A NEW REFERENCE-FREE IMAGE QUALITY INDEX FOR BLUR ESTIMATION IN THE FREQUENCY DOMAIN

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Abstract—*A new reference-free image quality index based on spectral analysis is proposed. The main idea is based on exploiting the limitations of the Human Visual System (HVS) in blur detection,. The proposed method consists of adding blur to the test image and measuring its impact. The impact is measured using radial analysis in the frequency domain. The efficiency of the proposed method is tested objectively by comparing it to some well known algorithms and in terms of correlation with subjective scores.*

Keywords—*Blur estimation, Fourier analysis, Subjective tests.*

I. INTRODUCTION

Image quality assessment plays nowadays an important role in various multimedia applications. This research carried in area has reached a certain level of maturity in the multimedia communications community. Several image quality metrics have been proposed in the literature [I. Avcibas et al., 2002]. Unfortunately, in the absence of a universal image quality index, people still continue to use the classical PSNR (Peak Signal to Noise Ratio) in many applications. Moreover, the problem of finding the best image quality index becomes more challenging when various types distortions are considered. As such, many of the researchers continue to propose new heuristic metrics based on psychophysical tests and some established databases.

The intend of this work is not to propose a quality index for all the known distortions but rather to focus on a particular artifact, namely blurring. This artefact mostly affects salient features such as contours and can result in drastic quality degradation. The fine details lost due to the blur correspond to the high frequencies in the image. This phenomenon is commonly found in compression applications in which high frequency components are generally neglected. We will discuss in what follows a number of techniques used in estimating blur, then we present our own approach and discuss how it is used in developing the new quality index.

In [H. Tong et al., 2004] a blur estimation method based on wavelets was proposed. An edge map is obtained after combining the coefficients of high frequencies of each decomposition level. The blur measure is then obtained by analyzing the type of the edge contained in the image.

In [X. Marichal et al., 1999], a no reference blur estimation method based on DCT is proposed. First, a block-wise DCT transform is applied to the image. By comparing the DCT coefficients inside each block 8x8 to some thresholds, a global blur measure is then derived.

In [J. Caviedes et al., 2004] the DCT is used to estimate the blur without a reference image. The idea is to measure the peakedness of each block 8x8 around each edge point by computing the kurtosis coefficient. Then, the kurtosis coefficient is computed in each block. The mean value of the kurtosis coefficients is then used as a global measure of the blur.

In this work, we propose a new blur estimation inspired by the idea developed in [F. Crete et al., 2007]. It is worth noting that since blurring affects mainly object contours, most blur estimation algorithms are based primarily on edge detection. However, in the case of highly blurred images, edge detection fails resulting in poor estimation of the blurring artefact. Here, we adopt another approach without referring to edge detection. The idea is to add blur to the distorted image and analyze its impact on the image quality. A radial analysis in the frequency domain is applied to both the distorted image and its filtered version. A Blur Index (BI) is then computed from this radial analysis.

The paper is organized as follows: Section 2 describes in details the proposed method. Section 3 is dedicated to the objective and subjective evaluations of the proposed method. Finally, some concluding remarks are discussed in the last section.

II. THE PROPOSED METHOD

As mentioned above, we propose to estimate the blurring effect by first adding blur to the test image, then analyzing its effect. Figure 1 displays three images with different levels of blur. One can note that the human perception of blur depends upon the original image ”blurriness” level of the original image. In figure 1, the application of a first blur yields the image displayed in Fig. 1.b whereas Fig. 1.c is the application of a second blur to image in Fig. 1b, using the same filter.

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We can see that the perceptual difference is more visible between the images in Fig. 1.a and Fig. 1.b than the images Fig. 1.b and Fig. 1.c in spite of having used the same filtering strength. Therefore, the perceived HVS estimation of blur is not monotonic. Also we can note that the impact of the blurring for a given image depends on the original image quality level, i.e. sharpness/blur strength. In other words, the blur effect on an already blurred image has less perceptual impact than on a sharpened image.

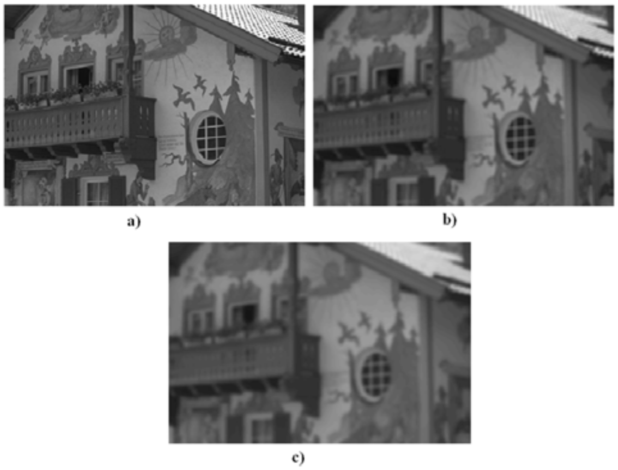

Fig. 1. a) Original image, b) Filtered image with a 3x3 binomial filter and c) Result of applying the same filter to the filtered image with a 3x3 binomial filter.

