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Image quality assessment based on edge preservation

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ABSTRACT

Objective image/video quality metrics which accurately represent the subjective quality of processed images are of paramount importance for the design and assessment of an image compression and transmission system. In some scenarios, it is also important to evaluate the quality of the received image with minimal reference to the transmitted one. For instance, for closed-loop optimization of a transmission system, the image quality measure can be evaluated at the receiver and provided as feedback information to the system controller. The original image – prior to compression and transmission – is not usually available at the receiver side, and it is important to rely at the receiver side on an objective quality metric that does not need reference or needs minimal reference to the original image. The observation that the human eye is very sensitive to edge and contour information of an image underpins the proposal of our reduced reference (RR) quality metric, which compares edge information between the distorted and the original image. Results highlight that the metric correlates well with subjective observations, also in comparison with commonly used full-reference metrics and with a state-of-the-art reduced reference metric.

1. Introduction

The main target in the design of modern multimedia systems is the provision of a satisfactory quality as perceived by the user. For the measurement and the provision of such quality level, the availability of an objective quality metric well representing the human perception is crucial. Measuring the quality through objective metrics, instead of relying on extensive subjective tests, reduces the costs involved in such testing, enables real-time measurements, and provides objective values which can be easily compared in different set-ups.

Objective quality assessment methods based on subjective measurements are based either on a perceptual model of the Human Visual System [1], or on a combination of relevant parameters tuned with subjective tests [2,3].

It is also important to evaluate the quality of a received image with minimal reference to the transmitted one [4]. For closed loop optimization of video transmission, the quality measure can be provided as feedback information to a system controller [5]. The original image – prior to compression and transmission – is not usually available at the receiver side and it is important to rely at the receiver side on an objective quality metric that does not need reference or needs minimal reference to the original image. Fig. 1 reports a schematic representation of an image/video processing system, consisting of an image/video encoder and/or a transmission network, with the calculation of a reduced reference quality metric. Reference features are extracted from the original image/video sequence and these are then compared with the same features extracted from the impaired images to obtain the RR quality metric.

We propose here a reduced reference image quality metric well correlated with the perceived quality, based

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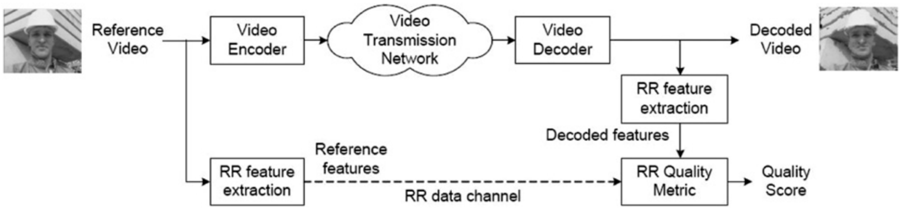

Fig. 1. Reduced reference scheme.

on the comparison of the edge information between the distorted image and the original one. The human eye is in fact very sensitive to the edge and contour information of an image, *i.e.*, the edge and contour information gives a good indication of the structure of an image and it is critical for a human to "capture" the scene [6].

Some works in the literature proposed considering edge structure information. For instance in [1] a parameter is considered to detect a decrease or loss of spatial information (*e.g.*, blurring). This parameter uses a 13 pixel spatial information filter (SI13) to measure edge impairments rather than Sobel filtering. Differently from [1] we consider here the Sobel operator [7] for edge detection, since this is one of the most used methodologies to obtain edge information due to its simplicity and efficiency.

