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Image Quality Assessment based on Perceptual Blur Metric

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ABSTRACT

The recent development of digital image acquisition technologies leads to better image quality, in terms of spatial resolution and sensitivity. Image quality is a characteristic of an image that measures the perceived image degradation. Several techniques and metrics are proposed which can be classified as Full-Reference (FR) method, No-Reference (NR) method and Reduced Reference (RR) method. In this field of image quality assessment, it is crucial to deep research the physiology and psychology of human visual system. However, it is obvious that strong correlation between the results and human visual perception is essential. In this paper, we propose a new approach for image quality assessment that combines the perceptual blur metric and the index of Structural Similarity (SSIM) in order to improve the image quality quantification.

Keywords : Image Quality, Image Assessment, Human Visual System, Structural Similarity, Blur perception

1. INTRODUCTION

Visual images are the most important and data intensive means for humans to acquire information, digital image acquisition, communication, storage processing, and display devices have become ubiquitous in daily life. Since digital images are subject to a wide variety of distortions in any of these, and since image traffic has become quite dense, the assessment of digital image quality has become an exceedingly important topic. In fact, the lack of information caused by the processing is results in an alteration of the original image, it is necessary to evaluate the loss of image quality by comparing the distorted image to the original one. The first approach involves using human observers to assess image quality. However, this method has several drawbacks. First, it uses the subjectivity of human beings which assess the image quality in different ways. In addition, it provides a qualitative result, as we would like to have a quantitative result. Finally, this subjective assessment is tedious and is difficult to apply when the number of images to be treated is important.

Therefore, objective methods for image quality assessment have been proposed. These metrics should provide quality scores consistent with human judgment which requires the integration of the main properties of the Human Visual System (HVS). The objective assessment of image quality or video is based on many criteria for determining an objective quality score. These criteria are classified into three categories according to the information necessary for the assessment: Full Reference (FR) [4][5], Reduced Reference (RR) [16][17] and No Reference (NR) [2][13]. The FR methods require the disposal of the reference image and the degraded version to assess. These approaches are used in introducing degradation systems, like systems of loss compression which aims to estimate the amount of distortion caused by the compression and quality of the resulting image. Generally, these approaches are based on modeling the Human Visual System (HVS) which they incorporate one or more properties of this model. The RR methods provide a measure of quality with only a small set of features measured on the reference. However, the use of a limited amount of information to develop a final quality score is much harder than full reference methods. They are used in a transmission where it is impossible to transmit all information related to both versions of the image; the reduced reference is then encoded and transmitted with the reference version to judge the quality. The NR methods assess the quality of an image without referring to the reference image. These methods were the most difficult to develop since they are based on claims that the image should be. These approaches are popular because they do not require the transmission of the reference version to evaluate the quality of the transmitted image.

This paper is organized as follows: In the next section, we briefly review some related works in the image quality assessment metrics. In section 3, we present the blur detection using discrete wavelet transform. The proposed method is presented in section 4. Experimental results are presented in section 5. Finally conclusion is given is section 6.

2. RELATED WORKS

In this section we briefly present some related works in the image quality assessment metrics; which are divided into two main classes as shown the Figure 1.

