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Full Reference Image Quality Assessment Algorithm based on Haar Wavelet and Edge Perceptual Similarity

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Abstract. The research on image quality assessment (IQA) has been become a hot topic in image processing. Many studies show that HVS edge information plays crucial role when human perceive the quality of an image. The proposed metric is called HEPSI. The method from HaarPSI metric is combined with edge structural similarity and a contrast map is added for pooling the structural similarity map, Validation is taken by comparing HEPSI with the well-known state-of-the-art IQA metrics: PSNR, SSIM, MSSIM, FSIM and HaarPSI over the LIVE database. Experiment shows that HEPSI achieved better performance than other 5 IQA metrics.

1. Introduction

Assessing image quality is significant in optimizing image processing performance. Many studies have been performed for the purpose of effectively measure image quality. Digital images often pass through several processing stages such as acquisition, processing, storage and transmission before they reach to the observers [1]. These images are subjected to different kinds of distortions during the stages such as transmission, processing, acquisition and compression. These stages may result in degradation of visual quality of the images.

For example, during the transmission stage, the quality of the received image may decrease because of dropping of some data due to limited bandwidth of the channels. Consecutively, it is significant for image acquisition, communication, processing systems and management to measure the quality of images at each stage. Hence, image quality assessment (IQA) is very important in order to maintain and conserve the quality of the images.

1.1. Image Quality Assessment (IQA)

Image quality measurement (IQA) techniques can be categorized as subjective and objectives. Subjective measurement consists of mean opinion scores (MOS) scored by a number of selected observers that has shown a series of test scenes. Although this measurement will give accurate results, subjective evaluation is usually time-consuming, too inconvenient and cannot be incorporate in real time.

To eliminate the need for expensive subjective studies, numerous efforts have been made to develop objective measurement that can correlate with perceived quality. The goal of objective IQA is to design algorithms that are able to predict the quality of an image automatically and accurately. Objective measurement are automatic algorithms for quality assessment that could analyse images and



report their quality without human involvement. Such methods could eliminate the need for expensive subjective studies. The most widely used and simplest full reference (FR) IQAs are the peak signal-to-noise ratio (PSNR) and mean square error (MSE), but due to the low correlation between their results with human opinion scores another FR IQAs have been presented [2].

Wang et al. proposed structural similarity index (SSIM) based on the assumption that HVS is highly adapted by extracting structural information from an image [3]. After the huge achievement of SSIM, it gives inspirations and ideas to numerous new IQAs. Besides, Zhang et al. [4] proposed a low-level feature similarity index (FSIM), to assess phase congruency and gradient magnitude with the assumption that the HVS distinguishes images according to low-level features. Recently, Reisenhofer et al. [5] proposed utilizes the coefficients obtained from a Haar wavelet decomposition to assess local similarities between two images, as well as the relative importance of image areas.

2. Proposed quality assessment methods

Given image i is the reference image and image j is the distorted image. Coefficients obtained from a Haar wavelet decomposition is used to calculate the local similarities and the relative importance of image areas between image i and image j . The local similarity measure included chroma channels I and Q from the color images in the YIQ color space. These are calculated according to the method in [5]. This generalization is given by

$$S_{1i,j} = \lfloor_{\alpha}^{-1} \left(\frac{\sum_x \sum_{k=1}^3 HS_{i,j}^{(k)}[x] \cdot W_{i^Y,j^Y}^{(k)}[x]}{\sum_x \sum_{k=1}^3 W_{i^Y,j^Y}^{(k)}[x]} \right)^2 \quad (1)$$

where \lfloor_{α} is non-linear mapping to the local similarities obtained from high-frequency Haar wavelet filter response. $HS_{i,j}^{(k)}[x]$ is the local similarity measure that is based on the first two stages of two dimensional Haar wavelet transform where $HS_{i,j}^{(1)}$ and $HS_{i,j}^{(2)}$ differentiates between horizontal and vertical filters and $HS_{i,j}^{(3)}$ is the chroma-sensitive local similarity measure.

