https://doi.org/10.2352/ISSN.2470-1173.2017.12.IQSP-221

No-reference image contrast assessment based on just-noticeable-difference

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Abstract

Image quality assessment (IQA) has been important issue in image processing. While using subjective quality assessment for image processing algorithms is suitable, it is hard to get subjective quality because of time and money. A lot of objective quality assessment algorithms are used widely as a substitution. Objective quality assessment divided into three types based on existence of reference image : full-reference, reduced-reference, and no-reference IQA. No-reference IQA is more difficult than full-reference IQA because it does not have any reference image. In this paper, we propose a novel no-reference IQA algorithm to measures contrast of image. The proposed algorithm is based on just-noticeable-difference which utilizes the human visual system (HVS). Experimental results show the proposed method performs better than conventional no-reference IQAs.

Introduction

There are so many digital images in real world captured with not only digital cameras but also smart phones. Advances in technology make capturing photos and videos more easily. These images are reproduced with many enhancement algorithms to improve image quality. Image quality assessment (IQA) algorithm, which measures degree of enhancement, is necessary. The ideal approach is measuring human populace for each image. Averaging across these opinions produces a mean opinion score (MOS), which is typical subjective quality assessment. Subjective quality assessments are considered best indicators to assess visual quality, but have difficulty in use: time consuming and money.

To solve these problems, objective quality score which has high correlation with subjective quality assessment is used. Objective quality assessment can be divided into three categories based on type of reference image : Full-reference (FR) algorithms, reduced-reference (RR) algorithms, and no-reference (NR) algorithms [1].

FR algorithms are provided with original images and measure local pixelwise differences as local measurements. Overall quality difference is represented by sum of these local measurements. Widely used FR algorithms are mean-squared-error (MSE) and peak signal-to-noise ratio (PSNR). More complicated FR algorithms have employed : based on the HVS, or measuring image structure. RR algorithms are used when original images are not fully accessible. These methods are operated by extracting a set of parameters from the reference image. Later, image quality is estimated with parameters of distorted image and reference image. These algorithms are widely used in image transmission. Finally, NR algorithms are used when reference image is not available. These algorithms are performed with no information of reference image. Most of NR algorithms calculate specific types of distortion such as JPEG compression artifact, blurring, and blocking. For contrast enhancement, enhanced image's statistical characteristic is different from original one, NR algorithm is requested to evaluate image quality.

In this paper we propose a method for NR IQA based on the HVS. In the rest of the paper, we review existing NR IQA methods, and propose a new contrast measure based on the HVS with experimental results.

Previous NR contrast measure methods

Most IQA algorithms assume that distortion exists between original image and output image. However, for contrast enhancement, it is hard to define difference between them as a distortion. For this reason, many previous works on contrast measurement are no reference IQA. The most widely used NR measurements are based on image's statistical measures. These algorithms use image's mean, variance, or entropy as a measurement of contrast. These algorithms are applied on the grayscale image. However, due to extracting only image's global statistical characteristics, these algorithms are lack of meaningful information for image. More developed algorithms are proposed for grayscale NR quality assessment [2][3]. These algorithms, however, are specific about the certain type of distortions like JPEG compression or JPEG2000 compression. Morrow *et al*. [4] introduced a measure using the contrast histogram, which has much more meaningful measurement than statistical models. After this approach, more specified IQA approaches developed.

There are two different approaches for measuring image's contrast. First one is contrast measurement based on Michelson contrast, which is one of the most widely used algorithms for measuring contrast [5]. He used concept of bidimensional pattern. Michelson contrast measures sinusoidal frequency contrast for global image. Another contrast measurement is based on Weber's law. The Weber fraction which is defined in (1), is used to measure the local contrast of a single target of uniform luminance seen against a uniform background [6].

$$W = \frac{\Delta I}{I}, \tag{1}$$

where W is Weber fraction, I is luminance, and ΔI is change of luminance.

By using Weber's law, many contrast measurement algorithms are proposed to calculate image's contrast locally. Rizzi developed RAMMG [7], and Panneta developed Root Mean Enhancement (RME) [8], using the concept of Root Mean Square

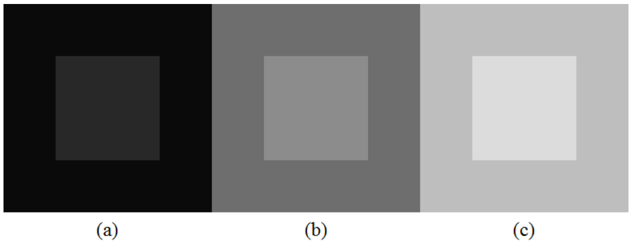

Figure 1. *Ideal patch test set.*

Table 1. Comparison of measure metrics

Measure	(a)	(b)	(c)
RMS	0.00	0.00	0.00
RME	0.76	0.56	0.51
RAMMG	0.17	0.17	0.17

(RMS) and the HVS. The RME measure is expressed in (2).