A few reduced-reference metrics have been proposed, with different characteristics in terms of complexity, of correlation with subjective quality and of overhead associated to the transmission of side information. The ITS/NTIA (Institute for Telecommunication Sciences/National Telecommunications and Information Administration) has developed a general Video Quality Model (VQM) [1] that was selected by both ANSI and ITU as a video quality assessment standard based on its performance. This general model requires however a bit-rate of several Mbps (more than 4 Mbps for 30 fps, CIF size video) of quality features for the calculation of the VQM value, which prevents its use as a RR metric in practical systems. The possibility to use spatial–temporal features/regions was considered in [8] in order to provide a trade-off between the correlation with subjective values and the overhead for side-information. Later on a low-rate reduced reference metric based on the full reference metric [9] (10 kbits/s VQM) was developed by the same authors. A subjective data set was used to determine the optimal linear combination of the eight video quality parameters in the metric. The performance of the metric was presented in terms of a scatter plot with respect to subjective data, although numerical performance results are not provided in [9]. The quality index in [4] is based on features associated to wavelet coefficients. Two parameters describe the distribution of the wavelet coefficients of the reference image using a generalized Gaussian density (GGD) model, hence only a relatively small number of RR features are needed for the evaluation of image quality. Other metrics were either developed for specific impairments (*e.g.*, the metric in [10] for the detection of blocking and blurring artifacts) or involved a high computational complexity [11]. Other metrics, such as [12], require a training process for parameter estimation for a number of parameters (five in [12]).

In this paper we propose a low complexity reduced-reference metric based on edge preservation, which can be calculated in real time, performs comparably with the mostly used full reference metrics, and requires a limited overhead for the transmission of side information.

The remainder of this paper is organized as follows. In Section 2 edge detection methodologies are introduced and the proposed reduced reference image quality metric is described, together with the image databases considered for the evaluation of the proposed metric. Results are reported in Section 3. Conclusions about the novelty and the performance of the metric are then reported in Section 4.

2. Materials and methods

2.1. Sobel filtering

There are many methods to perform edge detection, including Canny, LoG (Laplacian of Gaussian), Robert, Prewitt, and Sobel filtering. Canny's edge detection algorithm and LoG are more computationally intensive than Sobel filtering, although under noisy conditions they perform better than Sobel filtering. In our case, the goal is to have real-time computation of the edge mask, hence a low computational complexity is a must. Furthermore, since the goal of filtering is here to assess the quality of a possibly noisy/corrupted image, we prefer an edge detection methodology where the edges are not exactly detected in the presence of noise, but where the presence of relevant artifacts is detected through the missed detection of edges.

The Sobel operator belongs to the class of gradient methods, where edges are detected by finding the maximum and minimum in the first derivative of the image. A pixel location is declared as an edge location if the value of the gradient exceeds a threshold. For 2-D signals (images) the Sobel operator performs a 2-D spatial gradient measurement. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3×3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). The mask is then slid over the image, manipulating a square block of pixels at a time. This is equivalent to calculating partial derivatives in 3×3 neighborhood.

The partial derivatives in x and y directions are given as

$$S_x = f(x+1,y-1)+2f(x+1,y)+f(x+1,y+1) \\ -[f(x-1,y-1)+2f(x-1,y)+f(x-1,y+1)] \quad (1)$$

and

$$S_y = f(x-1,y+1)+2f(x,y+1)+f(x+1,y+1) \\ -[f(x-1,y-1)+2f(x,y-1)+f(x+1,y-1)] \quad (2)$$

The gradient of each pixel is calculated according to $g(x,y)=\sqrt{S_x^2+S_y^2}$ and a threshold value t is selected. If $g(x,y)>t$, this point is regarded as an edge point.

2.2. Proposed metric

Since the structural distortion of an image is tightly linked with its edge degradation, we propose a reduced reference (RR) quality metric which compares edge information between the distorted image and the original one. We propose to apply Sobel filtering locally, only for some blocks of the entire image, after subsampling the images.

We propose to divide images into sub-windows, as shown in Fig. 2. For instance, if images have size 512×768, after subsampling of a factor of two, we could consider 16×16 macroblocks of size 16×24 pixels each, or, after subsampling of a factor 1.5, we could consider 18×16 macroblocks with size 19×32 pixels each. The example in Fig. 2 reports the second option. The block size is chosen such that it is sufficiently large to account for vertical and/or horizontal activities within each block, but small enough to reduce complexity and the size of side information. In addition, sub-windows are non-coincident with macroblocks, to enable a better detection of DCT artifacts in the case of DCT compressed images and video.