$$\lfloor_{\alpha}(x) = \frac{1}{1 + e^{-\alpha x}} \quad (2)$$

$$HS_{i,j}^{(1,2)}[x] = \lfloor_{\alpha} \left(\frac{1}{2} \sum_{n=1}^2 S \left(\left| (g_n^{(1,2)} * i)[x] \right|, \left| (g_n^{(1,2)} * j)[x] \right|, C \right) \right) \quad (3)$$

$$HS_{i,j}^{(3)}[x] = \lfloor_{\alpha} \left(\frac{1}{2} \left(S(|(m * i^I)[x]|, |(m * j^I)[x]|, C) + S(|(m * i^Q)[x]|, |(m * j^Q)[x]|, C) \right) \right) \quad (4)$$

where S denotes the scalar similarity measure, m is 2×2 mean filter, $*$ is the two-dimensional convolution operator and C is a constant. Meanwhile, $W_{i^Y,j^Y}^{(k)}[x]$ is the weight map that is derived from single low frequency Haar wavelet filter.

$$W_{i,j}^{(k)}[x] = \max \left(W_i^{(k)}[x], W_j^{(k)}[x] \right) \quad (5)$$

$$W_{i^Y,j^Y}^{(3)}[x] = \frac{1}{2} \left(W_{i^Y,j^Y}^{(1)}[x] + W_{i^Y,j^Y}^{(2)}[x] \right) \quad (6)$$

Mean square of detail subband (horizontal, vertical & diagonal) used to compute the edge map functions for i and j .

$$i_E(m, n) = \frac{1}{3}(i_H^2(m, n) + i_V^2(m, n) + i_D^2(m, n)) \quad (7)$$

$$j_E(m, n) = \frac{1}{3}(j_H^2(m, n) + j_V^2(m, n) + j_D^2(m, n)) \quad (8)$$

where i_E and j_E represent the edge maps of i and j respectively. (m, n) represents the sample position within the wavelet subbands. i_H , i_V and i_D denote horizontal, vertical and diagonal detail subbands of image i while j_H , j_V and j_D denote detail subbands of image j . The edge SSIM map is calculated between the two images.

$$SSIM_E(i_E, j_E) = \frac{2\sigma_{i_E j_E} + c}{\sigma_{i_E}^2 + \sigma_{j_E}^2 + c} \quad (9)$$

where $\sigma_{i_E j_E}$ is the cross correlation between image patches i_E and j_E while $\sigma_{i_E}^2$ and $\sigma_{j_E}^2$ are the variances of i_E and j_E respectively. Next, contrast map is formed for weighted pooling of the edge SSIM map. It is well known that the HVS is more sensitive to areas near the edges [6]. The contrast map is calculated within a local Gaussian square window that moves (pixel-by-pixel) over the entire approximation subband i_A and edge map i_E .

$$Contrast(i_E, i_A) = (\mu_{i_E} \sigma_{i_A}^2)^{0.1} \quad (10)$$

$$\sigma_{i_A}^2 = \sum_{k=1}^N w_k (x_{A,k} - \mu_{i_A})^2 \quad (11)$$

$$\mu_{i_E} = \sum_{k=1}^N w_k i_{E,k}, \quad \mu_{i_A} = \sum_{k=1}^N w_k i_{A,k} \quad (12)$$

$$S_2 = \frac{\sum_{n=1}^M Contrast(i_{E,n}|j_{A,n}) \cdot SSIM_E(i_{E,n}, j_{E,n})}{\sum_{n=1}^M Contrast(i_{E,n}|j_{A,n})} \quad (13)$$

The edge similarity scores, local similarities and the relative importance of image areas are combined to obtain overall quality measure between images i and j . The final quality score is calculated using the following formula.

$$HEPSI(i, j) = \gamma S_1 + (1 - \gamma) S_2 \quad (14)$$

where γ is a constant. We set $\gamma = 0.99$ in this paper.

3. Evaluation of results

3.1. Image database

All the IQAs are validated on a publicly available image database which is LIVE database. LIVE image quality database contains 29 reference images and 779 distorted images in 24-bpp color BMP format at different image resolutions ranging from 634×438 to 768×512 pixels. There are five different types of distortions in this database: JPEG compression, JPEG2000 compression, additive Gaussian white noise, Gaussian blurring and JPEG2000 with bit errors via a simulated Rayleigh fading channel.

