A Perceptual Blind Blur Image Quality Metric

Fatma Kerouh and Amina Serir

U.S.T.H.B, L.T.I.R, Faculté d'Electronique et d'Informatique
B.P. 32 El Alia Bab Ezzouar, Alger 16111, Algérie.
E-mail: f.kerouh@usthb.dz, aserir@usthb.dz

ABSTRACT

This paper turns on a perceptual blind blurred image quality assessment method developed in the wavelet domain. The proposed blur quality metric considers the association of an objective measure based on edge analysis through the wavelet transform resolutions and the Just Noticeable Blur concept (JNB). Unlike the existing objective metrics, the proposed one is able to assess the perceptual blurred image quality relying on the human vision system (HVS). The idea is to estimate the perceptual blur in the edge map through resolutions using the psychometric function. Tests on blurred images from different datasets provide high correlations against subjective scores compared to some existing methods.

***Index Terms*—**blurring, no reference quality metric, wavelet transform, Human Vision System (HVS), Just Noticeable Blur (JNB).

1. INTRODUCTION

The image quality could be affected by different artifacts. In this paper blurring is considered as the most common problem. In fact, it could be introduced into images during acquisition for instance object moving or during some treatment as filtering or compression. There exist in the literature three cases of quality assessment metrics: full-reference (FR), reduced reference (RR) and no reference (NR) metrics. In the FR case, the original image is used in the quality assessment process however in the RR case only some properties of the original image, as its statistics, are used. The NR case is the most difficult since only the degraded image is used. No reference algorithms are extensively needed since humans can often effortlessly judge the image quality in the absence of a reference image. As blurring affects especially edges [1, 21] which represents high frequency components of an image, most blur analysis methods are based primarily on edge detection [2, 3, 11, 22]. There exist in the literature several methods for edge extraction. Herein, the wavelet transform is considered for edge characterization through resolutions [19, 20]. In our previous work [2], a multi resolution edge analysis method using the wavelet transform is adopted to develop a no reference blurred-image quality metric. This is done by analyzing blurred pixels through wavelet resolutions. This approach considers the blur effect as correlated only with the source of distortion and does not take into account the human perception that ultimately the sole judge of the image quality. Here in, we aim to introduce the JNB concept to our previously published blur metric [2], which may improve the performance in terms of correlation with subjective scores. The proposed perceptual method performance has been evaluated compared to some existing perceptual and non perceptual methods in terms of correlation with subjective scores and executing time using different existing databases.

This paper is organized as follows. Section 2, introduces the Just Noticeable Blur (JNB) concept. The proposed method is presented in section 3. Section 4 presents experiments, results and discussions. The last section concludes this work with some perspectives.

2. THE JUST NOTICEBLE BLUR CONCEPT (JNB)

By definition, the JNB is the minimum amount by which a stimulus intensity must be changed relative to background intensity in order to produce a noticeable variation in sensory experience [3]. Herein, the JNB concept could be defined as the minimum quantity of blurring that could be perceived by the human visual system.

To explain the need of introducing the JNB concept in the image quality evaluation process, let us consider blurred images from the Glur LIVE database [4]. In this dataset, each image is characterized by:

- An objective score: relying on the source of distortion. It represents the standard deviation value (*SD*) of the Gaussian function used to introduce blurring in each image.
- A subjective score: represents the Difference Mean Opinion Scores (*DMOS*), relying on the Human Visual System judgment.

