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Histogram modelling-based no reference blur quality measure

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ABSTRACT

Blurring is a common artefact detrimental to the image quality. It affects especially edges and texture features that represent high frequency components of an image. The purpose of this paper is to propose a simple, fast, and faithful measure able to blindly assess blur amount in images. The main idea turns on analysing the frequency response at the multiresolution transitions. To achieve that, the histogram of the *discrete cosine transform* coefficients of the edge map is modelled by using an exponential probability density function (pdf). Tests revealed that the steepness of the pdf depends on the blur amount, hence, it is used as a cue to characterize the blur effect. Comprehensive testing demonstrates good consistency of the proposed measure with subjective quality scores as well as satisfactory performance when compared with representative state-of-the-art blind blur quality measures.

1. Introduction

Over the past decade, we have witnessed a proliferation of artificial visual systems including acquisition, processing, and display. The quality of the image has become a criterion for choosing one technology among others. This strengthened the developments of methodologies and algorithms for image quality assessment (IQA).

There exist mainly two categories of IQA techniques subjective and objective. The subjective evaluation is implicit. Indeed, human observers are asked to deliver a quality score according to a specific scale in some specific conditions [1]. The obtained scores are analysed and used to define a quality score. Subjective scores have the advantage of being reliable since the human visual system (HVS) still is the most accurate mechanism used for quality evaluation. However, the approach is infeasible in real-time applications because of the human in the loop. To overcome such limit, objective measures are highly required. In this case, an algorithm is used to substitute psychovisual experiments.

In order to define an objective quality measure, prior knowledge about the original image (a reference) may be required. In this case, we talk about full reference (FR) or reduced reference (RR) measures depending on, the total or the partial use of the reference image. When the reference image is not available, we talk about no reference (NR) measures, called also *blind* [2]. In this case, to assess the quality, only the distorted image content is used. The NR IQA measures are highly desirable when a reference image is not available or expensive to obtain. Owing to its intrinsic difficulty, the issue of NR quality measures is challenging indeed and remains largely unexplored. Note that most existing NR quality measures are dedicated to a specific distortion [2]. Fortunately, the distortion process is often known in real applications and the task of developing distortion-specific NR quality measures is of practical importance.

In this work, we develop a NR objective IQA measure dedicated especially to blurring artefact. Blur commonly occurs in compression or filtering process where high frequency components are attenuated [3,4]. Although intensive research has been carried out in the field of IQA [4,5], the issue of NR measures still is challenging and many questions still are open [6,7]. The proposed quality measure fulfils the following three requirements:

- Achieving the trade-off simplicity/accuracy: The proposed quality metric has to be easy to reproduce while delivering satisfying scores.
- Normalization: The proposed measure has to be normalized to make it easy the interpretation of the obtained scores.
- Generalization: The proposed measure has to generalize well on different existing blur image collections

Among the variety of existing works, some measures are simple to reproduce while delivering low correlation scores [8]–[9]. To improve the scores, two strategies are introduced, classification-based and HVS

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properties-based measures. The first category requires a learning step and more importantly, it does not generalize well to the non learned cases [10]–[11]. Moreover, the statistics of natural scenes form the feature space used by some of them for learning [11]–[12]. Nevertheless, these characteristics are useful only on a subset of images, natural images, and useless for manmade and indoor scenes. The other category of methods propose to mimic the HVS by modelling some of its features [13]–[14]. However, modelling some of HSV features can be computationally heavy and difficult to reproduce such as the Visual Difference Predictor [15]. Furthermore, the HSV still is not totally understood.

To assess the blur effect, high frequency components are generally analysed either in the spatial [16,17] or a transform domain [18–20]. We are planning to use the frequency domain. Low frequencies means that pixel values are changing slowly over space, while high frequencies means that pixel values are abruptly changing in space. Thus, high frequency coefficients contain information about edges and texture. In a blurred image, the number and the persistence of edge pixels, or their contrast through resolutions, depends on the blur intensity. This postulate is at the basis of the quality measure we propose. The intent is to model the histogram of the multiresolution DCT coefficients using an adequate probability density function (pdf). The proposed blur measure is related on the pdf steepness. The generalization of proposed blur quality measure on six blur image collections reveals its advantage of being objective, blind, simple, fast, and faithful. Moreover, it does not consider any assumption about the origin of blur (acquisition, processing, or transmission).

