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Assessment Of Image Quality Using Gradient Similarity Approach

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***ABSTRACT*- The objective of image quality assessment (IQA) is to provide computational models to measure the perceptual quality of an image. Here we deal with a new image quality assessment (IQA) scheme, with emphasis on gradient similarity . Image intensities carry a great deal more information about three-dimensional shape. Gradients convey important visual information and are very important to scene understanding. Using such information, structural and contrast changes can be effectively captured. Therefore, we use the gradient similarity to measure the change in contrast and structure in images. Apart from the structural/contrast changes, image quality is also affected by luminance changes, which must be also accounted for complete and more robust IQA. Hence, the proposed scheme considers both luminance and contrast–structural changes to effectively assess image quality. Finally, the effects of the changes in luminance and contrast–structure are integrated via an adaptive method to obtain the overall image quality score.**

I. Introduction

Image quality assessment plays an important role in image processing systems. Existing image quality evaluation methods can be divided into two categories: Subjective evaluation and objective evaluation. The HVS is our terminal of image processing systems, thus the most correct Method of quantifying image quality is through subjective evaluation. In practice, however, subjective evaluation needs to organize the observers to mark the distorted images, which is too inconvenient, time-consuming and expensive. PSNR and MSE are still the most widely used objective metrics due to their low complexity and clear physical meaning. However they were also widely criticized for not correlating well with HVS for a long time. During the last several decades, many researchers have tried to find a mathematic model to simulate HVS characteristics, and a great deal of effort has been made to develop new image quality assessment methods based on HVS.Digital images are usually affected by a wide variety of distortions during acquisition and processing, which generally results in loss of visual quality. Therefore, image quality assessment (IQA) is useful in many applications such as image acquisition, watermarking, compression, transmission, restoration, enhancement, and reproduction. The goal of IQA is to calculate the extent of quality degradation and is thus used to evaluate/ compare the performance of processing systems and/or optimize the choice of parameters in processing. For example, the well-cited structural similarity (SSIM) index [1] has been used in image and video coding. The human visual system (HVS) is the ultimate receiver of the majority of processed images, and evaluation based on subjective experiments is the most reliable way of IQA. However, subjective evaluation is time consuming, laborious, expensive, and non-repeatable; as a result, it cannot be easily and routinely performed for many scenarios. These limitations have led to the development of objective IQA measures that can be easily embedded in image processing systems. The simplest and most widely used IQA scheme is the mean squared error (MSE)/peak signal-to-noise ratio (PSNR) (which is calculated using MSE). Peak Signal-to-Noise Ratio is the ratio between the reference signal and the distortion signal in an image, given in decibels. The higher the PSNR, the closer the distorted image is to the original. In general, a higher PSNR value should correlate to a higher quality image, but tests have shown that this isn't always the case. However, PSNR is a popular quality metric because it's easy and fast to calculate while still giving okay results. The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codec's (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codec it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric;it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content. It is popular due to its mathematical simplicity and it being easy to optimize. It is, however, well known that mse/psnr does not always agree with the subjective viewing results, particularly when distortion is not additive in nature. This is simply an average of the squared pixel differences between the original and distorted images. The well-known schemes proposed in recent ten years include PSNR-HVS-M [4], SSIM [1], visual information fidelity (VIF) [2], visual signal-to-noise ratio (VSNR) [3]), In PSNR-HVS-M [5], MSE/PSNR in the discrete cosine transform domain is modified so that errors are weighted by the corresponding visibility threshold (which accounts for the masking effects of the HVS) and the schemes based on the SSIM. The SSIM [1] is widely accepted due to its reasonably good evaluation accuracy. But SSIM does not work well with blurred images. Hence we propose an IQA scheme that is based on the edge/gradient. Similar to the SSIM, the proposed scheme considers luminance and contrast–structural changes. The main contributions are as follows-

- We demonstrate that gradient information that captures both contrast and structure of the image allows more emphasis on distortions around the edge regions in the proposed IQA scheme, leading to a more accurate assessment of image quality;
- Our scheme matches better with the contrast masking, particularly for the cases when both masked and masking signals are small; and
- We devise an adaptive approach to integrate the different components (i.e., luminance and contrast–structure) of distortion.