In case subjective scores (*DMOS*) are directly and solely related to the blur source (*SD*), Correlations between *SD* and *DMOS* scores reache a maximum (~ 1). Figure 1 depicts the scatter plot of the objective values (*SD*) evolution versus the subjective scores (*DMOS*) corresponding to each blurred image from the Gblur LIVE dataset. Obtained data are interpolated using the logistic function (equation 1).

$$DMOS_i = \frac{\alpha_1 - \alpha_2}{1 + e^{\frac{SD_i - \alpha_3}{|\alpha_4|}}} + \alpha_2 \qquad (1)$$

where α_1, α_2, α_3 *and* α_4 are the logistic parameters, $DMOS_i$ corresponds to the subjective score of the image *i*, and SD_i stands for the Standard Deviation value of the Gaussian function used to introduce blurring in the image *i*.
To appreciate the obtained interpolation model, the Spearman's Rank Ordered Correlation Coefficient ($SROCC$) defined by equation (2) and the Root Mean Absolute Error (MAE) between the obtained data and the interpolation model are computed.

$$SROCC = 1 - \frac{\sum D^2}{n(n^2-1)} \qquad (2)$$

D and *n* are the difference between interpolating model and samples and the total number of samples, respectively.
The estimated $SROCC$ and MAE values from the obtained model (Figure1) are 0.7425 and 8.4548, respectively. The resulting values show that, there is even a discrepancy between the Gblur LIVE database objective and subjective scores. Whence the importance of developing a quality metric taking into account the human perception that ultimately the sole judge of the image quality. So the aim of this work is to consider the human perception in a previously published non perceptual blur assessment metric in order to improve the correlation with the subjective scores (*DMOS*) relying on the HVS.

3. THE PROPOSED PERCEPTUAL BLUR IMAGE QUALITY METRIC ($PBIQA$)

In this section, the proposed perceptual blur quality assessment metric is presented. The JNB concept is introduced to take into account the human perception and possibly correct objective quality measures weaknesses related to the blurring source and ignores what is perceived or not. The idea is to sense the perceptual blur in the extracted edge pixels through the wavelet transform resolutions. The proposed method involves three main steps. First, an edge map is constructed at each resolution level using the wavelet transform. The second step consists of extract perceptual edge map at each resolution level by introducing the JNB concept. Finally, the quality metric is defined by analyzing blur effect on the extracted perceptual edge maps. Each step will be detailed in the following.

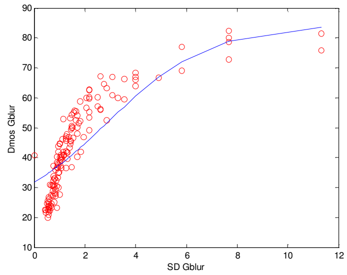


Fig. 1 . The Gblur Live SD versus DMOS evolution

Step1. Construct the Edge map $Cont_j$ at each resolution level: To achieve this step, the wavelet transform is used as follows:

1. Apply the wavelet transform on the blurred image (im_b) at *J* resolutions. To each resolution level *j* ($0<j<J$), corresponds three detail images in the horizontal D_{hj}, vertical D_{vj} and diagonal D_{dj} directions, respectively.
2. Construct the contour map "$Cont_j$" as follows:

$$Cont_j(k,l) = \begin{cases} E_j(k,l) & if \;\; E_j(k,l) > Th_j \\ 0 & Otherwise \end{cases} \qquad (3)$$

with,

$$E_j(k,l) = \sqrt{D_{hj}^2(k,l) + D_{vj}^2(k,l)} \qquad (4)$$

While evaluating the blur level at different resolutions using the wavelet transform, it could be observed 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 edge detection we found that, it is useful to propose a set of thresholds Th_j depending on the resolution level as follows:

$$Th_j = \frac{2^{j-1}}{N_j \times M_j} \sum_{k=1}^{k=N} \sum_{l=1}^{l=M} \left(E_j(k,l)\right) \qquad (5)$$

where $(N_j \times M_j)$ corresponds to the detail image size at the resolution level *j*.