The next section details the proposed approach. Experimental results and analysis are described in Section 3. The last section concludes this work pointing out some issues.

2. Proposed blur quality measure (BQM)

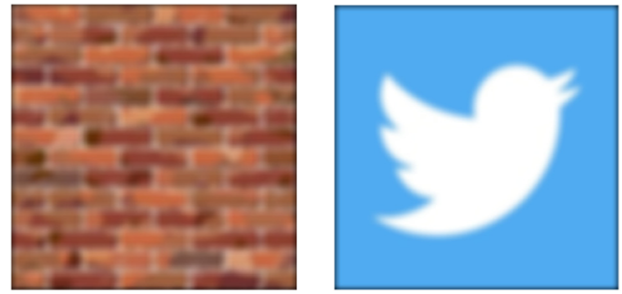
The proposed BQM is based on the assumption that blur visual impairment alter mainly high frequencies of an image such as edges and texture. Therefore, to assess the blur amount, we propose to model the histogram of high frequency coefficients using a suitable pdf. The statistical parameter of the pdf is used as a cue to characterize blur effect.

Before providing details about the proposed approach, we will verify first the considered assumption. To achieve that, two blurred images are simulated using a *Gaussian* filter of length 11 × 11 and a standard deviation value of 3 ($SD = 3$). Obtained images are depicted in Fig. 1. Accordingly, the first image appears to be more blurred compared to the second even if both are blurred using the same filter. Actually, it depends on the image content. The first image contains more edges and texture compared to the second hence the clear appearance of the blur. However, the blur appear to be weak in the second image because few details are present. Thus, the image content seems to be relevant for the perceptual quality evaluation of blurred images. These observations led us to analyse blur effect specially on edges where the human visual system is sensitive to the blur effect. To achieve that, edge analysis is the main step [21]. For a deeper study, edge persistence through resolutions will be tackled.

We will now focus on detailing the proposed quality measure (BQM) used for blur assessment. It is composed of two main steps. First, the multiresolution edge map is constructed and second the high frequency components are analysed to deliver a quality score.

2.1. Edge map construction

The edge map is constructed using the luma component of a test image. Edges are enhanced through the decomposition in the wavelet basis at J resolution levels. For the purpose of edge enhancement, it is useful to interpret the wavelet transform as a multiscale differential operator. Thus, edge enhancement relies on the difference of behaviour along the



(a) Blurred image1. (b) Blurred image2.

Fig. 1. Blur effect on textured and non textured images.

wavelet scales of the noise in front of the edges. Over resolutions, the noise is progressively smoothed, and it is almost spatially uncorrelated between scales. At each resolution of the two dimensional wavelet transform, three bandpass components are obtained, where each one enhances the discontinuities in a different direction, horizontal $Dh^{(j)}$, vertical $Dv^{(j)}$, and diagonal $Dd^{(j)}$. To construct the edge map $Edge^{(j)}$, at each edge pixel (k,l), only the horizontal and vertical details are considered. Diagonal details are neglected since they mostly represent the redundant features. $Edge^{(j)}$ is constructed as follows.

$$Edge^{(j)}(k,l) = \begin{cases} E^{(j)}(k,l) & if \quad E^{(j)}(k,l) > Th^{(j)} \\ 0 & otherwise \end{cases} \tag{1}$$

with

$$E^{(j)}(k,l) = \sqrt{Dh^{2(j)}(k,l) + Dv^{2(j)}(k,l)},\ j \in [1,\ J]. \tag{2}$$

Herein, $E^{(j)}(k,l)$ stands for the detected edge pixel magnitude at the jth resolution level. While evaluating the blur amount at different resolution levels using the *wavelet* transform, it is observed that for a fixed threshold, the edge magnitude decreases with resolutions. This is due to smoothing introduced by the *wavelet* transform filters. Consequently, the thresholding must be adaptive to the resolution level. Indeed, for a given resolution j, we observed that the threshold is proportional to the edge magnitude average. That is:

$$Th^{(j)} = \frac{1}{2^{j-1} N^{(j)} M^{(j)}} \sum_{k=1}^{N^{(j)}} \sum_{l=1}^{M^{(j)}} E^{(j)}(k,l) \tag{3}$$

where $N^{(j)}M^{(j)}$ corresponds to the edge map size at the jth resolution. Thus, while going down in resolutions, the threshold value decreases in order to consider more edge pixels and overcome the wavelet filters smoothing effect.