In order to reduce the overhead associated with the transmission of side information, only 12 blocks are selected to represent the different areas of the images. The block pattern utilized for our tests is chosen after several investigations based on visual attention (VA). Various experiments have been proposed in the literature for VA modeling. For instance in [13] a framework is proposed in order to extend existing image quality metrics with a simple VA model. It was observed that the ROI's center coordinates are around the image center for most of the images, and the mean of the ROI dimensions are very similar in both x and y directions. This confirms that the salient region is often placed in the center of the picture.

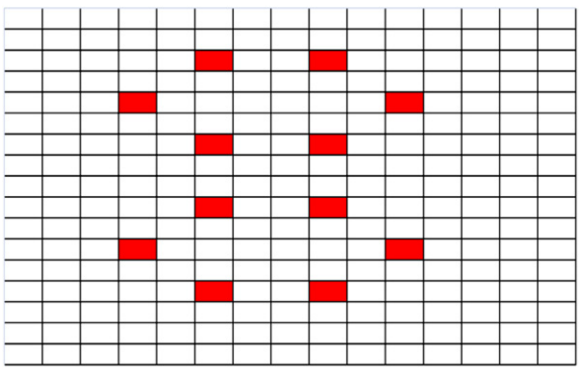

Fig. 2. Example of block pattern selected based on visual attention models.

Following these guidelines we have chosen the block pattern as a subset of the ROI with a central symmetry, minimizing the number of blocks to reduce the overhead associated to the transmission of side information. Fig. 2 shows an example of block pattern.

For the assessment of the quality of the corrupted image, the edge structure of the blocks of the corrupted image should be compared to the structure of the correspondent blocks in the original image. For the identification of edges we use Sobel filtering, which is applied locally in these selected blocks.

For each pixel in each block we obtain a bit value, where one represents an edge and zero means that there are no edges. If m and n are the block dimensions, we denote the corresponding blocks l in the original and the possibly corrupted image as the $m\times n$ matrices O_l and C_l respectively, and the Sobel-filtered version of blocks l as the $m\times n$ binary matrices $SO_l=\mathcal{S}(O_l)$, with elements $so_{i,j}$, with $i=1,\dots,m, j=1,\dots,n$, and $SC_l=\mathcal{S}(C_l)$, with elements $sc_{i,j}$, with $i=1,\dots,m$, $j=1,\dots,n$. We denoted above with $\mathcal{S}()$ the Sobel operator. The similarity of two images can be assessed based on the similarity of the edge structures, *i.e.*, by comparing the matrices SO_l associated to the filtered version of the block in the original image, and SC_l associated to the filtered version of the block in the possibly corrupted image.

We propose here to measure the "displacement" of the edges. We define hence two threshold values, θ_1 and θ_2, where θ_1 and θ_2 represent two different distance values (in pixels) between original and displaced edges, for instance $\theta_1=2$ pixels and $\theta_2=5$ pixels; we define Δ_{θ_1} as the number of edge pixels with a displacement after processing lower than θ_1 and $\Delta_{\theta_1,\theta_2}$ the number of edge pixels with a displacement after processing θ, such that $\theta_1\leqslant\theta\leqslant\theta_2$. In the quality assessment metric we consider all the edges displaced less than θ_2 pixels through the following weighted sum:

$$\Delta = w_1\Delta_{\theta_1}+w_2\Delta_{\theta_1,\theta_2} \quad (3)$$

The weights w_1 and w_2 and the thresholds θ_1 and θ_1 can be determined experimentally.

Hence, for each block l of image s the metric can be computed as

$$I_{s,l} = \Delta_l/p_l \quad (4)$$

where Δ_l is the weighted sum in (3) calculated for the l-th block and $p_l=m\times n$ is the total number of pixels in the l-th block.