Step2. Extract the perceptual edge map $PCont_j$ at each resolution level: In this step, the psychometric function, relating the subject's response to the physical stimulus, is used. It is defined as follows:

$$P = 1 - \exp\left(-\left|\frac{\sigma}{\sigma_{JNB}}\right|^{\beta}\right) \qquad (6)$$

σ is the standard deviation of the Gaussian blur filter. σ_{JNB} is the standard deviation corresponding to the JNB threshold. The aim is to estimate the probability that an edge pixel could be perceived. The likelihood "$\mathcal{L}Cont_j$" used to detect a perceptual edge pixel is defined as follows:

$$\mathcal{L}Cont_j(k,l) = \left(\sum_{e_j \epsilon (Cont_j)} \left|\frac{w(Cont_j(k,l))}{w_{JNB}}\right|^{\beta}\right)^{\frac{1}{\beta}} \quad (7)$$

Here $w(Cont_j(k,l))$ represents the detected edge pixel spread. It is computed by counting the total number of pixels between two consecutive maxima or minima arount the edge pixel. w_{JNB} represents the just noticeable edge pixel spread. According to [3], w_{JNB} is measured to be 5 for $C \leq 50$ and 3 if $C \geq 51$. C is the image (im_b) contrast defined as:

$$C = |\max(im_b) - \min(im_b)| \quad (8)$$

The parameter β is fixed at 3.6.
The pixel is said outline perceptual contour if its probability is higher than 63% [5]. Then the detected perceptual edge map matrix $PCont_j$.

$$PCont_j(k,l) = \begin{cases} Cont_j(k,l) & if\ \mathcal{L}Cont_j(k,l) > 0.63 \\ 0 & otherwise \end{cases} \quad (9)$$

Step 3. Define the proposed blur metric
The proposed metric is defined as the weighted average of the ratio between the total number of blurred pixels to the total number of perceptual edge pixels extracted at each resolution level. To detect blurred edge pixels at a given resolution level j, the idea is to estimate the difference PD_j between the detected perceptual edge pixel and the average of its neighbors. This edge pixel is considered as blurred if the estimated PD_j is less than a fixed threshold ξ_j depending on a resolution j.
Let us consider $PA_{cj}(k,l)$ with 'c' stands for 'hj' or 'vj', the average value estimated from two neighbor pixels in the horizontal and vertical direction, respectively.

$$PA_{hj}(k,l) = \frac{1}{2}(PCont_j(k,l+1) + PCont_j(k,l-1)) \quad (10)$$

$$PA_{vj}(k,l) = \frac{1}{2}\left(PCont_j(k+1,l) + PCont_j(k-1,l)\right) \quad (11)$$

Hence, the relative variation of the edge pixel compared to the average $PA_{cj}(k,l)$ is defined as follows.

$$PBR_{cj}(k,l) = \frac{|PCont_j(k,l) - PA_{cj}(k,l)|}{PA_{cj}(k,l)} \quad (12)$$

The largest value between $PBR_{hj}\ and\ PBR_{vj}$ is selected for the final decision.

$$PD_j(k,l) = \begin{cases} 1 & if\ max(PBR_{hj}, PBR_{vj}) < \xi_j \\ 0 & otherwise \end{cases} \quad (13)$$

As the edge intensity depends on the resolution level, it is judicious to consider a set of threshold depending on the resolution level j as:

$$\xi_j = 0.5 \times 2^{j-1}. \quad (14)$$

To define the proposed metric, one could compute the total number of perceptual edge pixels PNE_j and the total number of perceptual blurred ones PNB_j at each resolution level j. The perceptual blur quality factor PQ_j could then be defined.

$$PQ_j = \frac{PNB_j}{PNE_j}, \quad (15)$$

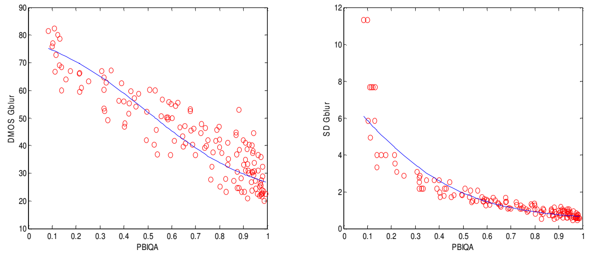
Finally, the Perceptual Blurred Image Quality Assessment ($PBIQA$) is proposed.

$$PBIQA = 1 - \frac{\sum_{j=1}^{j=J} 2^{J-j} \times PQ_j}{\sum_{j=1}^{j=J} 2^{J-j}} \quad (16)$$

$PBIQA$ takes into account all perceptual edge pixels detected by the wavelet transform at each resolution level j. Obtained $PBIQA$ quality scores range between zero and one, as the image blurriness increases, the quality score is expected to decrease from 1 to 0.

