Advanced Objective Metric for Image Quality Assessment

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ABSTRACT:

Image Quality Assessment (IQA) goal is to use computational models to measure the image quality consistently with subjective evaluations. In this paper, a peculiar feature-similarity (FSIM) index for full reference IQA is proposed based on the fact that human visual system (HVS) perceives an image mainly according to its low-level features. Specifically, the phase congruency (PC), which is a dimension less measure of significance of a local structure, is used as the primary feature. Considering that PC is unaffected by contrast, while the contrast information does affect the HVS' perception of image quality, the image gradient magnitude is employed as the secondary feature in FSIM. After obtaining the local quality map, we use PC again as a weighting function to derive single quality score. Extensive experiments performed on TID2008, a widely using bench mark IQA database demonstrated that FSIM can achieve much higher consistency with the subjective evaluations than state-of- the - art IQA metrics.

Index Terms: *Image quality assessment, phase congruency, gradient, low-level feature.*

1. INTRODUCTION

With the advancements in digital imaging and communication technologies, image quality assessment has been becoming an important issue in numerous applications, such as image acquisition, transmission, compression, restoration and enhancement. Any processing applied to an image may cause an important loss of information or quality. Image quality evaluation methods can be divided into objective and subjective methods. Subjective methods are based on HVS' judgment (i.e. Mean opinion score (MOS)). In practice, however subjective evaluation is usually very inconvenient, time taking and

expensive. They also cannot be integrate into automatic systems that adjust themselves in real-time based on the feedback of output quality. Objective methods are based on comparisons using explicit numerical criteria. According to the possibility of the reference image, objective IQA metrics can be classified as full reference (FR), no-reference (NR) and reduced-reference (RR) methods. In this paper the discussion is confined to FR methods, where the original "distortion-free" image is known as the reference image.

EXISTING OBJECTIVE METRICS:

The simplest and most widely used full-reference quality metric is the mean squared error (MSE), computed by averaging the squared intensity differences of distorted and reference image pixels, along with the related quantity of peak signal-to-noise ratio (PSNR). These are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the last three decades, a great deal of effort has gone into the development of quality assessment methods that take advantage of known characteristics of the human visual system (HVS). Peak signal-to-noise ratio

(PSNR) and mean squared error (MSE) operate directly on the intensity of the image, and they do not correlate well with subjective fidelity ratings. SSIM [6] is the image quality assessment of an image based on the degradation of structural information. The multiscale extension of SSIM, called MS-SSIM [7], produce better results than its single-scale counterpart. Multi-scale method is a convenient way to incorporate image details at different resolutions. However, the main drawback of these two methods is that when calculating a single quality score from the local quality map they have considered all positions to have the same importance. In visual information fidelity (VIF), images are divided into different sub-bands and these sub-bands can have different weights at pooling stage. However within each sub-band, each position is still given same importance. The choice of a proper distortion model is crucial for image fidelity assessments that are expected to reflect perceptual quality. In essence we want the distortion model to characterize what the HVS perceives as distortions. In this paper, although FSIM is designed for grayscale images (or the luminance components of color images), the chrominance information can be easily incorporated by means of a simple extension of FSIM, and we call this

extension $FSIM_c$, which has been implemented in this paper.

PHASE CONGRUENCY (PC):

Under the definition of PC, there can be different implementations to compute the PC map of a given image. In this paper we adopt the method developed by Kovesi [2], which is widely used in literature. We start from the 1D signal $g(x)$. Denote by M_n^e and M_n^o the even-symmetric and odd-symmetric filters on scale n and they form a quadrature pair. Responses of each quadrature pair to the signal will form a response vector at position x on scale n is

$$[e_{n(x)}, o_{n(x)}] = [g(x) * M_n^e, g(x) * M_n^o],$$

and the local amplitude on scale n is $A_n(x) = \sqrt{e_{n(x)}^2 + 0_{n(x)}^2}$.

let $F(x) = \sum_n e_{n(x)}$ and $H(x) = \sum_n o_{n(x)}$. The 1D PC can be computed as

$$PC(x) = E(x)/\left(\varepsilon + \sum_n A_{n(x)}\right)$$ Where,

$E(x) = \sqrt{F^2(x) + H^2(x)}$ and ε is the positive constant. The quadrature pair of filters, i.e. M_n^e and M_n^o, can be obtained by using log-Gabor filters. The transfer function of log-Gabor filter in frequency domain is,

$$G(\omega) = exp(-(\log(\omega/\omega_o))^2/2\sigma_r^2)$$

Where, ω_o is the filter's center frequency and σ_r controls the filter's bandwidth.