$$RME = \frac{1}{k_1 k_2}\sqrt{\sum_{i=1}^{k_1}\sum_{j=1}^{k_2}\left|\frac{\log\left|I_{i,j}-\frac{I_1+I_2+\cdots+I_n}{n}\right|}{\log\left|I_{i,j}+\frac{I_1+I_2+\cdots+I_n}{n}\right|}\right|}, \tag{2}$$

where k_1, k_2 denote the number of block, i, j denote for pixel location, $I_{i,j}$ is the center pixel intensity in block, $\left|\frac{I_1+I_2+\cdots+I_n}{n}\right|$ is the average intensity of block, and n is the total number of pixel within each block. However, even though these algorithms measure image's contrast locally and use the concept of the HVS, they have some limitations. Figure 1 shows ideal patch images. Each set composites of outer region and inner region. Each outer region's value is different to simulate different background luminance. To make mathematical contrast constantly, difference between outer region and inner region set equally. Table 1 is the result of three contrast measurement algorithms: RMS, RME, and RAMMG.

The results of RMS and RAMMG are same even though the contrast of three test sets look different. That is because the difference between inner region and outer region is same. For RME, results for three test sets are different because it considers the HVS. But, RME value decreases as a absolute value of outer region increases. Because RME is based on log scale, when backgorund luminance is small while difference is same, the RME value is high at the dark test set. These problems causes contrast measure unsuitable for applications.

The proposed method

The proposed measure is expressed as

$$Score_{i,j} = \left(\frac{1}{mn}\sum_{a=1}^{m}\sum_{b=1}^{n}\left|I_{a,b}-\bar{I}\right|\right) - Th_{i,j}, \tag{3}$$

where $I_{a,b}$ denotes intensity of a pixel at (a,b) point, and m,n are mask size. $\bar{I}$ means local mean of the image. Th means visibility threshold at background luminance.

To calculate the visibility threshold, we use just-noticeable-difference (JND) model proposed by Chou[8]. While existing measures are based on Weber's law, which is JND, this model

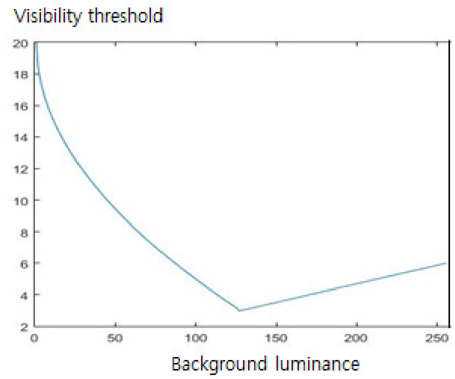

Figure 2. *Visibility thresholds due to background luminance.*

calculates the visibility threshold of JND using it's background luminance. It is because, for real world image, background luminance of image affects image's contrast and using just Weber's law has limitations to measure contrast in real world. Model for the visibility threshold of JND is expressed in (4).

$$JND(k) = \begin{cases} T_0[1-(\frac{k}{127})^{\lambda}]+3, & \text{if } k \leq 127 \\ \gamma(k-127)+3, & \text{otherwise .} \end{cases} \tag{4}$$

Figure 2 depicts JND model (4). Visibility threshold of JND is decreasing when background luminance is smaller than 127, and increasing when background luminance is larger than 127. Parameter T_0, γ and λ are set to 17, 3/128, 1/2 respectively. These values are calculated for when using 8-bit image.

The proposed method calculates image's contrast quality by using this model. Figure 3 is a block diagram of the proposed algorithm. First, we calculate each block's background luminance to obtain visibility threshold of JND. To calculate local background luminance, we convert the image's domain RGB to YUV. Then we calculate each block's visibility threshold by using (4). This process is expressed in (5) and (6).

$$\bar{I}_{i,j} = \frac{1}{mn}\sum_{a=1}^{m}\sum_{b=1}^{n} I_{a,b}. \tag{5}$$

$$Th_{i,j} = JND(\bar{I}_{i,j}). \tag{6}$$

We measure each local region's contrast using (3). $Score_{i,j}$ first calculates sum of absolute difference between each pixel's intensity and the local mean at each pixel i, j. Then, $Score_{i,j}$ measures difference between the calculated value and the local region's minimum visible threshold. The minimum visible threshold for local region should be changed according to it's background luminance, while people's visibility threshold differs by its background luminance.

Finally, for pooling stage, we use a visual saliency model as a weight for score pooling. This is expressed in (7).

$$Score = \sum_{i=1}^{N}\sum_{j=1}^{M} w_{i,j}\cdot Score_{i,j}, \tag{7}$$

where N,M denote size of image, $w_{i,j}$ and $Score_{i,j}$ denotes weight and contrast measurement at each point (i,j).