If N_b is the number of blocks in the selected block pattern, the similarity index I_s for image s is finally defined here as

$$I_s = \frac{1}{N_b}\sum_{l=1}^{N_b} I_{s,l} \quad (5)$$

For instance, for the pattern considered below, $N_b=12$. The lower the N_b, the lower the overhead associated to the transmission of side information. We have observed – results are not reported here for brevity – that by selecting only some blocks in the image slightly reduces the performance with respect to the corresponding metric obtained with all the blocks, although the difference is not remarkable if the blocks are selected appropriately (*e.g.*, according to visual attention studies, as in this work).

2.2.1. Threshold selection

The threshold value is an important parameter that depends on a number of factors, such as image brightness, contrast, level of noise, and even edge direction. The selection of the threshold in Sobel filtering is associated to the sensitivity of the filter to edges. In particular, the lower the value of the threshold, the higher the sensitivity to edges. Too high values of the threshold do not detect edges which are important for quality assessment. On the other side, if the value of the threshold is too small, large parts of the image are considered as edges, whereas these are irrelevant for quality assessment. The threshold can be selected following an analysis of the gradient image histogram. Based on this consideration and on the analysis of Sobel filtering performance for the images of the considered databases, the selected threshold value is $t=0.001$.

2.2.2. Parameters selection

According to a number of tests performed on the different image databases, we have found that appropriate values for the metric parameters are $\theta_1=2$ pixels, $\theta_2=5$ pixels, $w_1=0.6$ and $w_2=0.4$. These are the values we consider in the following for the performance evaluation of the metric.

2.2.3. Complexity

The selection of Sobel filtering results in a low complexity metric. The Sobel algorithm is characterized, in fact, by a low computational complexity and consequently high calculation speed. In [14] some edge detection techniques are compared for an application which uses a DSP implementation: the Sobel filter exhibits the best performance in terms of edge detection time in comparison with the other wavelet-based edge detectors. Sobel filtering has been implemented in hardware and used in different areas, often when real-time performance is required, such as for real-time volume rendering systems, and video assisted transportation systems [15,16]. This makes the proposed metric suitable for real-time implementation, an important aspect when an image/video metric is used for the purpose of "on the fly" system adaptation as in the scenario considered here.

2.2.4. Overhead

In order to perform the proposed edge comparison, we should transmit the matrices composed of one's and zeros's in the reference blocks. By considering the pattern in Fig. 2, this would result for images of resolution 512 $\times$ 768 in the transmission of 19 $\times$ 32 $\times$ 12 $=$ 7.29 kbits per image. Note that the size of the original image (not compressed) is 3 $\times$ 512 $\times$ 768 $\times$ 8 $=$ 9.4 Mbits.

In the worst case (side information not compressed) our metric reduces thus the needed reference with respect to FR metrics of a factor 1290:1. As a comparison, the RR metric in [10] reduces it of a factor 1024:1 and the metric in [17] of 64:1.

Since side information is in our case composed of a large number of zeros appearing in long runs, it is possible to further reduce the overhead by compressing the relevant data, *e.g.*, through run-length encoding, or to transmit only the positions of ones in the matrix.

2.3. Image databases considered for the performance evaluation

In order to test the performance of our quality assessment algorithm, we considered publicly available databases.

The first one is provided by the Laboratory for Image & Video Engineering (LIVE) of the University of Texas Austin (in collaboration with The Department of Psychology at the same University). An extensive experiment was conducted to obtain scores from human subjects for a number of images distorted with different distortion types. The database contains 29 high-resolution (typically 768 $\times$ 512) original images (see Fig. 3), altered with five