The 1D log-Gabor filters described above can be extended to 2D ones by simply applying spreading function across the filter perpendicular to its orientation. By using Gaussian as the spreading function, the 2D log-Gabor function has the following transfer function,

$$G_2(x) = exp\left[-\frac{(log(\omega/\omega_o))^2}{2\sigma_r^2}\right] . exp\left[-\frac{(log(\theta-\theta_j))^2}{2\sigma_\theta^2}\right]$$

Where $\theta_j = \frac{j\pi}{j}, j = \{0,1,2,\dots\dots,j-1\}$ is the orientation angle of the filter, J is the number of orientations and σ_θ determines the filter's angular bandwidth.

By modulating ω_o and θj and convolving G2 with the 2D image, we get a set of responses at each point x. as $[e_{n,\theta_j}(x), o_{n,\theta_j}(x)]$. The local amplitude on scale n and orientation θ_j is

$$A_{n,\theta_j}(X) = \sqrt{e_{n,\theta_j}(x)^2 + o_{n,\theta_j}(x)^2}$$ and

the local energy along orientation θ_j is

$$E_{n,\theta_j}(x) = \sqrt{F_{\theta_j}(x)^2 + H_{\theta_j}(x)^2}$$

Where $F_{\theta_j}(x) = \sum_n e_{n,\theta_j}(x)$ and $H_{\theta_j}(x) = \sum_n o_{n,\theta_j}(x)$.

The 2D PC at x is defined as shown in below equation $PC_{2D}(x)$,

$$PC_{2D}(x) = \frac{\sum_j E_{\theta_j}(x)}{\varepsilon + \sum_n \sum_j A_{n,\theta_j}(x)}$$

It should be noted that $PC2D(\mathbf{x})$ is a real number with in 0 ~ 1.

GRADIENT MAGNITUDE:

Image gradient computation is a conventional topic in image processing. Gradient operators can be expressed by convolution masks. Three commonly used gradient operators are the Sobel operator, the Prewitt operator and the Scharr operator. Prewitt, Sobel and Scharr 3x3 gradient operators are very familiar for

edge detection. Among these three Scharr is found to give promising results compared to other two. The partial derivatives $G_X(\mathbf{x})$ and $G_y(\mathbf{x})$ of the image $f(\mathbf{x})$ over horizontal and vertical directions using the three gradient operators are listed in Table 4.1.1 The gradient magnitude (GM) of $f(\mathbf{x})$ is then defined as

$$G = \sqrt{G_X{}^2 + G_Y{}^2} \ .$$

Sobel	Prewitt	Scharr
$G_x(X) = \frac{1}{4}\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} * f(x)$	$\frac{1}{3}\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} * f(x)$	$\frac{1}{16}\begin{bmatrix} 3 & 0 & -3 \\ 10 & 0 & -10 \\ 3 & 0 & -3 \end{bmatrix} * f(x)$
$G_y(X) = \frac{1}{4}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * f(x)$	$\frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * f(x)$	$\frac{1}{16}\begin{bmatrix} 3 & 10 & 3 \\ 0 & 0 & 0 \\ -3 & -10 & -3 \end{bmatrix} * f(x)$

Table1: Partial derivative of f(x) using different Gradient operators

CALCULATION OF FSIM:

With the extracted PC and GM feature maps, we present a novel Feature similarity (FSIM) index for IQA. Suppose that we are going to calculate the similarity between images $f_1(x)$ and $f_2(x)$. Denote PC_1 and PC_2 the PC maps, G_1 and G_2 the GM maps extracted from them. It should be noted that for color image, PC and GM are extracted from their luminance channels.

The similarity measure for $PC_1(x)$ and $PC_2(x)$ is defined as

$$S_{PC}(x) = \frac{2PC_1(x).PC_2(x)+T_1}{PC_1^2(x)+PC_2^2(x)+T_1}$$

Where T_1 is a positive constant to improve the stability of $S_{PC}(x)$. In practice, determination of T_1 depends on dynamic range of PC values. The GM values $G_1(x)$ and $G_2(x)$ are compared and similarity measure is defined as

$$S_G(x) = \frac{2G_1(x).G_2(x)+T_2}{G_1^2(x)+G_2^2(x)+T_2}$$

Where T_2 is a positive constant depends on the dynamic range of GM values. Thus the overall similarity between f_1 and f_2 can be calculated using $S_{PC}(x)$ and $S_G(x)$. However, different locations will have different contributions to HVS' perception

of the image. Since human visual cortex is sensitive to phase congruent structures, the PC value at a location can reflect perceptible significance of that location.

$$FSIM = \frac{\sum_{x \in \Omega}[S_{PC}(x)]^{\alpha}.[S_G(x)]^{\beta}.PC_m(x)}{\sum_{x \in \Omega} PC_m(x)}$$

Where Ω means the whole image spatial domain, α and β are the parameters used to adjust the relative importance of PC and GM features.