2.2. Quality measure specifications

Having the edge maps at different resolution levels, we will move to the frequency domain by applying the discrete cosine transform (DCT). The absolute values of the quantized DCT coefficients are only considered. The study is restricted only of the absolute values because the sign of the DCT coefficients is not informative about the degradation caused by the blur. Indeed, in the Fourier domain, the blurred image is equal to the product of the Fourier transform of the sharp image and the Gaussian function. Because the Fourier transform of the Gaussian function is a non negative real function, then, the sign of the DCT coefficients is inferred only from the sharp image and it is independent from the blur. Furthermore, absolute values are quantified to transform the uncountable set of DCT coefficients into a finite set of prescribed values. In the state of the art, the quantization is implemented through linear or non linear transforms [22]. For our purpose, quantization is seen as the process of reducing the precision. In other words, absolute DCT coefficients are quantized by rounding to the nearest integer, other

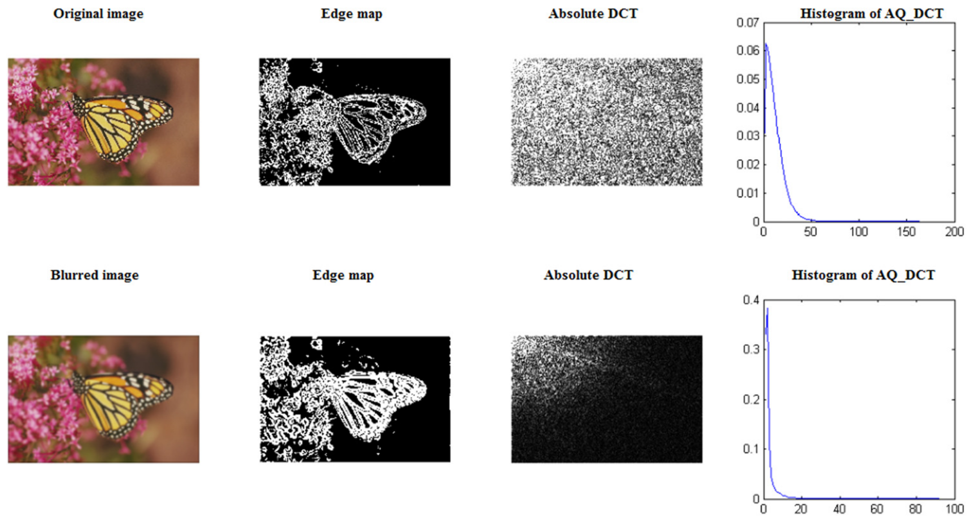


Fig. 2. AQ_DCT histograms of an original and a blurred image.

quantization transforms can be tried [22]. In what follow, to simplify the writing, the AQ_DCT is used to denote the absolute values of quantized DCT coefficients.

We argue that the blur and hence the image quality could be explained by the distribution of the AQ_DCT. Fig. 2 depicts one original image and its blurred version in addition to their corresponding edge map, absolute DCT, and the histogram of the AQ_DCT. Two main observations are achieved. First, the energy of the original image is more localized than the one of the blurred image. Indeed, the DCT coefficients of the blurred image are localized at the low frequencies while those of original image are spread over all the frequencies. This is expected because the blur can be caused by a low pass filter. Second, according to the histograms, the blurred image is sparser because there are more frequencies having almost null energy. These observations are common for a significant sample of images from the $Gblur$ LIVE image collection [23]. The quality measure is based on these dependent observations; the second is a consequence of the first.