II. The SSIM INDEX

The structural similarity (SSIM) index is one of the method that is used in Image quality assessment. The structural similarity (SSIM) index is used for measuring the similarity between two images. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. As proposed in [1], the SSIM assumes that natural images are highly structured, and the HVS is sensitive to structural distortion. The structural information in an image is defined as those attributes that represent the structure of objects in the scene, independent of the average luminance and contrast [1]. The SSIM is calculated for each overlapped image block by using a pixel-by-pixel sliding window, and therefore, it can provide the distortion/similarity map in the pixel domain. It has been also extended using the multiscale analysis, complex wavelets [5], and discrete wavelets [6]. For any two image blocks and , the SSIM models the distortion/similarity between them as three complementary components, namely, luminance similarity, contrast similarity, and structural similarity, and these three components are mathematically described as (1)–(3) below, respectively

$$l(x,y) = \frac{2\mu_x\ \mu_y + c_1}{\mu_x 2 + \mu_y 2 + c_1} \qquad (1)$$

$$c(x,y) = \frac{2\sigma_x\ \sigma_y + c_2}{\sigma_x 2 + \sigma_y 2 + c_2} \qquad (2)$$

$$s(x,y) = \frac{2\sigma_{xy}\ + c_3}{\sigma_x \sigma_y + c_3} \qquad (3)$$

where $\mu_x, \mu_y, \sigma_x^2, \sigma_y^2$, and σ_{xy} are the mean of , the mean of ,the variance of x , the variance of y , and the covariance of x and y, respectively;c_1 ,c_2 ,c_3 and are claimed as small constants to avoid the denominator being zero.

The SSIM for the image blocks is given as

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \qquad (4)$$

where α, β and γ are positive constants used to adjust the relative importance of the three components. The higher the value of SSIM is, the more similar image blocks and are.. The overall image quality score is determined using the mean of the local SSIM (i.e., the SSIM for each image block) [1] or calculated as the IW average of the local SSIM [10]. The schemes in [7]–[10] and [11] are also based on the SSIM and take into account the importance of edge. In these schemes, one or more components of the SSIM are changed to calculate the value in the edge domain (note that (1)–(3) are calculated in the pixel domain). For example, the structure comparison component has been changed [7], [11] to the gradient domain, or both the contrast and structure comparison components have been modified [8]. In [9] and [11], the luminance comparison component has not been included. As minor variants of the SSIM, these schemes are lack of due consideration of the HVS' masking and visibility characteristics. Consider Fig. 1 shows the plot of DMOS versus SSIM for high-distortion images. where blur, contrast, jpeg, and Fnoise represent the distortion types of JPEG compression. Here the SSIM tends to underestimate the visual distortion.

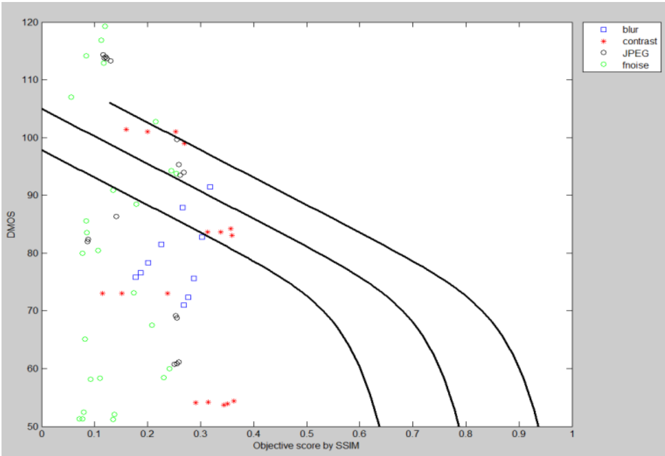

Fig.1.Plot DMOS verses SSIM

III. GRADIENT SIMILARITY SCHEME

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. In graphics software for digital image editing, the term gradient is used for a gradual blend of color which can be considered as an even gradation from low to high values, as used from white to black in the images to the right. Another name for this is *color progression*.