Each types of distortions were generated at five to six difference amounts of distortions. The scores were collected from 29 different subjects. LIVE database is intended for evaluation of FR IQA metrics. It allows estimating how a metric corresponds to mean human perception.

3.2. Performance evaluation

Four commonly used correlation coefficient (CC) are applied to assess the performance of the proposed technique between objective and subjective score pertaining to image quality. These four performance metrics are the Spearman rank order correlation coefficient (SROCC), Kendall rank-order correlation coefficient (KROCC), Pearson linear correlation coefficient (PLCC), and root-mean-squared error (RMSE). SROCC and KROCC assess the prediction monotonicity while PLCC and RMSE evaluate the prediction accuracy of an IQA [10].

In this research, a non-linear logistic regression function is chosen for non-linear mapping in the scatter plot. The function is recommended by the video quality experts' group (VQEG) and has been widely used by many IQA researchers [7]. The function is defined as following:

$$Q(x) = \beta_1 \left(\frac{1}{2} - \frac{1}{1 + e^{\beta_2(x - \beta_3)}} \right) + \beta_4 x + \beta_5 \quad (15)$$

where Q represents the predicted score after regression, x denotes the raw objective scores of a metric and β_1 , β_2 , β_3 , β_4 and β_5 are regression model parameters. The five regression model parameters are calculated by fitting the function to the objective and subjective data. The importance of this function is to analyse the performance in a common space and remove the non-linearity caused in the process of subjective scores [4], [8], [9].

4. Results and Discussion

4.1. Performance Comparison

The performance of HEPSI is compared with selected state-of-the-art IQAs which are SSIM [3], MSSIM [11], FSIM [4], HaarPSI [5] and PSNR models (MATLAB source code of all the methods are obtained from the original authors). The following Table 1 lists the SROCC, PLCC, KROCC and RMSE results of proposed metric and other 5 IQAs on LIVE database. The best one metric produces the highest CC and lowest RMSE is marked in **boldface**. The results show that HEPSI outperform all other metrics in terms of correlation coefficients and root mean square error. Thus, HEPSI performs better than other IQA metrics

Table 1. Performance comparison of IQA metrics on LIVE database.

	PSNR	SSIM	MSSIM	FSIM	HaarPSI	HEPSI
KROCC	0.6865	0.7963	0.8044	0.8337	0.8448	0.8488
PLCC	0.8723	0.9449	0.9489	0.9597	0.9695	0.9709
SROCC	0.8756	0.9479	0.9513	0.9634	0.9683	0.9703
RMSE	13.3597	8.9455	8.6187	7.6780	6.6935	6.5383