To derive the image quality measure, we assume that the histogram of AQ_DCT is sampled from a probability density function (pdf). Several $pdfs$ have been used for modelling the histogram of the quantized DCT coefficients such as the Laplace, the Gaussian, and generalized Gaussian [24]. We find that the exponential pdf is more suitable for three reasons. First, the target histogram is built for non-negative values; i.e., the absolute values of the quantized DCT coefficients. Second, it is simple in the sense of Occam's razor; i.e., only one parameter has to be estimated. Third, the estimated $pdfs$ are enough for having a faithful quality measure.

Let us now explain the *pdf estimation process*. The exponential pdf is given by:

$$h(x) = a\,e^{-ax},\ \ where\ x \geq 0\ and\ a > 0. \tag{4}$$

The parameter a stands for the curve steepness. If $\{x_1, \ldots, x_N\}$ stands for the set of the absolute values of the DCT coefficients of the edge map, then, its estimated maximum likelihood is $a = N/\sum_{i=1}^{N} x_i$. Moreover, both the mean and the standard deviation of these DCT coefficients are equal to $1/a$.

There is an important property that deserves to be explained. Let us consider $\{y_1, \ldots, y_N\}$ the set of AQ_DCT and $H(y_i)$ their normalized histogram. In this case, the maximum likelihood estimator can be rewritten as $a = \frac{1}{\sum_{i=1}^{N} y_i H(y_i)}$. Because the sum $\sum_{i=1}^{N} H(y_i) = 1$, and $y_i \geq 1$, thus the denominator $\sum_{i=1}^{N} y_i H(y_i) \geq 1$ and therefore a $\in [0, 1]$. The zero value of a is reached in the limit sense.

To illustrate, Fig. 3 depicts an original image and its five blurred versions from the $Gblur\ LIVE$ collection. Each image is characterized by the standard deviation SD of the used Gaussian filters to simulate blur effect available in the collection. For each image, the real histogram and the estimated pdf are depicted. Note that the maximum fitting mean square error is less than 6% of the histogram total surface. Furthermore, the obtained values of the parameter a increases with the blur amount. Fig. 4 presents the evolution of the parameter a versus SD values of the test images of Fig. 3. Accordingly, the parameter a is almost in linear relation with the blur amount (SD values) and the correlation is about 98%. Because the SD is a blur cue [25], then a is too. To conclude, the parameter $a \in [0, 1]$ is a cue that informs about the amount of blur in images.

Another issue concerns the considered edge map resolution level to assess the blur amount. If the resolution is low, blur is enhanced and cannot lead to a faithful estimate of a realistic image quality. Conversely, the highest resolution is noisy and may also lead to a biased estimation. The proposed idea consists of combining the quality measures of the J highest resolutions. The choice of the suitable J will be tackled in Section 3. Even if several combination rules can be used, we propose a weighted sum of the estimated J quality measures. Because the blur increases when the resolution decreases, then the weights decrease with resolutions. Hence, we propose the following Blur Quality Measure (BQM)

$$BQM = \frac{\sum_{j=1}^{J} 2^{J-j}\, BQM^{(j)}}{\sum_{j=1}^{J} 2^{J-j}}. \tag{5}$$

The BQM ranges between zero and one. It is around one for highest quality and tends to decrease proportionally to blur amount, $BQM^{(j)}$ is given by:

$$BQM^{(j)} = 1 - \frac{1}{a^{(j)}} \tag{6}$$

where

$$a^{(j)} = \frac{1}{\sum_{y_i=1}^{N^{(j)}} y_i H^{(j)}(y_i)} \tag{7}$$

$N^{(j)}$ stands for the length of the histogram H at the jth resolution level.

3. Experiments, tests, and results

The proposed BQM is used for quality assessment of blurred images across six collections, $Gblur$ and $JPEG2000\ LIVE$, $TID2008$, $TID2013$, IVC, and $CISQ$ [23–26]. Each collection is characterized by the number of, original images and degraded versions per image. Moreover, each image is associated with a subjective quality score, provided by

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Table 1
Characteristics of the used image collections.