Mathematically, the *gradient* of a two-variable function (here the image intensity function) is at each image point a 2D vector with the components given by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction.

Since the intensity function of a digital image is only known at discrete points, derivatives of this function cannot be defined unless we assume that there is an underlying continuous intensity function which has been sampled at the image points. With some additional assumptions, the derivative of the continuous intensity function can be computed as a function on the sampled intensity function, i.e., the digital image. It turns out that the derivatives at any particular point are functions of the intensity values at virtually all image points. However, approximations of these derivative functions can be defined at lesser or larger degrees of accuracy.

The Sobel operator represents a rather inaccurate approximation of the image gradient, but is still of sufficient quality to be of practical use in many applications. More precisely, it uses intensity values only in a 3×3 region around each image point to approximate the corresponding image gradient, and it uses only integer values for the coefficients which weight the image intensities to produce the gradient approximation.

The gradient of the image is one of the fundamental building blocks in image processing. For example the canny edge detector uses image gradient for edge detection. Image gradients are often utilized in maps and other visual representations of data in order to convey additional information. GIS tools use color progressions to indicate elevation and population density, among others. The similarity in the gradient can be expressed as given below.

$$g(x,y) = \frac{2g_x\ g_y + c_4}{{g_x}^2 + {g_y}^2 + c_4} \quad (5)$$

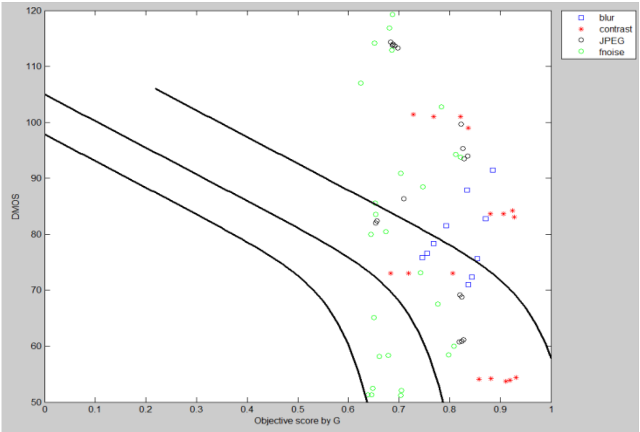

Fig2.Plot DMOS verses gradient.

Consider Fig. 2 in which the x-axis represents the predicted
Value from the scheme under consideration and the y -axis represents the subjective DMOS. We show the four-parameter logistic mapping curve between the objective outputs and the subjective DMOS .From Fig.1 and Fig.2 when compare we can see that the proposed scheme is more effective.

A. Gradient and intensity

It is better to use gradient along with intensity for the better assessment of image quality**.** Traditionally, image intensities have been processed to segment an image into regions or to find edge-fragments. Image intensities carry a great deal more information about three-dimensional shape, however. To exploit this information, it is necessary to understand how images are formed and what determines the observed intensity in the image. Since there will be a change in the intensity whenever there is a pixel wise movement in the edge regions. The average intensity can be expressed as

$$Ms_{xy} = \sum_{i=0}^{L-1} r_i p_{xy}(r_i) \quad (6)$$

It can be also classified as the local intensity. Where s_{xy} denotes the neighborhood pixels. Suppose if we consider a gray scale image then intensity is nothing but the value which ranges from 0-255 corresponding to different shades. There should be continuous intensity function otherwise we should assume that intensity is continuous and should be sampled at image points.

IV. Conclusion

Human visual system is ultimate system and HVS is highly adapted to extract structural information from the viewing field. Therefore all the structural information in an image should be carefully and explicitly incorporated in designing of an IQA scheme. The proposed IQA scheme based on the concept of gradient similarity along intensity can be considered to alleviate the shortcoming of the existing relevant schemes in this regard. We have demonstrated that the proposed gradient similarity measure can be used to gauge contrast and structural changes effectively.

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