An Image Quality Metric based on Corner, Edge and Symmetry Maps

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Abstract

Image quality metrics have been widely used in imaging systems to maintain and improve the quality of images being processed and transmitted. Due to the close relationship between image quality perception and the human visual system, the development of image quality metrics has been contributed to by both psychologists and computer scientists. In this paper, three novel image quality metrics are proposed by improving the well-known image quality metric structural similarity index (SSIM). In this new approach, images are not compared directly, but their feature maps are (preprocessing is incorporated to extract the corner, edge and symmetry maps). The similarity measured (by SSIM) between corner, edge and symmetry maps of images being compared is used as an indicator of image quality, and named C_SSIM, E_SSIM and S_SSIM respectively. The experiments show that all the proposed image quality metrics have a better performance than SSIM, and E_SSIM has the best performance among them.

1 Introduction

Image quality assessment provides a useful tool for evaluating the visual effect of a wide range of artifacts imposed on digital images in the process of image acquisition, processing, transportation, compression, storage. Because humans are considered to be the observers and consumers of most imaging systems and products, the most reliable method to evaluate image quality is by subjective assessment. However its complication and inconvenience to implement has prevented its application in real-time experiments and its use as a systematic performance evaluator of image processing algorithms.

Therefore objective methods have attracted more attentions in recent years. Depending on the existence of reference images, there are three categories of image quality metrics (IQMs): *Full reference (FR) Image Quality Metrics, Reduced reference (RR) Image Quality Metrics*, and *No reference (NR) Image Quality Metrics*, where full, partial, and no information of reference images is available, respectively. This paper will mainly deal with full reference image quality metrics.

Traditionally, there are two approaches taken to quantify the similarity between images. One of them predicts the image quality by modelling the human vision system

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(HVS), and the other considers images as 2D and 3D signals, where image quality metrics are proposed, according to assumptions about the source where image quality degradation comes from.

2 Background

In recent years, many image quality metrics have been proposed. Here we will only introduce two widely-used ones, PSNR and SSIM.

2.1 PSNR

Based on the assumption that image quality degradation comes from the error between image pixels, the Peak Signal to Noise Ratio (PSNR) is one of the most widely-used image quality metrics and defined as the ratio of the signal (the reference image) to the noise (the error between two images X and Y of size $M \times N$ pixels):

$$PSNR(X,Y) = MN \max_{m,n} \left(X_{m,n}^2 \right) \Big/ \sum_{m,n} (X_{m,n} - Y_{m,n})^2$$

2.2 SSIM

Wang's structural similarity index (SSIM)[13] has been constructed on another assumption, which presumes that image quality degradation is often caused by the loss of underlying structured information in images .

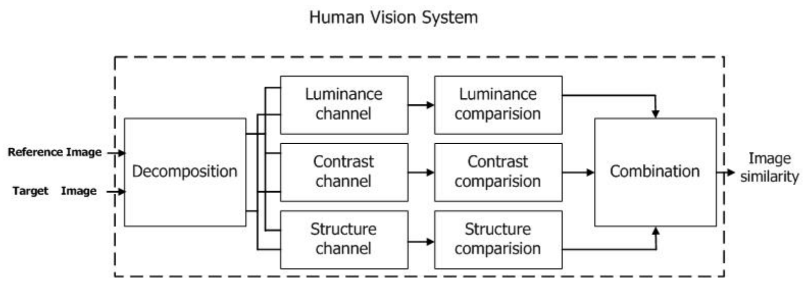

Figure 1: The scheme of HVS modeling in SSIM

Derived from this simple assumption, SSIM attempts to decompose the human vision system into independent visual pathways: *Luminance, Contrast* and *Structure* (shown in Figure. 1).

Given $x = \{x_1, x_2, ..., x_N\}$ and $y = \{y_1, y_2, ..., y_N\}$ are the signals extracted from image patches (taken from the same locations in an original image X and distorted image Y), the similarity between *Luminance, Contrast* and *Structure* of two signal x and y is defined as follows:

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

$$c(x,y) = \frac{2\delta_x\delta_y + c_2}{(\delta_x)^2 + (\delta_y)^2 + c_2} \quad (2)$$

$$s(x,y) = \frac{\delta_{xy} + c_3}{\delta_x\delta_y + c_3} \quad (3)$$

where the mean value μ_x, the standard variation δ_x of the signal x, and the correlation coefficient δ_{xy} between signals x and y are defined as:

$$\mu_x = \frac{\sum_{i=1}^{N} x_i}{|x|} \quad (4)$$

$$\delta_x = (\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_x)^2)^{\frac{1}{2}} \quad (5)$$

$$\delta_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \quad (6)$$

where the mean value μ_y, the standard variation δ_y of the signal y are defined similarly. It is worth noting that, the luminance comparison in equation (1) has satisfies Weber's law inherently, one of the most important properties of HVS (Weber's Law: The magnitude of a just-noticeable luminance change is approximately proportional to the background luminance for a wide range of luminance values). The Structural SIMilarity (SSIM) index is defined as:

$$\mathrm{SSIM}(x,y) = l(x,y)^{\alpha} \cdot c(x,y)^{\beta} \cdot s(x,y)^{\gamma} \quad (7)$$

3 Image Quality Metric Based on Corner, Edge and Symmetry Maps

In this paper, a novel scheme of constructing the IQMs on the basis of SSIM is proposed (shown in Fig.2). The image quality assessment consists of three steps: preprocessing, HVS modelling & similarity estimation.

3.1 Preprocessing

Corner, edge and symmetry are important features in computer vision. Corners are points where slope changes abruptly [2] and used in matching, tracking and motion estimation [1]; Edges characterize the intensity discontinuity of an image and are used many applications, for example image retrieval in [8]; Symmetries indicate the invariance of objects under some geometrical transformations [5]. The detection of corner, edge and symmetry maps follows the methods in [5, 7, 6].

3.2 HVS Modeling & Similarity Estimation

SSIM is used to estimate the similarity between corner, edge and symmetry maps of the images being compared, where we suppose that the HVS is still composed of three independent visual pathways (*Luminance, Contrast* and *Structure*).

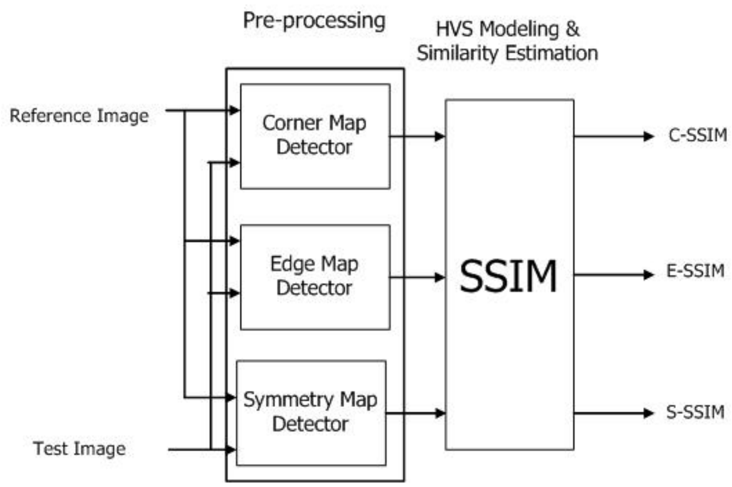

Figure 2: The proposed algorithmic scheme

Based on the different feature maps (*corner, edge and symmetry maps*), the resulting measures are named as C_SSIM, E_SSIM and S_SSIM, respectively. Note that, the default parameters of SSIM[11] are still used here: $c_1 = k_1 * L$, $c_2 = k_2 * L$ (,where k_1=0.01, k_2=0.03, L=255), and $\alpha = \beta = \gamma = 1$. Because SSIM has been proved to be a metric in [13], C_SSIM, E_SSIM and S_SSIM are metrics as well.

4 Experiments

4.1 Image Database

The database used here is the *LIVE Quality Assessment Database* developed by University of Texas at Austin, Texas, USA[3, 13, 9, 10, 12, 4]. The database is developed from a set of 29 source images which are quite representative in the content, structure, lighting condition, viewing distance, viewing angle, etc. The distortion types in the image database include: *JPEG2000 compression* (JPEG2000), *JPEG compression* (JPEG), *white noise* (WN), *Gaussian Blur* (Gblur), *Simulated Fast Fading Rayleigh (wireless) channel* (Fast-Fading). All these distortions represent a wide range of impairments which images might suffer from.

In developing of the LIVE database, psychological experiments are set up to measure the subjective similarity assessment using the single-stimulus methodology. After the removal of unqualified subjective observations and possible outliers, all the raw data are transformed into subjective scores (MOS, mean opinion scores) ranging between 0 and 100. In details, subjective are asked to drag a slider on a quality scale (that is divided into five equal sections labelled by “Bad”, “Poor”,“Fair”, “Good”, and “Excellent”), to express their perception of image quality. The position of the slider is then converted into a quality score by linearly mapping the whole scale to the interval [1,100], which is known as raw scores. The raw scores are transform to Z-scores and rescaled within each database to the range [1,100]. Mean opinion scores are then computed for each image.