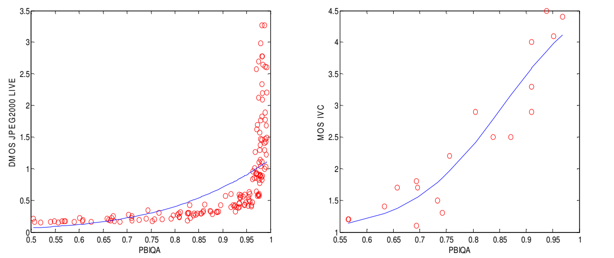
4. RESULTS AND DISCUSSIONS

Experiments are conducted with the MATLAB platform using the Hp 630 (Intel P6200/2.13 hz, 2G Ram) laptop. Different datasets have been considered: LIVE (Gblur and JPEG 2000) [4], IVC [6], Tomaya Image Database (TID) [7] and CISQ [8]. Subjective and objective scores are available in the Gblur database (SD and DMOS). Only subjective scores are available in the TID, IVC, LIVE JPEG2000 and CISQ datasets.
In the experiment part, the wavelet transform is applied using the Daubechies wavelet (Db2) [9], at three resolutions (*J=3*) to achieve a trade-off between reducing the run-time and edge persistence through resolutions.
The proposed $PBIQA$ performance is evaluated in terms of the correlation against subjective scores (DMOS) and the algorithm run-time (seconds). Correlation between obtained data and the fitting model is made using a variety of statistical measures. The Spearman correlation (*SROCC*), the linear correlation coefficient (*LCC*) and the Mean Absolute Error (*MAE*). *SROCC* and *LCC* values close to 1 and *MAE* close to 0 indicate that the algorithm performs well.
Figures (2-4) depict the scatter plots of the proposed approach evaluated on all the considered databases. Table 1 summarizes the quantitative evaluation of $PBIQA$ applied on all considered databases. Obtained results revealed that $PBIQA$ values correlate well to the DMOS scores. In fact high correlation values are obtained for a reasonable run-time (8.23 seconds).
Tables (2-5) summarize the proposed ($PBIQA$) evaluation against some existing methods using the considered datasets. Accordingly, one could notice that the proposed $PBIQA$ outperforms the considered ones in terms of *LCC*, *SROCC* and *MAE.* The proposed $PBIQA$ performance is



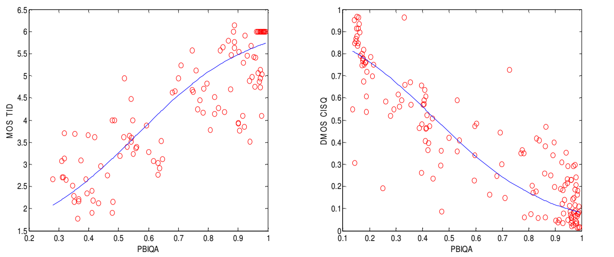
(a) (b)

Fig. 2. Subjective Evaluation on the Live Gblur dataset, (a) PBIQA versus DMOS, (b) PBIQA versus SD.



(a) (b)

Fig. 3. Subjective Evaluation on (a)the Live JPEG2000 database, (b) the IVC dataset.