The FSIM index is designed for grayscale images or the luminance components of colour images. Since the chrominance information will also impact HVS in understanding the images, it can be incorporated by applying a straight forward extension to the FSIM framework. At first, the original RGB colour images are converted into another color space, where the luminance can be separated from the

Therefore we use $PC_m(x) = \max(PC_1(x), PC_2(x))$ to calculate the overall similarity. Accordingly the FSIM index between f_1 and f_2 is defined as

chrominance. To this end, we adopt the widely used YIQ colour space. The transformation from RGB space to YIQ space can be accomplished via:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix}\begin{bmatrix} R \\ Y \\ B \end{bmatrix}$$

Let I_1 (I_2) and Q_1 (Q_2) be the I and Q chromatic channels of the image f_1 (f_2), respectively. Similar to the definitions of $S_{PC}(\mathbf{x})$ and $S_G(\mathbf{x})$, we define the similarity between chromatic features as

$$S_I(x) = \frac{2I_1(x).I_2(x) + T_3}{I_1^2(x) + I_2^2(x) + T_3},$$

$$S_Q(x) = \frac{2Q_1(x).Q_2(x) + T_4}{G_1^2(x) + G_2^2(x) + T_4}$$

Where $T3$ and $T4$ are positive constants.

$$FSIM_C = \frac{\sum_{x \in \Omega} S_{PC}(X).S_G(X).[S_I(X).S_Q(X)]^{\lambda}.PC_m(X)}{\sum_{X \in \Omega} PC_m(X)}$$
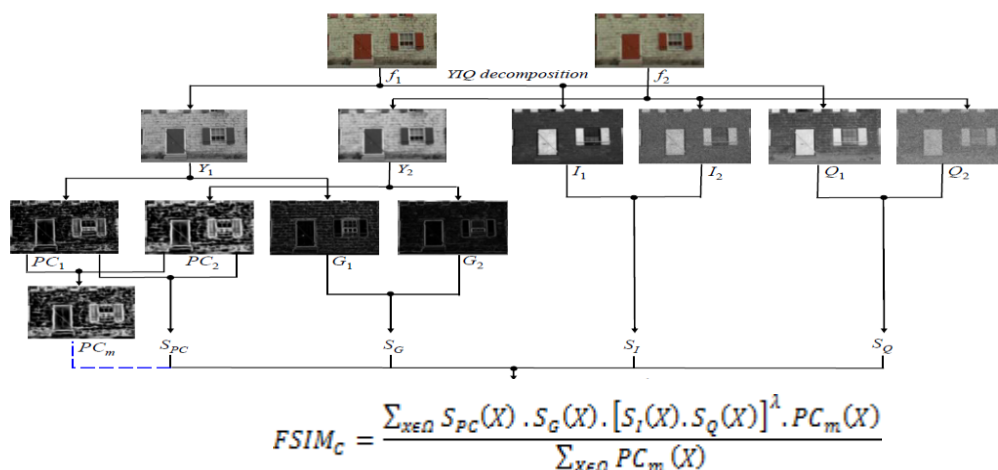
Fig.1: Illustration for the FSIM/FSIM$_C$ index computation. f_1 is the reference image and f_2 is a distorted version of f_1.

Where $\lambda > 0$ is the parameter used to adjust the importance of the chromatic

components. The procedures to calculate the FSIM/FSIMC indices are illustrated in

Fig.1. If the chromatic information is ignored in Fig, the FSIMC index is reduced to the FSIM index.

EXPERIMENTAL RESULTS:

(a) Reference image   (b) additive Gaussian noise   (c) spatially correlated noise

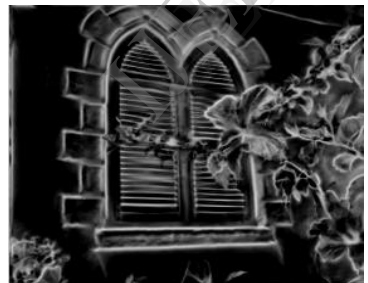(d) denoising   (e) JPEG2000 compression   (f) JPEG transformation errors

Fig.2: Reference image and distorted versions of reference image in TID2008 database.
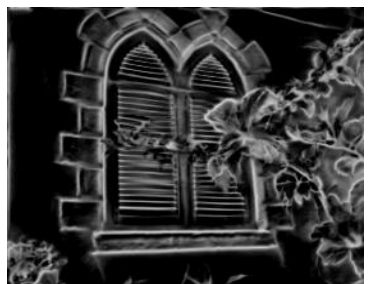

(a) Reference image   (b) additive Gaussian noise   (c) spatially correlated noise

(d) denoising   (e) JPEG2000 compression   (f) JPEG transformation errors

Fig.3: PC maps extracted from images 4a ~ 4f, respectively.