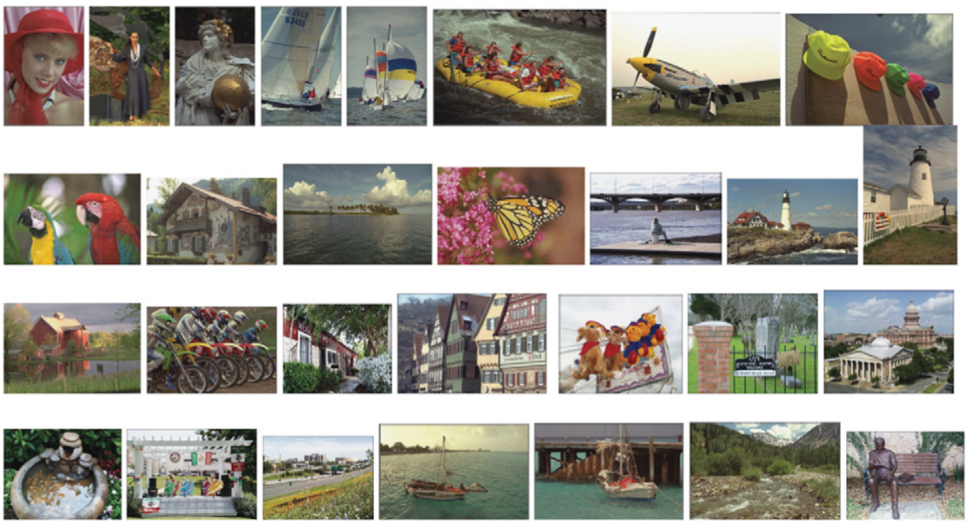

Fig. 3. Images in the LIVE [19] database.

types of distortions at different distortion levels: besides the original images, images corrupted with JPEG2000 and JPEG compression, white-noise, Gaussian blur and JPEG2000 compression and subsequent transmission over a fast fading (FF) Rayleigh channel are considered. The latter set of images is in particular interesting since it enables to assess the quality of images impaired by both compression and transmission errors. No viewing distance restrictions were imposed, display device configurations were identical and ambient illumination levels were normal indoor illumination. A short training preceded the session. Subjective results reported in the database were obtained with observers providing their quality score on a continuous linear scale that was divided into five equal regions marked with adjectives Bad, Poor, Fair, Good and Excellent. Two test sessions, with about half of the images in each session, were performed. Each image was rated by 20–25 subjects. No viewing distance restrictions were imposed, and normal indoor illumination conditions were provided. The observers received a short training before the session. The raw scores were converted into difference scores (between the test and the reference) and then converted to Z-scores [18], scaled back to 1–100 range, and finally a difference mean opinion score (DMOS) for each distorted image was obtained.

The second database, IRCCyN/IVC [20], was developed by the *Institut de Recherche en Communications et Cybernétique de Nantes*. It is a 512 $\times$ 512 pixels color images database. This database is composed of 10 original images and 235 distorted images generated by four different processing methods/impairments (JPEG, JPEG2000, LAR coding and blurring). Subjective evaluations were made at a viewing distance of 6 times the screen height, by using a Double Stimulus Impairment Scale (DSIS) method with five categories and 15 observers. During the subjective tests, observers were asked to assess the quality of the images which were presented under normalized conditions on a CRT Standard Definition TV monitor (with background luminance of 10.5 cd/m^2). The subjective quality scores were selected from an impairment scale with values ranging from 1 to 5 (1="very annoying", 2="annoying", 3="slightly annoying", 4="perceptible but not annoying", 5="not perceptible"). The images in the database are reported in Fig. 4.

The third database considered is the Toyama subjective database [21], that contains 182 images of 768 $\times$ 512 pixels, where 14 are original images (24 bit/pixel RGB). The rest of the images are JPEG and JPEG2000 coded images (84 compressed images for each type of distortion). Six quality scales and six compression ratios were respectively selected for the JPEG and JPEG2000 encoders. The subjective scores were collected using a calibrated CRT monitor in fixed viewing conditions. The subjective ratings were collected using a single stimulus absolute scaling. The overall ratings are presented in the form of MOS. The images in the database are reported in Fig. 5.

Fig. 4. Images in the IRCCyN/IVC [20] database.