(a) (b)

Fig. 4. Subjective evaluation on, (a) TID dataset, (b) CISQ dataset.

evaluated against some existing non perceptual methods [2][11][13] and perceptual ones [3][18] in terms of the algorithm run time. Table 6 shows that the non perceptual wavelet based methods [2] [13] are faster than gradient based non perceptual method [11]. Perceptual methods consume much executing time compared to the non perceptual ones. The proposed method realizes the tradeoff between accuracy and running time. In fact, it is more accurate than the non perceptual methods and faster than perceptual ones.

From all the obtained results, one could conclude that the proposed $PBIQA$, that exploits the multiresolution analysis using the wavelet transform and introduce the human vision system in the quality judgment, provides an encouraged results in terms of correlation versus subjective scores with a reasonable running time. Hence, the proposed $PBIQA$ could be used successfully in assessing the blurred image quality in different image processing applications.

Table1. Quantitative evaluation of $PBIQA$ on different datasets.

datasets	LCC	SROCC	MAE
Gblur DMOS	0.9028	0.9071	0.6783
Gblur SD	0.9196	0.9212	0.7190
JPEG 2000	0.8962	0.9357	0.2542
IVC	0.9395	0.9139	0.3861
TID	0.8099	0.8379	0.8002
CISQ	0.8652	0.8424	0.1494

Table 2. Comparative study on the Gblur LIVE dataset.

Gblur	LCC	SROCC	MAE
JNB [3]	0.8497	0.8344	0.6933
Gradient [10]	0.8073	0.7625	0.8189
Gradient 2 [11]	0.8408	0.8655	0.8007
Wavelet [12]	0.7458	0.7308	0.7559
IQA[2]	0.8669	0.8822	0.6865
Laplacien[13]	0.5868	0.891	0.74
Hist_freq[14]	0.804	0.893	0.72
PBIQA	0.9028	0.9071	0.6783

Table 3. Comparative study on the JPEG2000 LIVE dataset.

JPEG 2000	Considered compared algorithms				
	[15]	[16]	[3]	[2]	PBIQA
LCC	0.781	0.799	0.7492	0.881	0.8962
SROCC	0.761	0.732	0.8568	0.873	0.9357
MAE	0.482	0.5367	0.5157	0.320	0.2542

Table 4. Quantitative evaluation on the IVC dataset.

IVC	Considered compared algorithms				
	[12]	[17]	[11]	[2]	PBIQA
LCC	0.8406	0.8505	0.9144	0.9298	0.9395
SROCC	0.8374	0.874	0.8858	0.8989	0.9193
MAE	0.6143	0.5469	0.4567	0.4163	0.3861

Table 5. Quantitative evaluation on the CISQ dataset.

CISQ	LCC	SROCC	MAE
Wavelet[13]	0.7999	0.7907	0.1778
Gradient[12]	0.8218	0.7965	0.1714
IQA[2]	0.8263	0.8002	0.1689
PBIQA	0.8652	0.8424	0.1494

Table 6. Quantitative evaluation in terms of the algorithm RT.

metrics	[13]	[11]	[2]	[18]	[3]	PBIQA
RT (S)	1.9	19.48	2.53	22.53	20.17	8.23

5. CONCLUSION

A JNB-based perceptual blind blurred image quality metric developed in the wavelet domain is proposed in this paper. The subjective evaluation of the proposed method using different datasets proves its effectiveness compared to some existing perceptual and non perceptual methods. As perspective and for future work, we plan to develop a new iterative deblurring method based on the just noticeable blur concept and control the iterative process by the proposed perceptual quality metric.

6. REFERENCES

[1] S. Mallat, A wavelet tour of signal processing, *London Academic Press,* 1999.

[2] F. Kerouh and A. Serir, “A No Reference Quality Metric for Measuring Image Blur In the Wavelet Domain, ” *International journal of Digital Information and Wireless Communication*, vol. 1, no. 4, pp. 767-776, 2012

[3] R.Fezli and L.J. Karam, “ A No-Reference Objective Image sharpness Metric Based on the Notion of Just Noticeable Blur (JNB),” *IEEE Trans. Image Processing*, vol.18, no. 4, pp. 717-728, 2009.