In order to better visualize this effect, we consider a 2D random test signal. We analyze the energy spectrum of this signal and the result of applying a 3x3 binomial filter repeatedly, first to the original signal and then to this filtered version. The energy spectrum of the original and the filtered signals are displayed on Fig. 2. It could be noticed that the filter impact is effectively less visible on the energy spectrum as shown in Fig. 2b and Fig. 2c.

Based on the above observations, we propose to exploit this characteristic of the HVS to evaluate the blur in an image by applying a blurring operation, then analyzing the impact of this degradation to quantify the quality of the original image. After transforming both the original and the blurred images into the frequency domain, we apply a radial analysis and deduce a Blur Quality Index [A. Beghdadi et al., 2000]. The flowchart of the proposed algorithm is illustrated in figure 3.

The first step consists of adding blur to the degraded image. We propose to simulate the blur with a 3x3 binomial filter. Figure 4 shows an example of a test image. Figs. 4.a and 4.b show a real image and its degraded version, respectively. A zoomed zone taken from the original and filtered images is displayed in Fig. 4.c and Fig. 4.d.

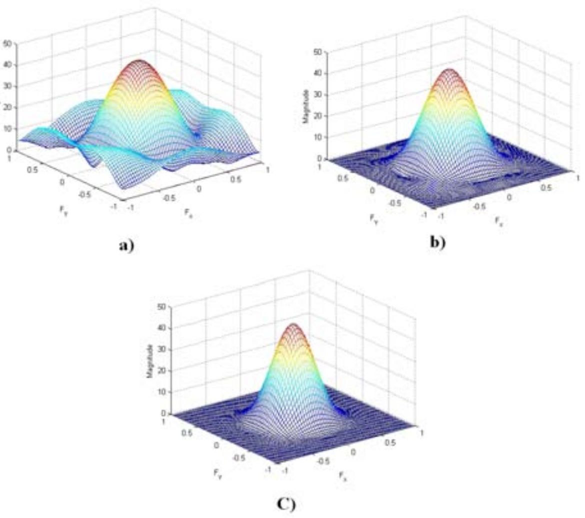

Fig. 2. a) Energy spectrum of the original signal, b) Energy spectrum of the filtered signal c) Energy spectrum of the refiltered signal.

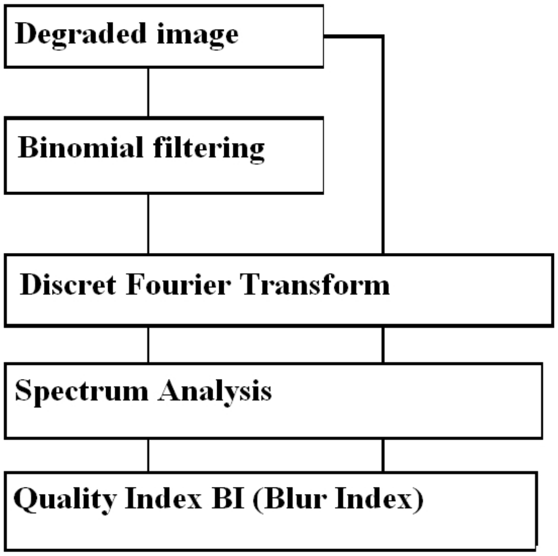

Fig. 3. Flowchart of the proposed method.

Once the test image and its filtered version are obtained, the discrete Fourier transform of the two images is computed using the following equation:

$$F(u,v) = \frac{1}{XY}\sum_{X}\sum_{Y} f(x,y).(-1)^{x+y}.e^{-2j\Pi(\frac{ux}{X}+\frac{vy}{Y})}$$

Where F(u,v) represent the centered Fourier coefficients corresponding the image f(x,y). (X,Y) represent the size of

Fig. 4. a) Original image, b) Filtered image with a 3x3 binomial filter and c) Result of applying the same filter to the filtered image with a 3x3 binomial filter

the image and (u,v) are the spatial frequencies.

The energy spectrum is obtained as follows:

$$|F(u,v)| = \sqrt{R^2(u,v) + I^2(u,v)}$$

with R(u,v) and I(u,v) are the real and imaginary parts of F(u,v), respectively.

F(u,v) is then transformed into polar coordinates represented by F(ω, θ_k).