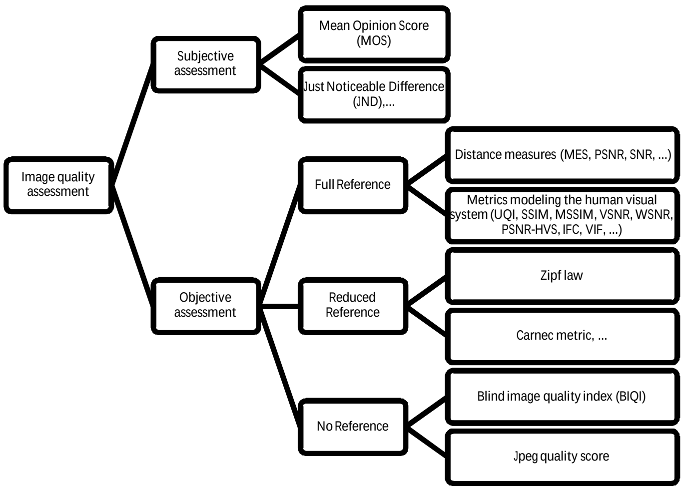

Figure 1: Image quality measures

The objective measure most commonly used is that of Index of Structural Similarity (SSIM) [19]. This metric is an enhanced version of UQI [18]. The index UQI is easy to implement and can be applied to different types of images. It measures the uncorrelation between the reference image and the distorted image, as well as the degradation of the luminance component and the contrast between the two versions of the image. This criterion is then determined by the product of these three measures for comparing the luminance $l(x, y)$, the contrast $c(x, y)$ and structure $s(x, y)$ between two signals x and y.

$$l(x,y) = \frac{2\mu_x\mu_y}{\mu^2+\mu^2},\ c(x,y) = \frac{2\sigma_x\sigma_y}{\sigma_x^2+\sigma_y^2}, \quad (1)$$
$$s(x,y) = \frac{cov_{xy}}{\sigma_x\sigma_y}$$

Where μ_x means the average of x, μ_y average of y, σ_x^2 the variance of x, σ_y^2 variance of y and cov_{xy} the covariance between x and y.
SSIM is obtained in case where $\mu_x^2 + \mu_y^2$ or $\sigma_x^2 + \sigma_y^2$ have values close to zero. The formula is then given by:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2cov_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (2)$$

where$c_1 = (k_1L)^2, c_2 = (k_2L)^2, with\ L$ refers to the dynamic values of the pixels, or 255 for images coded on 8 bits, by default $k_1 = 0.01$ and $k_2 = 0.03$.

Among the most recent objective measures incorporating the human visual system is the Visual Information Fidelity (VIF). The VIF metric [9] is the result of an improvement in the Information Fidelity Criterion [10] which is to integrate a normalization step. This metric is obtained by the relation:

$$VIF = \frac{\sum_j I(\vec{C}^{N,j};\vec{F}^{N,j} \backslash s^{N,j})}{\sum_j I(\vec{C}^{N,j};\vec{E}^{N,j} \backslash s^{N,j})} \quad (3)$$

where $I(\vec{C}^{N,j};\vec{F}^{N,j} \backslash s^{N,j})$ and $I(\vec{C}^{N,j};\vec{E}^{N,j} \backslash s^{N,j})$ refer to the information extracted from the original image and its degraded version from the sub-band *j*.

Other objective measure that integrates the SVH is that of Visual Signal to Noise Rate (VSNR) [6]. The VSNR metric is a quality measure based on analysis of wavelet coefficients; it is divided into two steps. The first is to ensure that degradation is well above the threshold of visibility before measuring. This check is performed in each sub-band of wavelet decomposition. The second step is to evaluate the perception of degradation above the threshold of visibility.
VSNR is determined by:

$$VSNR = 10log\left(\frac{C^2(x)}{DP^2}\right) \quad (4)$$

Where C(x) denotes the average contrast of the reference image and DP is the perceptual distortion. This metric does not include color management or the spatial location of damage. However, measurements of distances and structural approaches are still consistent with the trial staff giving birth metrics based on the integration of the properties of HVS. Moreover, global quality measures have been defined recently such as the Neural Fusion Approach [1]. It's is a new metric with full reference based on the fusion of several conventional metrics with full reference using the learning algorithm artificial neural networks. The fusion brings performance more important than using individual metrics. Indeed, the existing metrics with full reference do not always produce excellent results for all types of degradation. To confront this limitation, it is appropriate to use a process of ranking and then use an artificial neural network. It is to combine the best performing metrics in a single metric called Index of Global Quality. The image database used TID 2008 shows that this Index provides assessment image quality results consistent with the subjective assessment.

3. PERCEPTUAL BLUR DETECTION

A blur detection scheme is proposed using Haar wavelet transform [11][14]. It may not only judge whether or not a particular image is blurred but also to identify how the data image is blurred which is based on edge sharpness analysis. The proposed scheme benefits from the ability of Haar wavelet transform in both discriminating various types of edges and sharp recovery of the blurred version. In fact, Wavelet transform is well known for its ability to analyze multiple resolutions. Based on an important fact that the local maxima of a wavelet transform to detect the localization of irregular structures is proved [2][12].