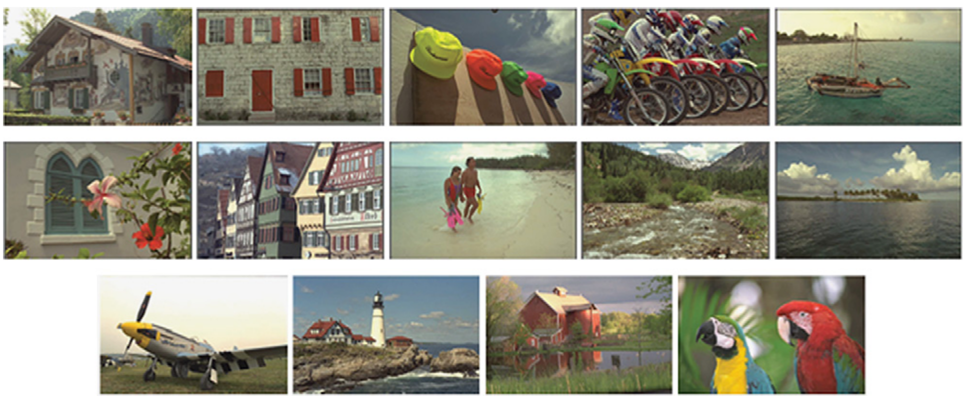

Fig. 5. Images from the Toyama database [21].

3. Results

With the aid of the databases above, we compare the performance versus subjective tests of our metric with respect to the most popular full reference metrics and to the reduced reference metrics with the best performance and whose results are directly comparable or reproducible.

Namely, we consider:

- MSSIM [2] (full reference);
- peak signal-to-noise ratio (PSNR) (full reference);
- [4] (reduced reference);
- [11] (reduced reference);
- proposed Sobel-based metric (reduced reference).

To apply the MSSIM metric, the images have been modified according to [22].

Example results for the Toyama database are reported in Figs. 6–11. In the scatter plots the objective quality metric is reported in the horizontal axis, whereas MOS/DMOS values are reported in the vertical axis. Each symbol in the plot refers to a different image in the database. In particular, Fig. 6 reports the scatter plot for the proposed reduced-reference metric for the JPEG2000 images and Fig. 7 reports the scatter plot for the MSSIM metric (full reference) for the JPEG2000 images. Figs. 8–11 report the scatter plots for the JPEG images in the database. In particular Fig. 8 refers to the proposed RR metric, Fig. 9 refers to the RR metric in [4], Fig. 10 refers to the MSSIM and Fig. 11 refer to the PSNR metric. We can observe that for JPEG compression our metric results in a scatter plot whose values are less dispersed not only with respect to the RR metric considered as a benchmark, but also with respect to the full reference SSIM and PSNR metrics.

Table 1 reports a summary of the results for the LIVE image database in terms of correlation coefficient, to enable an easy comparison with other metrics. We can

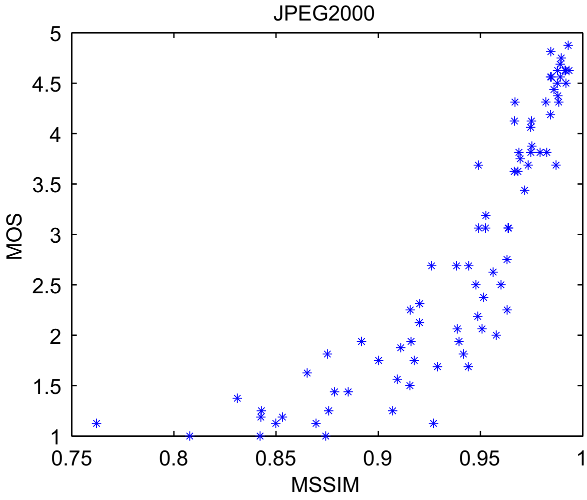

Fig. 7. JPEG 2000 compression, Toyama image database [21]—SSIM.