Collections	Proprieties			
	Orig.imgs	Degrads/img	Total Nbr.imgs	Subjective scores
Gblur LIVE	29	5	174	DMOS [0, 100]
JPEG2000 LIVE	29	7	232	DMOS [0, 3.5]
TID2008	25	5	125	MOS [7, 1]
TID2013	25	5	125	MOS [7, 1]
CISQ	30	5	150	DMOS [0, 1]
IVC	4	6	24	MOS [5, 1]

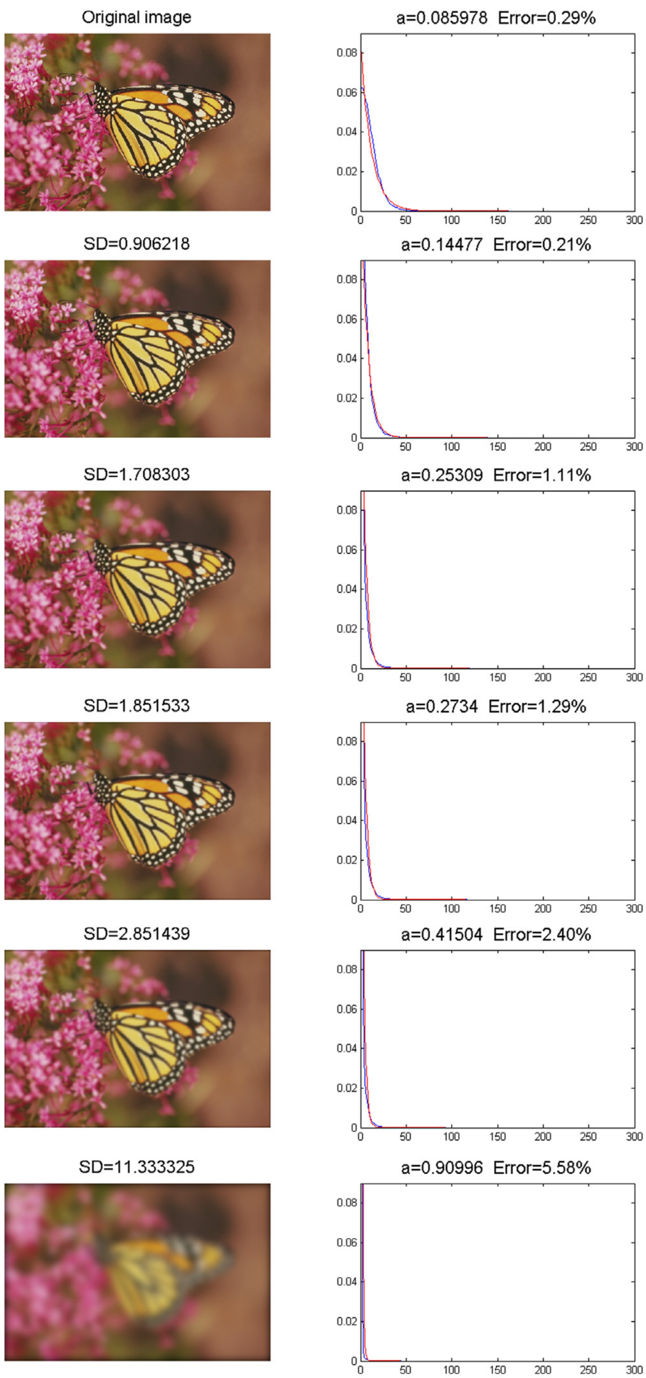

Fig. 3. Test images with their corresponding histogram of AQ_DCT (blue) and the estimated pdf (red).

Table 2
Interpretation of the correlation values.

Correlation scores ranges	Interpretation
0.0–0.19	Very weak
0.2–0.39	Weak
0.4–0.59	Moderate
0.6–0.79	Strong
0.8–1.00	Very strong

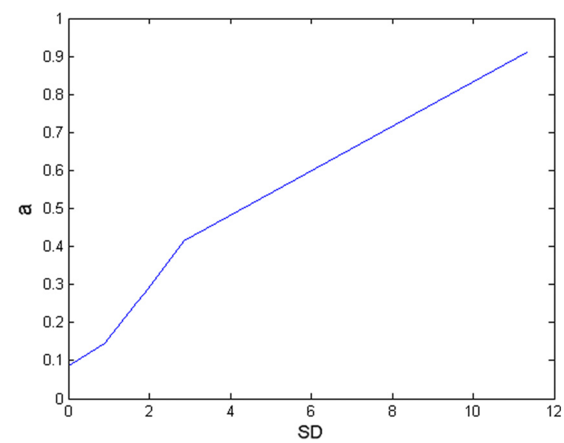

Fig. 4. Evolution of a versus SD.