4.2 Methodology

To verify the validity and usefulness of the proposed image quality metric, the experiments are designed to follow a procedure described in [9]:

- *Step 1*: Objective measures obtained from image quality metrics are transformed to predicted subjective scores (predicted MOS) via a nonlinear regression, and the fitting function used here is also used in [9], and optimized using MATLAB's *fminunc*.

$$\text{Quality}(x) = \beta_1 \text{logistic}(\beta_2, (x - \beta_3)) + \beta_4 x + \beta_5 \tag{8}$$

$$\text{logistic}(\tau, x) = \frac{1}{2} - \frac{1}{1 + exp(\tau x)} \tag{9}$$

- *Step 2*: After the nonlinear regression of objective measures, the performance of IQMs is indicated by several statistical measures (performance metrics), including Pearson correlation coefficient (CC), Spearman Rank Order Correlation coefficient (SROCC), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Performance metrics CC and SROCC indicate the consistency with subjective scores (perfect match = 1), and MAE and RMSE indicate a statistical distance to subjective scores (perfect match = 0). Given two arrays $a = \{a_1, a_2, ..., a_N\}$ and $b = \{b_1, b_2, ..., b_N\}$, CC, SROCC, RMSE and MAE are defined as follows:

$$\text{CC} = \frac{\sum_{i=1}^{N}(a_i - \overline{a})(b_i - \overline{b})}{\sqrt{\sum_{i=1}^{N}(a_i - \overline{a})^2} \cdot \sqrt{\sum_{i=1}^{N}(b_i - \overline{b})^2}} \tag{10}$$

$$\text{SROCC} = \frac{\sum_{i=1}^{N}(u_i - \overline{u})(v_i - \overline{v})}{\sqrt{\sum_{i=1}^{N}(u_i - \overline{u})^2} \cdot \sqrt{\sum_{i=1}^{N}(v_i - \overline{v})^2}} \tag{11}$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{N}(a_i - b_i)^2 / N} \tag{12}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|a_i - b_i| \tag{13}$$

where $\overline{a}$ and $\overline{b}$ are the mean value of a and b respectively, while $u = \{r(a_1), r(a_2), ..., r(a_N)\}$ and $v = \{r(b_1), r(b_2), ..., r(b_N)\}$ and r is a mapping function which transforms a real-value element of an array (a or b), to its corresponding rank in this array.

Note that nonlinear regression is used here, because it is generally accepted in the community of image quality assessment, that objective measures can predict subjective scores stably, only if the objective measures can be mapped into the subjective scores via a monotonic correspondence curve, despite objective measures and subjective scores (MOS) normally having different values.

5 Results and Discussion

In this section, the performance of the newly-proposed IQMs (C_SSIM, E_SSIM and S_SSIM), their prototype SSIM and PSNR, will be analyzed in terms of their ability to predict quality in a manner that agrees with human ratings. There are two experiments conducted: (1) experiment1 to evaluate the general performance of IQMs statistically on a fair basis, and (2) experiment2 to check their performance on individual distortion types.

5.1 General Performance

Firstly, objective measures of these IQMs are transformed to subjective scores, using the fitted curves between objective measures and subjective scores (MOS), which are shown in Figure 3. In Figure 3, each datapoint represents a test image in LIVE database, where the algorithmic estimation of the quality and MOS are indicated by the horizontal and vertical axis respectively.