An expression for the total radial energy is then obtained using the following:

$$ER(\omega) = \frac{1}{K}\sum_{K}|F(\omega,\theta_k)|$$

$$ER_f(\omega) = \frac{1}{K}\sum_{K}|F_f(\omega,\theta_k)|$$

with

$$\theta_k = \frac{k\pi}{K} \;\; and \;\; \omega = \sqrt{u^2 + v^2}$$

with ER(ω) and ER$_f(\omega)$ corresponding to the test image and its filtered version at the frequency ω, respectively.

Figures 5.a and 5.b display an example of a color image and its blurred version. Figs. 5.c and 5.d show the results from radial analysis of images 5.c and 5.d respectively.

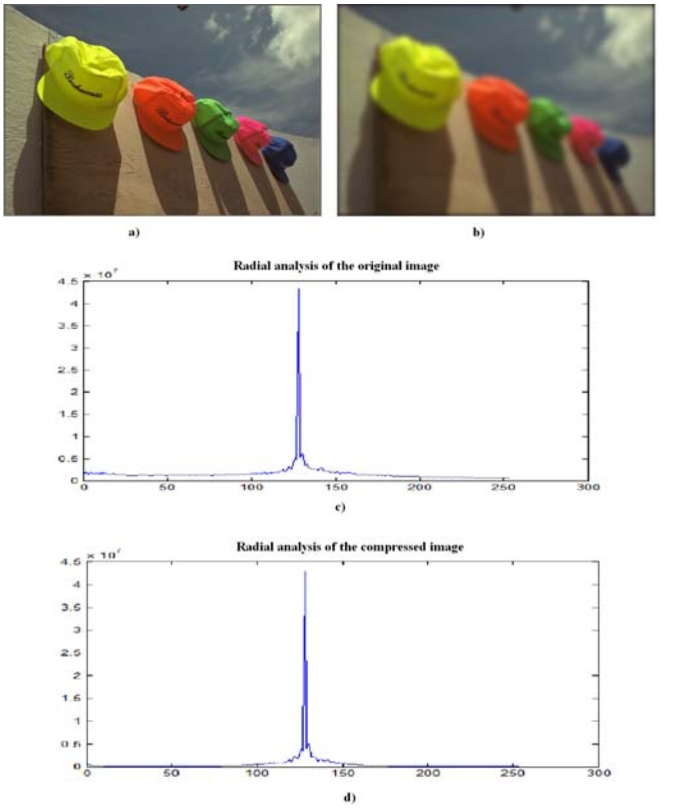

Fig. 5. a-b) Original and blurred images, c-d) Radial analysis of the images in 5.a and 5.b, respectively.

Based on the above energy measures, we propose a global Blur Index (BI) defined as:

$$BI = log(\frac{1}{\omega_{max}}\sum_{w}|ER(w) - ER_f(w)|)$$

where ω_{max} is the maximal frequency of w .

III. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed index, we carried both objective and subjective testing. These tests are described below.

A. Objective tests

The procedure described above was tested on a number of images containing different levels of blur. Fig. 6 shows an example from natural images. Fig. 6.a is the reference image while Fig. 6.b and 6.c are two distorted versions of the image 6.a. The resulting BIs are 9.56, 11.55 and 12.20, respectively which correspond well to perceptual quality ranking.

Fig. 6. a) Original image with BI = 9.5574 and DMOS= 35.0583, b) Degraded image with BI= 11.5492 et DMOS = 43.2751 et c) Degraded image with BI = 12.1937 et DMOS = 67.0564.

B. Subjective tests

In our experiments, the efficiency of the proposed method was tested using two image databases: LIVE database release 2 [H.R. Sheikh et al.] and IVC [P. Le Callet et al.]. The performance is evaluated in terms of correlation between the proposed index (BI) and subjective scores.

1) Database for subjective testing: The LIVE database provides the Difference Mean Opinion Scores (DMOS). The participants in the database were asked to provide their perception of quality on a continuous linear scale divided into five equal regions marked as ”‘Bad”’,”’Poor”’, ”‘Fair”’,”’Good”’and “Excellent”. Each image was rated by around 20 to 30 observers. Each distortion type was evaluated by different subjects in the same viewing conditions. A DMOS value of zero corresponds to a high image quality while a high DMOS value corresponds to a poor image quality. The database used contains different types of degradations. Here, the performance of our method is tested using only the Gaussian blur images. Some images from the database are displayed in Fig. 7.

For the IVC database, the authors describe it as follows: ”Subjective evaluations were made at viewing distance of 6 times the screen height using a DSIS (Double Stimulus Impairment Scale) method with 5 categories and 15 observers”. The IVC database provides the Mean Opinion Scores (MOS) where MOS equal zero corresponds to a poor quality of the image and higher the MOS is, high the quality of the image is. As far as the database used contains different types of degradations. Here, we test the proposed method using only the Gaussian blur images. Fig. 8 presents some reference images of the IVC database.