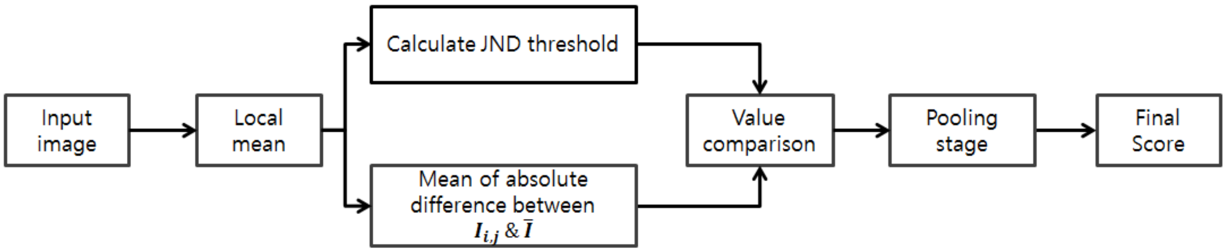

Figure 3. *Block diagram of the proposed method.*

Figure 4. *Images of TID2013 test set.*

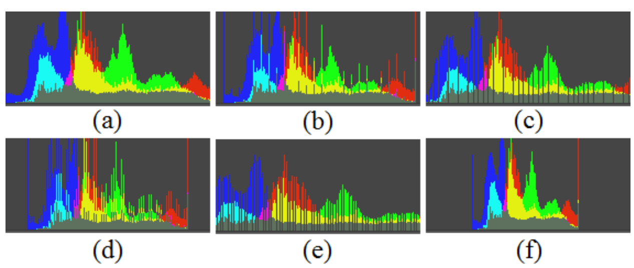

Figure 5. *Histograms of images at Figure 4.*

Each local regions weight, $w_{i,j}$, is calculated by visual saliency model. Visual saliency detects the salient regions in image by using prior models. These prior models are derived by physiological experiments. The proposed method is based on the HVS, so behavior of the HVS should be included in the pooling stage. By using visual saliency map as a weight, we put more weight for contrast in saliency region. We use visual saliency model proposed by Zhang [9], which uses simple priors to detect visual saliency region.

Experimental results

To verify our proposed method, we test our algorithm for two test sets. First, we test our measurement with ideal test set which is depicted in Figure 1. The result for conventional methods and proposed method are listed in Table 2. The result shows our proposed method measures contrast differently by each patch's background luminance, while RME and RMAAG measure it's contrast equivalently. In addition, when visibility threshold is lowest, proposed method value is the highest for (b), while RME has the highest value at (a). The negative measurement value means that region needs more enhancement in contrast for minimum visibility threshold even though we can distinguish two different rectangles.

Second, for real world images, TID2013 database [10] is used. TID2013 is a published benchmark for measuring image qualities. It has 24 types of distortions for each reference image, and 5 levels for each type of distortion.

We use one distortion type, contrast change, for our experiment. For contrast change, there are 5 levels of distortion: level 1 is small contrast decreasing, level 2 is small contrast increas-

Table 2. Measurement result with conventional methods and proposed method

Measure	(a)	(b)	(c)
RMS	0.00	0.00	0.00
RME	0.76	0.56	0.51
RAMMG	0.17	0.17	0.17
PM	-2.62	7.53	6.62

Table 3. Measurement on TID2013 images proposed method

(a)	(b)	(c)	(d)	(e)	(f)
17.25	16.62	18.14	15.72	18.97	14.23

ing, level 3 is larger contrast decreasing, level 4 is larger contrast increasing, and level 5 is largest contrast decreasing. Figure 4 is example of reference image and distorted images in TID 2013 and Figure 5 is histogram for each images.

Table 3 shows measurement value of the proposed method. Measurement values are high when contrast of images are increased, and low when contrast of images are decreased. This means our proposed method has good performance subjectively. To measure proposed method's performance objectively, correlation coefficients are used. We use Pearson's product moment correlation [11], and Spearman's rank order correlation [12]. Each of them measures how for each value deviates from the MOS, and the rank of image qualities. Table 4 summarizes the average correlations. The average correlation of Pearson's product moment correlation is higher than conventional methods.

Conclusion

NR image quality measurement method is essential in evaluating the performance of image processing algorithms. In this paper, NR contrast measure algorithm was proposed. Our measurement algorithm is based on minimum visibility threshold. The proposed method is compared with the conventional methods using contrast changed images in TID2013. Experimental results show that the proposed method performs better correlation with MOS.

Acknowledgement

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Science, ICT and future Planning (No. 2015R1A2A1A14000912)

Table 4. Comparison of measure metrics in accordance with average Peasrson and Spearman correlation with MOS

Measure	PRCC	SRCC
RMS	0.965	0.9
RME	0.986	0.9
RAMMG	0.983	0.9
PM	0.991	0.9

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