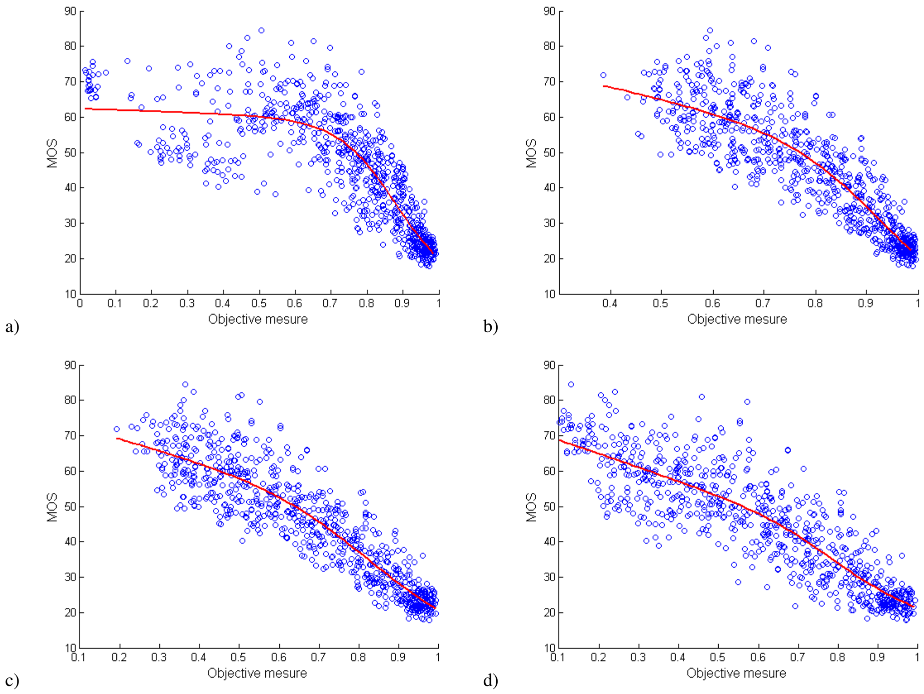

Figure 3: The fitting curve between MOS and the IQMs: a) SSIM b) C_SSIM c) E_SSIM d) S_SSIM.

It is observed from Figure 3, that the fitting curves of C_SSIM, E_SSIM, S_SSIM are almost the same. All the datapoints of C_SSIM, E_SSIM, S_SSIM are densely scattered around their fitted curves, while the datapoints of SSIM are more sparsely scattered.

Then the performance metrics (CC, SROCC, RMSE and MAE) are measured between the objective scores and subjective scores (MOS), which are predicted by the algorithms and human beings (shown in Table 1). There are several observations from Table 1.

First of all, all performance metrics indicate that, any of the proposed metric has a better performance than SSIM. Secondly, among the proposed metrics, E_SSIM performs better than the others.

Model	CC	SROC	RMSE	MAE
PSNR	0.8088	0.8017	9.4709	7.6672
SSIM	0.8575	0.8442	8.2848	6.3978
C_SSIM	0.8891	0.8882	7.3718	5.708
E_SSIM	0.9012	0.9	6.9809	5.3741
S_SSIM	0.8787	0.8769	7.687	5.8066

Table 1: The general performance of PSNR, SSIM, C_SSIM, E_SSIM and S_SSIM

5.2 Performance over distortion types

	SSIM				C_SSIM			
Type	CC	SROC	RMSE	MAE	CC	SROC	RMSE	MAE
JPEG2000	**0.9247**	0.9211	7.1141	5.5928	0.9175	0.9152	6.6429	5.1775
JPEG	0.9123	0.8905	7.0207	5.1887	**0.9144**	0.8934	6.8771	4.7886
WN	0.8201	0.9663	12.2107	10.87	0.8918	0.9169	8.654	7.5121
Gblur	0.8695	0.8975	7.9531	6.0214	0.8509	0.8737	8.436	6.4852
FastFading	0.9291	0.941	6.1582	4.6995	0.929	0.9341	6.1143	4.8547
	E_SSIM				S_SSIM			
Type	CC	SROC	RMSE	MAE	CC	SROC	RMSE	MAE
JPEG2000	0.9202	0.9183	6.5618	5.117	0.9078	0.9116	7.0683	5.5492
JPEG	0.9097	0.8897	6.9324	4.8602	0.8829	0.883	8.6843	5.831
WN	**0.8936**	0.9119	8.4431	7.1779	0.8824	0.9108	9.9083	8.3281
Gblur	0.9069	0.929	7.018	5.2188	**0.9281**	0.9379	6.6544	5.3045
Fastfading	0.9376	0.9408	5.7526	4.6457	**0.9514**	0.9455	5.0749	4.0579

Table 2: The peformance of SSIM, C_SSIM, E_SSIM and S_SSIM over different distortion types

The performance of the proposed metrics (C_SSIM, E_SSIM and S_SSIM) on individual distortion types is also investigated (shown in Table 2 and Figure 4). From Table 2, we can observe that, although E_SSIM statistically performs better than other IQMs (over all the distortion types), SSIM, C_SSIM and S_SSIM have their own advantage on individual distortion types. Note that, in this paper, the performance metric CC is considered to be more important than RMSE. Some comments about their relative importance are given in [10]. Although RMSE can give a more intuitive impression of the relative improvement of one IQM over another, the quality assessment community is more accustomed to using the correlation coefficient. Besides, SROCC operates only on the ranking of the data points (i.e., the relative distance between the data points is ignored), while MAE is just a beneficial supplement to RMSE.