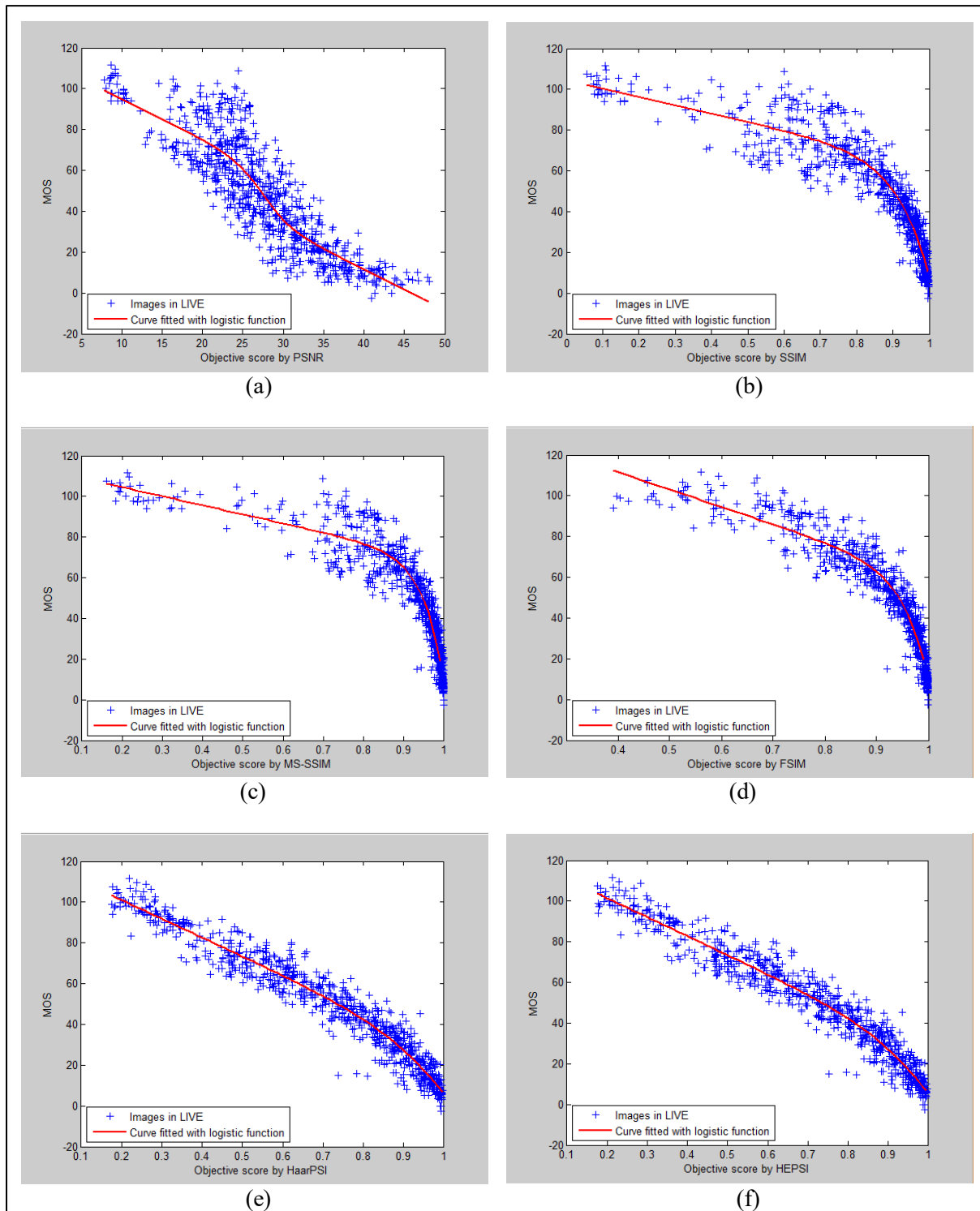


Figure 1 Scatter plots of 6 IQAs on LIVE database (a) PSNR, (b) SSIM, (c) MSSIM, (d) FSIM, (e) HaarPSI and (f) HEPSI

In order to provide a visual comparison of the proposed metric with five other IQAs (SSIM, MSSIM, FSIM, HaarPSI and PSNR), their scatter plots of subjective rating DMOS versus objective scores obtained by the IQAs on LIVE database are shown in Figure 1 above. Each point represents one

test image. Generally speaking, if the scatter plots are closer to the fitted curve (red line), the results will be with lower RMSE. Ideally, for an IQA metric, these points should lie on top of each other.

The fitted curve (red line) plotted in each graph is actually the logistic function defined in Equation 1 that is widely used in IQA researches. In comparison with other scatter plots, HEPSI's points (blue +) are closer to each other and fitted curve, which means that HEPSI correlates well with subjective scores. This shows that proposed metric HEPSI performs better than the other 5 IQA metrics which are PSNR, SSIM, MS-SSIM, FSIM and HaarPSI.

5. Conclusion

In this research, we proposed a full reference IQA metric that is called HEPSI. This metric combines the assessment of local similarity and the relative importance of image areas from HaarPSI with the edge similarity between two images. Experiments show that HEPSI achieved good and better performance than other 5 IQA metrics across LIVE database. The work also indicates the high correlation between the image edges and visual perception of image quality. Assessing the edges of reference and distorted image can well measure the image structural distortion and become an efficient IQA metric.

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