psychometric experiments, that are Difference Mean Opinion Score (DMOS) or Mean Opinion Score (MOS) [1]. Table 1 summarizes the characteristics of each collection. We can see that, the scales of subjective scores are different. For example, the $DMOS$ scores of the $Gblur$ $LIVE$ collection range between 0 and 100, where, 0 corresponds to the original sharp images and it increases, proportionally to blur amount, till 100.

While evaluating the proposed quality measure, the aim is to obtain a consistent relationship between the obtained BQM values and the subjective scores. This relationship is quantified using the Spearman Rank Order Correlation Coefficient ($SROCC$) and the Pearson Correlation (PC). $SROCC$ measures the intensity of the order relation while PC expresses the linear dependence between the BQM values and the subjective scores. In the state of art, the values of $SROCC$ and PC are re-sampled as shown in Table 2. Accordingly, a correlation value over than 0.8 is interpreted as very strong.

Before evaluating the proposed BQM on the six considered collections, a series of tests have been conducted to fix the suitable resolution level of the wavelet transform. To achieve that, the proposed BQM is computed on four resolutions using the $Haar$ wavelet on all images of the $Gblur$ collection. Obtained correlation values are tabulated on Table 3. We can conclude that the first and the second resolutions are sufficient to define the proposed quality measure. In fact, the correlation values are lower after the second resolution. This is due to the loss of edges and texture due to the smoothing effect introduced by the wavelet filters. Hence, the suitable resolution level that releases the trade-off between edge persistence and blur appearance is two. Hence, the