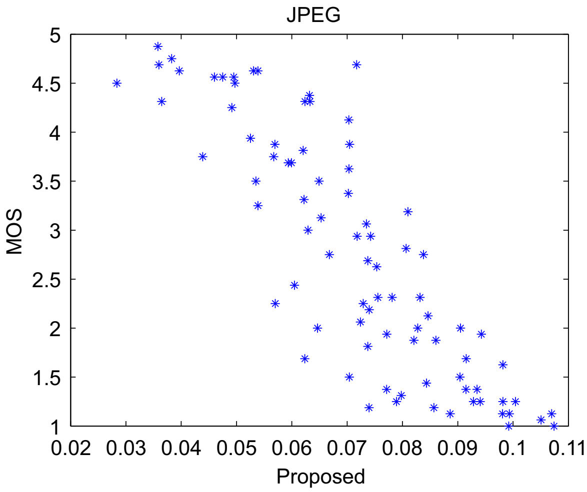

Fig. 8. JPEG compression—Toyama image database [21], Proposed metric.

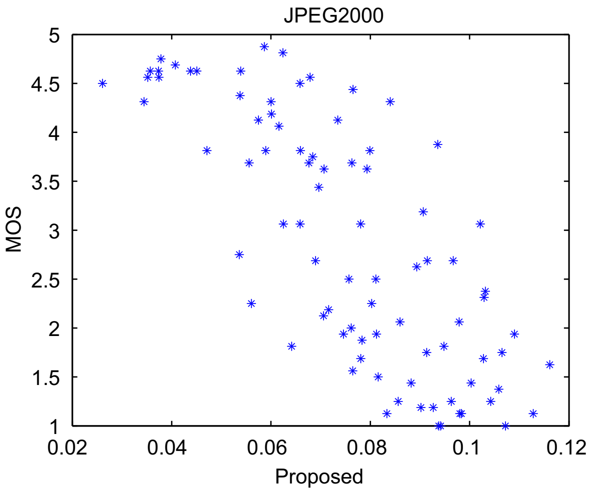

Fig. 6. JPEG 2000 compression, Toyama image database [21]—proposed metric.

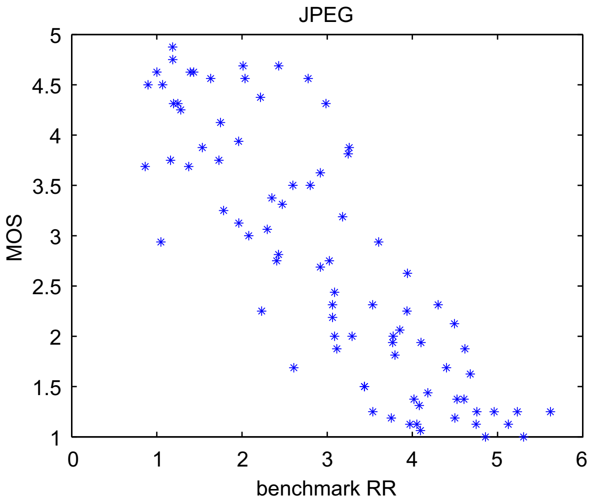

Fig. 9. JPEG compression—Toyama image database [21], Benchmark RR metric [4].

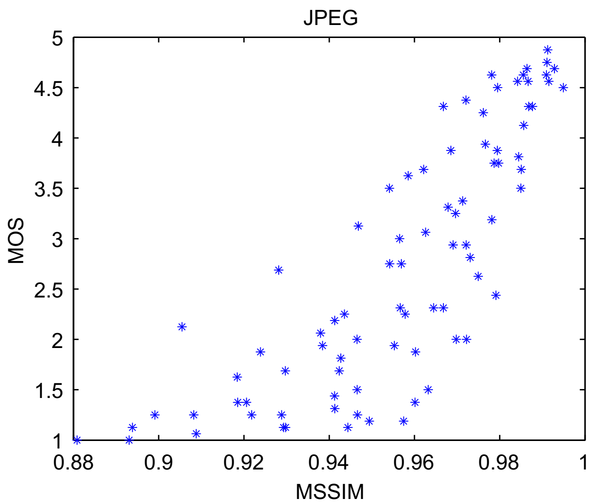

Fig. 10. JPEG compression – Toyama image database [21] – SSIM.