LL3	HL3	HL2	HL1: Horizontal Detail (level1)
LH3	HH3		
LH2		HH2	
LH1: Vertical Detail			HH1: Diagonal Detail (level1)

Figure 2: Haar wavelet decomposition at level 3

The procedure to be followed to detect edge using Haar wavelet transforms [8][15] starts by a Haar wavelet decomposition level 3 of the distorted image (Figure 2). Afterwards, it comes to build the edge map for each level by the following formula:

$$E_{map_i}=\sqrt{LH_i^2 + HL_i^2 + HH_i^2}; i = 1,2,3 \qquad (5)$$

The next stage consists in partitioning the edge maps and determines the local maximum for each window. For the highest level, the window size is 2x2. The low level is 4x4 and the lowest is 8x8. Eventually, for each edge map, the edges blurred must be determined. The Haar wavelet transform has the benefit to recover the thin edges blurred which leads to determine the number of edge blurred and so to extent the blur amount. The Haar wavelet transform ducts to different rules applied to detect the blur in the image presented. For each edge point, for a given threshold, it is to identify both of edges points which are more likely to be in the blurred image and edge points that lost their intense.

In fact, if $Emax_1(k,l)$>threshold or $Emax_2(k,l)$>threshold or $Emax_3(k,l)$>threshold then (k,l) is an edge point where $Emax_i$ is the local maximum for the level i. For each edge point, it comes to identify the type of edge. Most natural image contains all types of edges: Dirac-structure, Roof-structure and step-structure which is divided into Astep-structure and Gstep-structure.

For each edge point (k,l):

- ✓ if $Emax_1(k,l)>Emax_2(k,l)>Emax_3(k,l)$ then (k,l) is a Dirac-structure or Gstep-structure,
- ✓ if $Emax_1(k,l)<Emax_2(k,l)<Emax_3(k,l)$ then (k,l) is a Roof-structure or Gstep-structure,
- ✓ if $Emax_2(k,l)>Emax_1(k,l)$ and $Emax_2(k,l)>Emax_3(k,l)$ then (k,l) is Roof-structure.

For each edge point (k,l) Gstep-structure or Roof-structure, if $Emax_1(k,l)$<threshold then (k,l) is more likely to be in a blurred image.

Based on these Haar wavelet rules, an image is judged as blurred if the ratio between Dirac-Structure and Roof-Structure is superior of 0.05. Once there is presence of blur, it consists then to determinate the blur amount existing in the distorted image by calculating the ration between the numbers of edges blurred Gstep-Structure and Roof-Structure.

4. PROPOSED APPROACH

The proposed method as shown in Figure 3, is to merge the quality score obtained by the index of structural similarity with the blur amount measured in order to obtain a quality measure that takes account the perception of blur. The most important assumption is that the human eye is typically suitable for the extraction of structural information of an image. It is then necessary to measure the degradation of this structural information. The idea is to extract local structural attributes of the image from which each block is described by its brightness, contrast and structure.

We start the image quality assessment by using SSIM without introducing the blur factor. The results provided by SSIM are then compared to those delivered over the new metric proposed. The purpose is to develop a tool to improve the quantification of image quality. To achieve this aim, we exploit the objective methods based on measuring perceptual quality of an image. These methods consist in measuring the error between a visibility degraded image and a reference image using a variety of known properties of the visual system Human (HVS). By exploiting the concept of HSV to which the human visual is highly suitable for extract the structural information of an image. We have exploited this concept in quality assessment image. This is reflected in the measurement of structural information as an index structural similarity 'SSIM'. However, SSIM doesn't take account of the blur detection factor and to its extent [4].