	Fig. 1b	Fig. 1c	Fig. 1d	Fig. 1e	Fig. 1f
Subjective score	4	2.8235	3.9688	4.8335	2.3235
FSIM	0.9257	0.8218	0.9404	0.9700	0.7646
$FSIM_C$	0.9164	0.8016	0.9377	0.9689	0.7644

Table 2: QUALITY EVALUATION OF IMAGES in Fig.2.

Example to demonstrate effectiveness of FSIM/$FSIM_C$:

We use an example to demonstrate the effectiveness of FSIM/$FSIM_C$ in evaluating perceptible image quality. Fig2a is the I7 reference image in TID2008 database [1], and Figs. 2b ~ 2f show five distorted images of I7. We computed the image quality of Figs. 2b ~ 2f using FSIM and compared with other IQA metrics and their subjective scores are listed in Table 1.
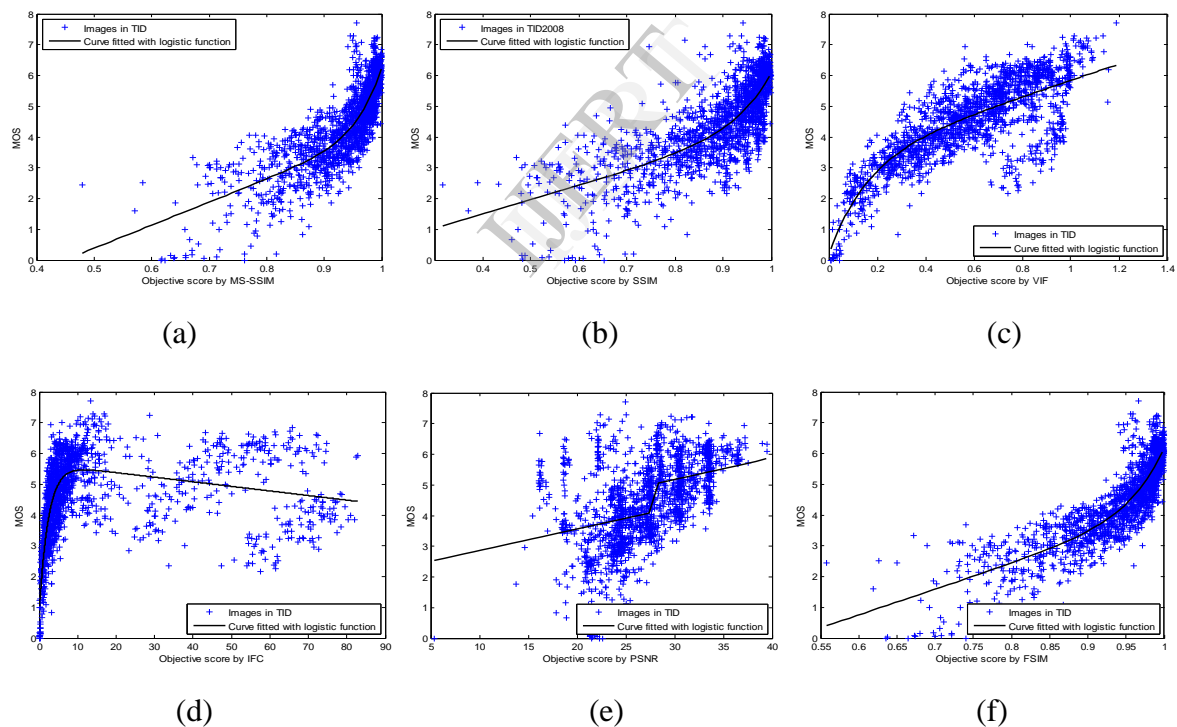

Fig.4: Scatter plots of subjective MOS versus scores obtained by model prediction on the TID20008 database. (a) MS-SSIM (b) SSIM (c) VIF (d) IFC (e) PSNR (f) FSIM

Fig.4 shows the scatter distribution of subjective MOS versus the predicted scores by FSIM and other 5 IQA indices on the TID2008 database. The curves shown in the Fig.4 were obtained by nonlinear fitting. From Fig. 4, one can see that the objective scores predicted by FSIM correlate much more consistently with subjective evaluations than the other methods.

CONCLUSION:

In this paper, we proposed a novel low-level feature based image quality assessment (IQA) metric, namely Feature SIMilarity (FSIM) index. The theme of FSIM is that HVS perceives an image mainly based its salient low-level features. Specifically, two features, the phase congruency (PC) and the gradient magnitude (GM), are used in FSIM, and they represent complementary aspects of image visual quality. The PC values also used to weight the contribution of each point to the overall similarity of two images. We then extended FSIM to $FSIM_C$ by incorporating the image chromatic features into consideration. The FSIM and $FSIM_C$ indices were compared with five prominent IQA

metrics on TID2008 database, and very promising results were obtained. Particularly, they perform consistently well across all the noises in TID2008 database, validating that they are very robust IQA metrics.

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