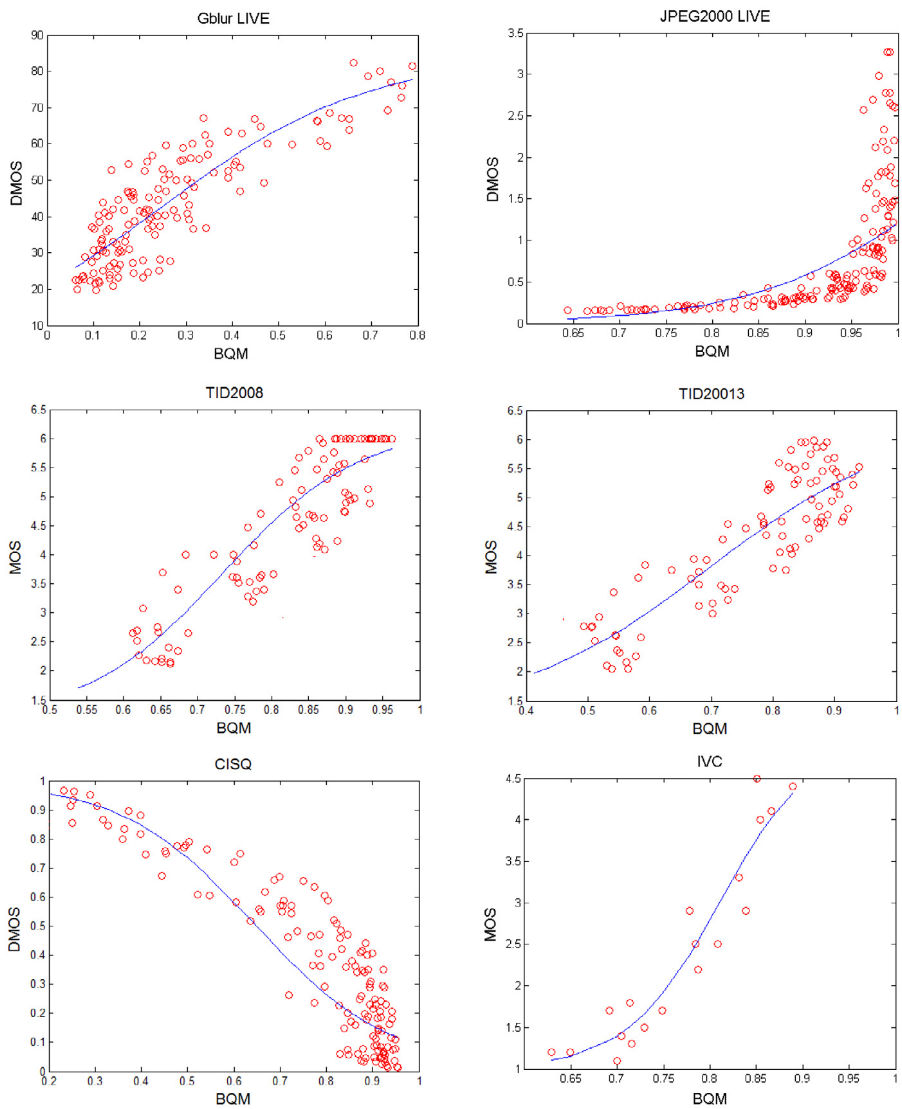

Fig. 5. BQM versus subjective scores of different image collections.

Table 3
BQM evaluation on Gblur images collection at different resolutions.

Correlation measures	Resolution levels			
	1st	2nd	3rd	4th
PC	0.9086	0.8901	0.7087	0.6255
$SROCC$	0.8922	0.8998	0.6610	0.5629

Table 4
Quantitative evaluation of BQM on considered image collections.

Image collections	Correlation scores	
	$SROCC$	PC
$Gblur$	0.8947	0.9002
$JPEG2000$	0.9394	0.8998
$TID2008$	0.8285	0.8162
$TID2013$	0.8189	0.8233
$CISQ$	0.8813	0.8672
IVC	0.9209	0.9561

proposed quality measure BQM is a weighted combination of BQM^1 and BQM^2. The formula is directly obtained by considering $J = 2$ in Eq. (5).

$$BQM = 1 - \frac{1}{3}(2BQM^{(1)} + BQM^{(2)}). \tag{8}$$

Let us now evaluate the proposed BQM on all the considered collections. Fig. 5 depicts the scatter plots of the obtained BQM values versus the subjective scores of the considered collections fitted by the logistic function. Three remarks can be achieved. First, the BQM values are normalized between zero and one. Second, for non blurred images, BQM values are around one and tends to decrease proportionally to blur amount. Third, the obtained BQM values are well correlated with subjective scores. Quantitative evaluation in terms of $SROCC$ and PC is reported on Table 4. Obtained values show that the proposed BQM provides a very strong correlation values against subjective scores related to the HVS. Moreover, it generalizes well on all considered collections.

The proposed BQM is now evaluated on out of focus images. For this kind of images, blur is intentionally created for artistic impression. Fig. 6 depicts an example of an original out of focus image and its blurred versions from the $Gblur$ $LIVE$ collection. Obtained quality scores show that the proposed BQM is suitable for quality evaluation of out of focus images. This can be explained by the fact that the proposed measure is based on edge analysis. Thus, even if the background is highly blurred, it will be ignored by the measure because it is poor of edges and texture. Hence, only the foreground will considered and evaluated. Fig. 7 illustrates the evolution of BQM values versus the subjective scores ($DMOS$). It can be noticed that the proposed BQM is

Fig. 6. BQM computed on out of focus images.

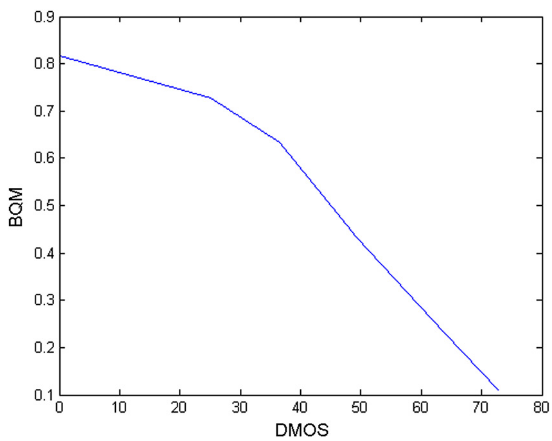

Fig. 7. $DMOS$ versus BQM computed on out of focus images.

well correlated with subjective scores ($SROCC = 0.9989, CC = 0.9847$). We conclude that the proposed measure can be effectively used to assess the blur effect in the case of out of focus images.