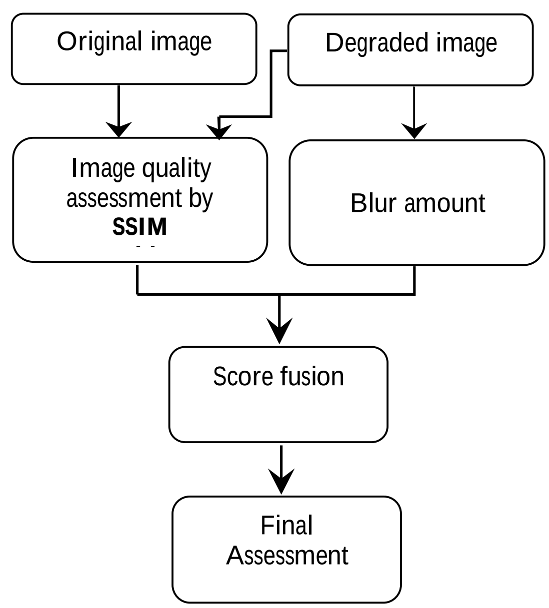

Figure 3: Flow chart of the Proposed Approach

5. EXPERIMENTAL RESULTS

We choose for our experimental results the CSIQ database [7]. It consists of 30 original images; each is distorted using six different types of distortions at four to five different levels of distortion. CSIQ images are subjectively rated base on a linear displacement of the images across four calibrated LCD monitors placed side by side with equal viewing distance to the observer. Each original image in the database is distorted using six different types of distortions at four to five different levels of distortion. The distortions used in CSIQ are: JPEG compression, JPEG-2000 compression, global contrast decrements, additive pink Gaussian noise, and Gaussian blurring the purpose of our research. In our experiments, we used a few set original images presented by the Figure 4.

Figure 4: The original images of CSIQ data base

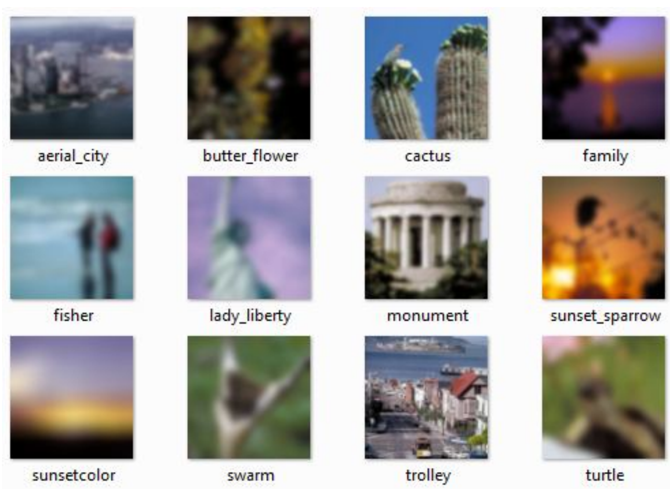

Figure 5: Blur images

The Figure 6 shows the mean of SSIM values versus blur standard deviation of a set of blurred images (Figure 5).
For each blur image, it comes to determinate the score of SSIM for a number of iteration well defined.

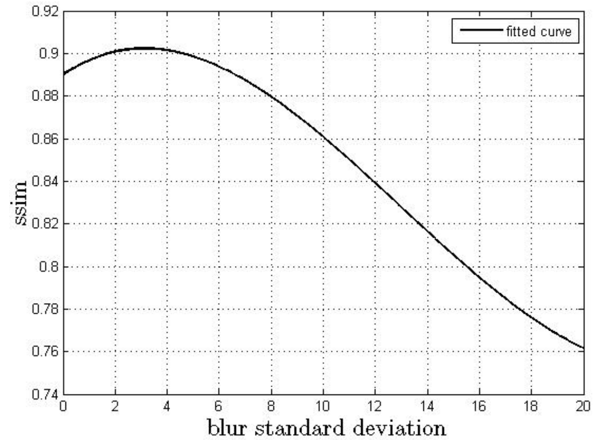

Figure 6: Mean of SSIM

The mean of SSIM values is represented by a decreasing curve (Figure 6), a rise in the value of blur standard deviation resulted in a decline in score of SSIM.
The fitted curve is a cubic polynomial:

$$ssim(x) = p1 * x\text{^}3 + p2 * x\text{^}2 + p3 * x + p4 \qquad (6)$$

where the coefficient of the polynomial (with 95% confidence bounds):
$p_1 = 3.89e-005$; $p_2 = -0.001516$; $p_3 = 0.008339$; $p_4 = 0.8899$.