Following this criterion, we can draw some conclusions about the relative performance of these IQMs: (1) SSIM, C_SSIM and E_SSIM perform best on the distortion types *JPEG2000, JPEG* and *white noise in RGB space* respectively, while S_SSIM performs best on both the distortion type *Gaussian blur* and *transmission errors in JPEG2000 stream over fast-fading Rayleigh channel*. 2) the improvement of E_SSIM over SSIM is mostly contributed to by having an outstanding performance on the distortion types *white noise in RGB space*, *Gaussian blur* and *transmission errors in JPEG2000 stream over fast-fading Rayleigh channel*, but maintaining a similar performance on the distortion types *JPEG2000* and *JPEG*.

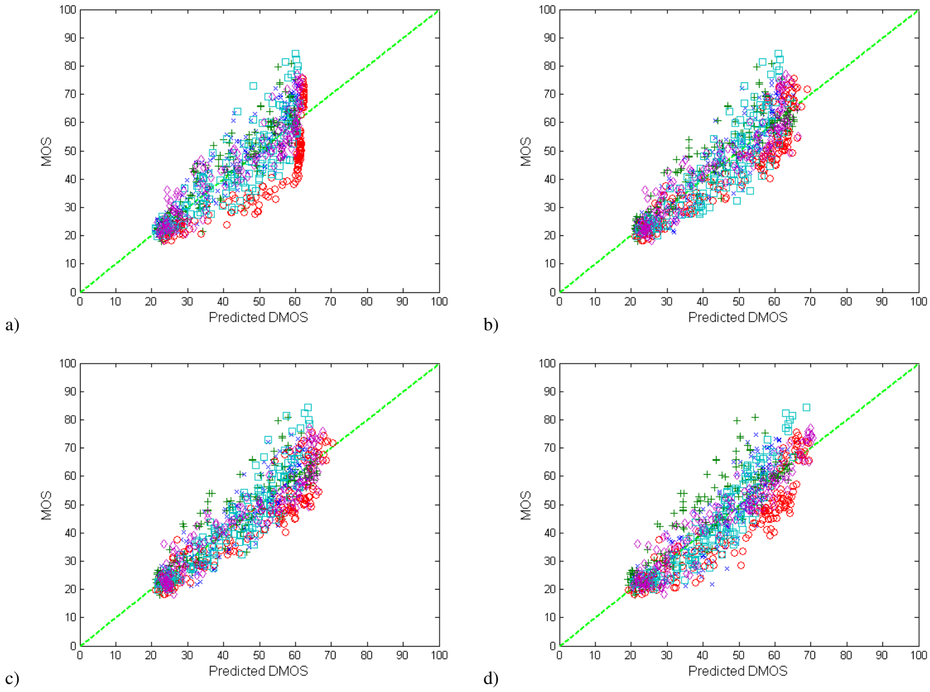

Figure 4: Scatter plots for the image quality predictions by four IQMs after compensating for quality calibration: a) SSIM b) C_SSIM c) E_SSIM d) S_SSIM. The distortion types are: JPEG2000(×), JPEG(+), white noise in RGB space(○), Gaussian blur(□) and transmission errors in JPEG2000 stream over fast-fading Rayleigh channel(◇).

6 Conclusions

This paper provides a novel approach for image quality assessment, i.e., measuring the image quality on feature (corner, edge and symmetry) maps rather than the images themselves. Although these features are believed to contain the information about the foreground/background configuration, structure and content of images, they are usually used only for object recognition. The experiments have shown that, although all the proposed metrics have a better performance than the well-known SSIM, E_SSIM is the best one. Besides, further analysis of their relative performance shows that: (1) The IQMs (SSIM, C_SSIM, E_SSIM and S_SSIM) perform best only on specific distortion types; (2) E_SSIM has a better performance than SSIM because, compared with SSIM, E_SSIM not only has a outstanding performance on the distortion types *white noise in RGB space*, *Gaussian blur* and *transmission errors in JPEG2000 stream over fast-fading Rayleigh channel*, but also maintains a similar performance to SSIM on the distortion types *JPEG2000* and *JPEG*.

In the future, more effort will be made to optimize the parameters for C_SSIM, E_SSIM and S_SSIM (at the current stage, the default parameters of SSIM are used). Besides, it is also very important to merge the proposed metrics C_SSIM, E_SSIM and S_SSIM, into a new, uniform image quality metric.

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