrate the obtained quality assessment ($IQ_A$) against $DMOS$ (Difference Mean Opinion Scores) values of Gaussian blurred images. Figures 6 illustrate the obtained $IQ_A$ from the proposed method against $DMOS$ values of JPEG 2000 blurred images. For fitting a Logistic regression has been considered. It is defined as:

$$DMOS_{pi} = \frac{\alpha_1 - \alpha_2}{\alpha_3 - \alpha_3} + \alpha_2 \quad (21)$$

Where $\alpha_1, \alpha_2, \alpha_3$ and $\alpha_4$ are the logistic parameters, $DMOS_{pi}$ is the predicted $DMOS$, and $IQ_A$ is the proposed quality measure.

**Figure 2.** LIVE data base.

**Figure 3.** Image quality measure against difference mean opinion scores estimated from the gradient-based method.
The proposed method was evaluated against the LIVE DMOS scores using Spearman rank order correlation coefficient (SROOC), the root mean square error (RMSE) and the algorithm runtime (ART).

In a second step, the proposed algorithm has been compared to the useful non perceptual approaches. The Live DMOS scores using the Spearman correlation coefficient (SROCC) of the reported subjective and the predicted DMOS are used.

5 DISCUSSION

According to figures 3, 4 and 5, one could notice that for the proposed approach, the logistic function map the data points fairly and an appropriate fitted curve is obtained. Almost all the data point, especially for averagely blur images are located at short distance from the fitted curve.

The results for both of the considered and the proposed methods are presented in table I.

In Table I, the proposed IQA model provides the best performances amongst the considered algorithms in terms of quality accuracy, root mean square error and execution time. Results indicate that for an accurate quality measure, \(IQA>0.85\), with a parallel implementation on a HP, the proposed method takes 1.083 second to evaluate a single image quality (a speed up of 25 compared to gradient based method).

To compare the obtained performances to those of existing approaches, one could consider the main useful non perceptual methods. Table II illustrates some obtained performances by testing the considered approaches on LIVE data base.

In table III, we compare the SROOC values obtained from the proposed method when applied to JPEG 2000 blurred images with some existing methods.

It can be seen from the obtained results (Table II and III) that, the proposed metric significantly outperforms the considered no perceptual metrics and
provides the best correlation with subjective scores. The best overall performances for the proposed metric may be attributed to the wavelet transform effectiveness in edge characterization through resolutions.

Our aim is to find an objective measure to characterize the defocusing blur. Then evaluating the proposed method performances as a function of the standard deviation (SD) values relative to the Gaussian filters used for blurring process, is suitable. Results are represented in figures 7, 8 and 9.

**TABLE 1.** DMOS Evaluation

<table>
<thead>
<tr>
<th>Considered algorithms</th>
<th>Gradient based method</th>
<th>Wavelet based method</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>SROCC</td>
<td>0.8655</td>
<td>0.7308</td>
<td>0.8822</td>
</tr>
<tr>
<td>RMSE</td>
<td>8.0077</td>
<td>15.5943</td>
<td>7.9275</td>
</tr>
<tr>
<td>ART(Second)</td>
<td>28.5034</td>
<td>0.6402</td>
<td>1.0830</td>
</tr>
</tbody>
</table>

**TABLE 2.** Proposed method evaluation compared to some existing methods

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>SROCC</td>
<td>0.7305</td>
<td>0.7</td>
<td>0.75</td>
<td>0.7</td>
<td>0.882</td>
</tr>
<tr>
<td></td>
<td>0.06</td>
<td></td>
<td>54</td>
<td></td>
<td>2</td>
</tr>
</tbody>
</table>

**TABLE 3.** Evaluation of the proposed metric performances when applied to JPEG 2000 blur images

<table>
<thead>
<tr>
<th>Considered compared algorithms</th>
<th>Marziliano et al [2]</th>
<th>Ong et al. [17]</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>SROCC</td>
<td>0.761</td>
<td>0.732</td>
<td>0.8568</td>
</tr>
</tbody>
</table>

**Figure 7.** Image quality measure against standard deviation values estimated from the gradient based method.

**Figure 8.** Image quality measure against standard deviation values estimated from the wavelet-based method.

**Figure 9.** Image quality measure against standard deviation values estimated from the proposed method.

Figures 7, 8 and 9 represent the evolution of both the considered and the proposed methods respectively as a function of Standard Deviation (SD) values of the used Gaussian filters, when applied to all 29 original images and
their blurred versions. It is observed from the figures that the IQA remains

<table>
<thead>
<tr>
<th>Table 4. SD Evaluation</th>
<th>Considered algorithms</th>
<th>Gradient based method</th>
<th>Wavelet based method</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>SROCC</td>
<td>0.8981</td>
<td>0.7016</td>
<td>0.9163</td>
<td></td>
</tr>
<tr>
<td>RMSE</td>
<td>1.0532</td>
<td>1.3383</td>
<td>1.0046</td>
<td></td>
</tr>
</tbody>
</table>

Close to one when the standard deviation of the Gaussian filter is close to zero. As expected, one could note that overall the images quality decreases when the standard deviation increases (blur level increases). This degradation provides a loss of information at high spatial frequencies, which translated in a visible blur effect.

While studying the fits goodness of the considered and the proposed methods, one could use the Spearman correlation as well as the Root mean scare error. Results are presented in tables IV.

According to table IV, it can be clearly seen that the proposed method provides the best performances compared to the considering methods.

Moreover, the suggested method is effective to evaluate the image quality where the blur is purposely introduced to emphasize precise objects in the image (artistic blur). Figure 10 illustrate examples from Live data base images.

![Figure 10](image1.png)

**Figure 10.** Artistic blur images quality evaluation.

The effectiveness of this method to evaluate artistic introduced blur is due to the fact that it is based on edge detection, therefore the homogeneous zones (absence of transitions) will not be considered as blurred.

**6 CONCLUSION**

In this work, we presented a no-reference blur image quality metric based on wavelet transform. Our tests using Live database images (Gblur and JPEG 2000) show that the proposed approach offers the best overall performances for quality evaluation. The multi resolution analysis allows effectively a good blur characterization and an improved executing time compared to spatial methods. As perspective for future work, we prospect to develop a new adaptive blur reduction method based on the proposed metric.

**7 REFERENCES**