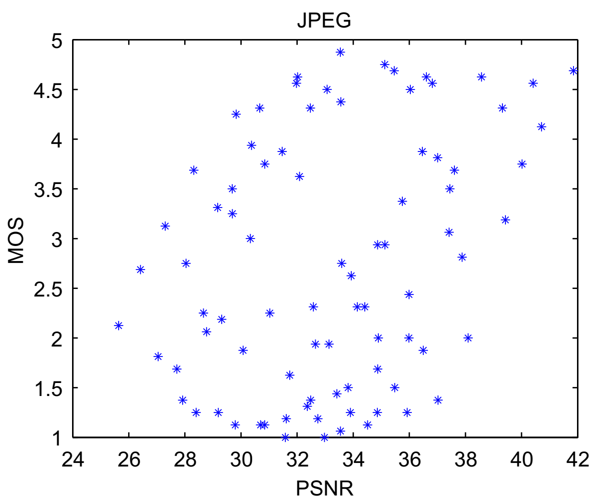

Fig. 11. JPEG compression – Toyama image database [21] – PSNR.

observe that our metric well correlates with subjective tests, with results comparable to those achieved by full reference metrics. For the images in the LIVE database our metric outperforms the considered state-of-the-art reduced reference metric except for the case of JPEG2000 where the benchmark reduced reference metric [4], based on the wavelet transform, provides a better performance in terms of norm of residuals. For the same type of impairment (JPEG2000 compression) our metric performs slightly worse than the benchmark one also when the images in the IRCCyN/IVC database [20] are considered, but it presents an evident improvement in the case of JPEG2000 compression. We should not neglect that the metric [4] relies on the Wavelet transform, as well as the JPEG2000 compression scheme. Table 2 reports the results for the IVC image database in terms of correlation coefficient. We observe that our metric outperforms both the RR metric in [4] and the full-reference metric PSNR for JPEG compression, but not for JPEG2000. We reported for completeness the results in terms of correlation coefficient for the metric [11]. This metric has very high correlation with subjective results; it is however too complex when real time implementation is required. Finally, Table 3 reports the results for the Toyama image database in terms of correlation coefficient. We can observe that the results in terms of correlation coefficient confirm what observed based on the scatter plots.

4. Conclusion

We proposed in this paper a perceptual reduced reference image and video quality metric which compares edge information between portions of the distorted image and the original one by using Sobel filtering. The algorithms is simple and has a low computational complexity. Results highlight that the proposed metric well correlates with subjective observations, also in comparison with commonly used full-reference metrics and with state-of-the-art reduced-reference metrics.

Table 1
Correlation coefficient versus DMOS, LIVE image database [19].

Image impairment	PSNR	RR [4]	Proposed RR	MSSIM
Fast fading	0.8556	0.9175	0.9418	0.9439 [4]
White noise	0.981	0.8889	0.9573	0.9706 [4]
Gaussian blur	0.79491	0.8872	0.9627	0.9361 [4]
JPEG comp.	0.8245	0.8927	0.9529	0.958 [11]
JPEG2000 comp.	0.8703	0.9663	0.9536	0.942 [11]

Table 2
Correlation coefficient versus MOS, IRCCyN/IVC image database [20].

Image impairment	PSNR	RR [4]	Proposed RR	MSSIM	C4 [23,11]
JPEG compression	0.5957	0.4644	0.66	0.8897	0.92
JPEG2000 compression	0.8143	0.8043	0.72	0.8149	0.925

Table 3
Correlation coefficient versus MOS, Toyama image database [21].

Image impairment	PSNR	Reduced reference [4]	Proposed RR	MSSIM	C4 [23,11]
JPEG compression	0.61	0.8486	0.8502	0.8141	0.887
JPEG2000 compression	0.82	0.9108	0.7629	0.8581	0.934

Acknowledgements

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