[4] H.R. Sheikh, M. F. Sabir and A. C. Bovik. “A statistical evaluation of recent full reference image quality assessment algorithms,” *IEEE Transactions on image processing*, vol. 15, no. 11, pp. 3440-3451, Nov 2006.

[5] I. Hontsch and L.J.Karem,” Adaptive image coding with perceptual distortion control,” *IEEE Trans. Image Process,* vol. 11, no. 3, pp. 213-222, Mars. 2002.

[6] P. Le Callet and F.Autrusseau, “Subjective quality assessment irc-cyn/ivc data base. http ://www.irccyn.ec-nantes.fr /ivcdb/, 2005.

[7] Toyama image database. http://mict.eng.u-toyama.ac.jp/mict/index2.html .

[8] http://vision.okstate.edu/cisq/.

[9] R.Singh R.Vasquez. “Comparaison of Daubechies, coiflet and symlet for edge detection,” *Visual information Processing, Conference N°6*, Orlando FL,Etat Units, April 1997.

[10] X. Zhu and P. Milanfar, “A no-reference sharpness metric sensitive to blur and noise,” *1st International Workshop on Quality of Multimedia Experience* (QoMEX), 2009.

[11] M. G. Choi, J. H. Jung, and J. W. Jeon. “No-Reference Image Quality Assessment using Blur and Noise,” *Word Academy of Science, Engineering and Technology*, vol. 50, pp. 163-167, 2009.

[12] H. Tang, LI. Ming jing, H. J Zhang and C. Zhang. “Blur Detection for images using Wavelet transform”. *Conference of multi-media and expositions*, vol . 1, pp. 17- 20, 2004.

[13] C. F. Batten, “Autofocusing and Astigmatism Correction in the Scanning Electron Microscope,” *M.Phil. thesis, Univ. Cambridge, Cambridge, U.K.,* 2000.

[14] X. Marichal, W. Ma, and H. J. Zhang, “Blur determination in the compressed domain using DCT information,” *in Proc. IEEE Int. Conf Image Processing*, vol. 2, pp. 386–390. Oct. 1999,

[15] P. Marziliano, F. Dufaux, S. Winkler, T. Ibrahimi. “A no reference perceptual blur metric”. *International conference on image processing*, vol. 13, pp.57-60, Rochester, NY 2002.

[16] E. P. Ong, W. S. Lin, Z. K. Lu, S. S. Yao, X. K. Yang and L.F. Jiang, “No reference quality metric for measuring image blur,” in *Proc IEEE int. Conf. Image processing*, pp. 469-472, sp. 2003,

[17] F. Crête. “Estimer, mesurer et corriger les artefacts de compression pour la télévision,” *Rapport de Thès*e, Université Joseph Fourier, 2007.

[18] Ming-Jun Chen and Alan Bovic, “ No reference image blur assessment using multiscale gradient,” *Journal of image and video processing*, 2011.

[19] F.Kerouh and A.Serir, “Wavelet-based blind blur reduction,” *International Journal of Signal, image and video processing, Springer*, DOI: 10.1007/s11760-014-0613-z, Jan. 2014.

[20] F. Kerouh, A. Serir, “A Quality Measure Based Stopping Criterion for Iterative Deblurring Algorithm,” *IEEE, Workshop on Systems, Signal Processing and their Applications (WOSSPA)*, pp. 372-377, Algiers, 2013.

[21] F. Kerouh, A. Serir, “An adaptive Deblurring method based on the Multiplicative Multiresolution Decomposition,” *IEEE, European Workshop on visual information Processing (EUVIP)*, pp. 88-93, Paris, 2013.

[22] A. Serir, A. Beghdadi and F. Kerouh, “No-reference blur image quality measure based on multiplicative multiresolution decomposition,” *Journal of Visual Communication and Image Representation*, vol. 24, no. 7, pp. 911–925, October 2013.