In the validation step, a comparative study against ten blind blur quality measures is performed. The performance criteria are the correlation with the subjective scores and the algorithm runtime. Because PC and $SROCC$ provides similar performance, only $SROCC$ values are provided. Note that, we have implemented the ten measures in Matlab software. Table 5 summarizes the obtained correlation scores on the six considered collections. We notice that the proposed BQM delivers very high correlations scores. Furthermore, compared to existing measures, BQM provides a competitive correlation scores on all considered collections.

From apart the correlation, the proposed BQM is validated in terms of the algorithm runtime. The considered existing blur measures are evaluated while applied on an image of size $512 * 768$ using $Matlab$ software and a laptop (hp 630, CPU i3, 2.10 GHz, Ram 4Go). As can be seen on Table 6, the proposed measure is fast and it provides a significant improvement in terms of the algorithm runtime. Fig. 8 visualizes the relationship between the correlation scores and the runtime of the considered measures while considering the $Gblur$ collection. It can be clearly seen that BQM overcome the considered measures since it realizes the trade-off between accuracy in terms of the correlation with subjective scores and the algorithm runtime.

Table 6
Comparative study of BQM by considering the algorithm runtime.

Blur measures	*Runtime* (s)
QS_SVM [20]	22.53
Mari [19]	21.02
JNB [13]	20.17
PBIQA [27]	19.4
MMD [4]	17.51
BBQM [30]	13.71
BBIQM [28]	10.33
MGC [16]	8.23
Thong [18]	3.28
IQA [29]	2.53
BQM	0.80

4. Conclusion

In the present paper, a no reference blur quality measure is proposed. The main idea is based on the analysis of the blur effect on image high frequencies. This is achieved by analysing the histogram of the absolute quantized DCT coefficients applied on two edge maps obtained at different resolutions. Tests achieved on the proposed BQM show a high performance in terms of blur assessment on different image collections including out of focus and highly blurred images. The proposed blur quality measure has the advantage of being, objective, simple to

Table 5
Comparative study on all image collections in terms of SROCC.

Blur measures	$Gblur$	$JPEG2000$	$TID2008$	$TID2013$	IVC	$CISQ$
MMD [4]	0.8976	0.9002	0.8289	0.8193	0.8286	0.8301
Mari [19]	0.8903	0.7787	0.7591	0.7603	0.8889	0.8298
JNB [13]	0.8203	0.7989	0.7765	0.7864	0.8301	0.8109
PBIQA [27]	0.8898	0.8901	0.7909	0.8165	0.9193	0.824
Thong [18]	0.7308	0.7539	0.7198	0.7209	0.8374	0.7965
QS_SVM [20]	0.6136	0.7398	0.5709	0.6064	0.6109	0.6009
BBIQM [28]	0.8559	0.8212	0.8053	0.8190	0.9085	0.8802
MGC [16]	0.8655	0.8092	0.8290	0.8010	0.8858	0.8101
IQA [29]	0.8822	0.8537	0.7892	0.7967	0.8989	0.8002
BBQM [30]	0.8909	0.9134	0.8002	0.8001	0.9132	0.8761
BQM	0.8947	0.9394	0.8285	0.8189	0.9209	0.8813

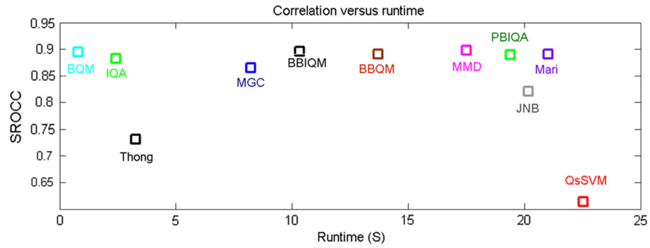

Fig. 8. Algorithm runtime versus correlation scores of the state of the art blur measures on the Gblur collection.

reproduce, blind, faithful, and fast. Comparative study against some well known blur quality measures provides an encouraging performance. Future research will involve introducing the proposed blur quality measure to develop different adaptive image processing systems as deblurring and compression.

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