Fig. 7. Some reference images of the LIVE database

Method	LIVE	IVC
Wavelets [2]	0.722	0.848
BlurM [5]	0.885	0.874
Blur-SSIM [9]	0.64	0.67
BI (proposed method)	0.8674	0.938

Table 1. Correlation results unsig the LIVE and IVC database.

2) Analysis of the results: To test the efficiency of the proposed method, we compare our method with some previously developed techniques [2, 5]. Also, we implement the proposed radial analysis and BI estimation using the original image and its blurred version. For benchmarking purposes, we chose the popular SSIM metric [Z. Wang et al., 2004], named here Blur-SSIM.

Table 1 summarizes the results for the correlation coefficients for both the LIVE and IVC databases. The best correlation is obtained for the proposed method excepted for the LIVE database, the BlurM obtained sensibly a higher correlation than the proposed method. Indeed, the obtained correlation is equal to 0.938 using the IVC database.

To observe the distribution of the BI compared with subjective scores, we plot also the BI versus DMOS of the LIVE database curve in figure 9. Note that scatters of these distributions are smaller.

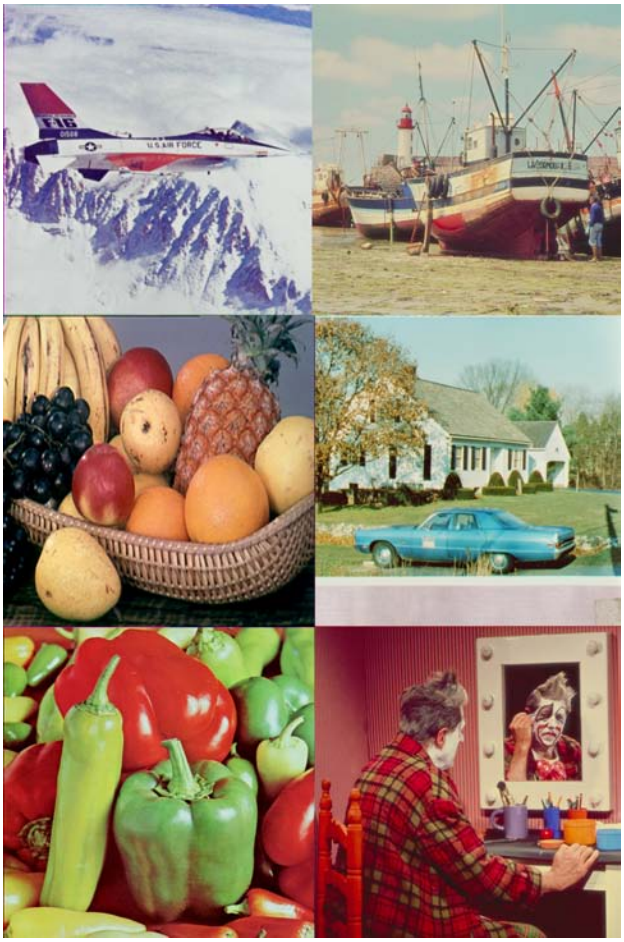

Fig. 8. Some reference images of the IVC database.

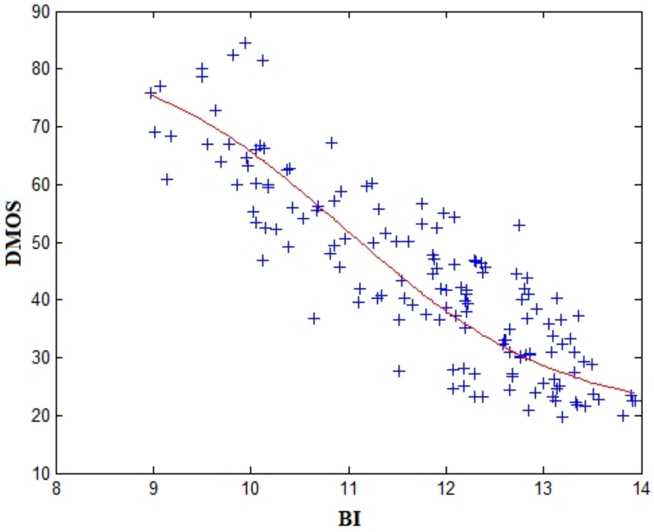

Fig. 9. BI of the proposed method vs DMOS of the LIVE database.

IV. CONCLUSIONS AND PERSPECTIVES

An efficient no-reference blur quality index is proposed. The method is not based on edge detection as most existing methods. Instead, we use a basic radial analysis in the frequency domain to measure the impact of blur added to the original image. The obtained results in terms of correlation with the subjective tests prove the efficiency of the proposed method.

The efficiency of the proposed method could be improved by taking into account some HVS properties as contrast sensibility function.

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