According to results, SSIM is less sensitive to the change of blur amount in an image. So, it becomes vital to determinate the blur extent of an image. The Figure 7 presents the mean of blur amount already calculated for all degraded images.

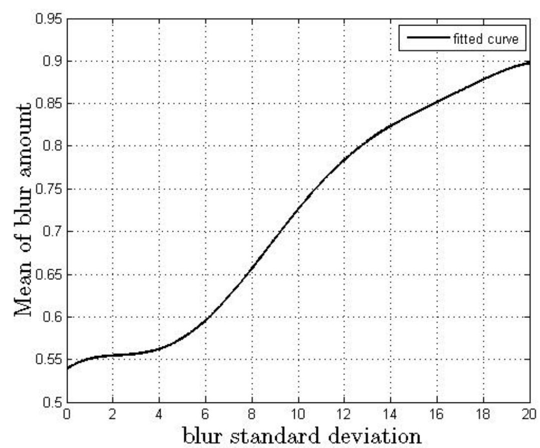

Figure 7: Mean of blur amount

The fitted curve of Blur amount is determined by the following formula:

$$blur(x) = a1 * sin(b1 * x + c1) + a2 * sin(b2 * x + c2) + a3 * sin(b3 * x + c3) \qquad (7)$$

Where the coefficients are determined with 99% confidence bounds:

$$a1 = 1.388\,;\ b1 = 0.129\,;\ c1 = 0.04447\ ;$$
$$a2 = 0.7787;\ b2 = 0.2232\,;\ c2 = 2.307;$$
$$a3 = 0.1553;\ b3 = 0.3624;\ c3 = 3.842$$

It should then apply the proposed formula to get the final score of a blur image:

$$\textbf{SSIM\_blur = SSIM\_Score-(Blur Extent*}\alpha\textbf{)} \qquad (8)$$

where α=10. If BlurExtent=0, the image is judged unblurred and the quality measure takes the value of SSIM score.

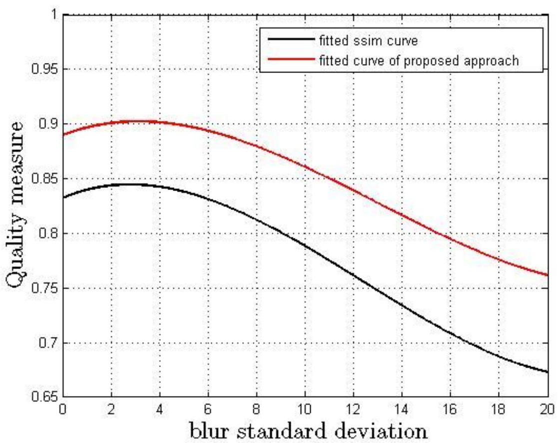

Figure 8: Mean of SSIM_blur

The proposed approach is presented by the figure below (Figure 8); this is a downward curve. An increase in the value of the blur standard deviation leads to a lower score of the proposed quality measure. According to experiments, the scores provided by the proposed approach are more declined than SSIM; which reflects its effectiveness in assessing quality of blurred images. The fitted curve of the proposed approach is a cubic polynomial which is determined by the following formula:

$$ssim_{blur}(x) = p1 * x\text{^}3 + p2 * x\text{^}2 + p3 * x + p4 \qquad (9)$$

where the coefficients are determined with 99% confidence bounds:

$$p1 = 5.048e - 005\,;\ p2 = -0.001869;$$
$$p3 = \ 0.009232;\ p4 = 0.8323$$

As it shown the results, the integration of the blur factor in measuring the structural metric SSIM improves scores obtained for the assessment measure of image quality and provides satisfactory and relevant results that are consistent with the human eye.

6. CONCLUSION

In this paper, a new approach for image quality assessment has been proposed based on blur estimation. Experimental results indicate that our metric significantly exceeds the performance of the SSIM and provided results also correlate with the human visual system. These results are encouraging as an approach to conception of a metric of image quality taking into account the perception of blur. They confirm the relevance of the develop approach by incorporating a model to aim psycho visual the aspect in this calculation.

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