Applied Mathematics and Computational Intelligence
Volume 7, No.1, 2018 (33-38)

Analysis of Different Types of Full Reference Image Quality Assessment Algorithm

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ABSTRACT

Measurement of Image Quality plays an important role in numerous image processing applications such as forensic science, image enhancement, medical imaging, etc. In recent years, there is a growing interest among researchers in creating objective image quality assessment (IQA) algorithms that can correlate well with perceived quality. A significant progress has been made for full reference (FR) IQA problem in the past decade. In the meantime, several works has been made to compare and evaluate the performance of existing FR IQA methods. In this paper, we are comparing 5 selected FR IQA algorithms on TID2008 image datasets. The performance and evaluation results are shown in graphs and tables.

Keywords: Full Reference, Image Quality Assessment, PSNR, UIQI, SSIM, MSSIM, WSSI.

1. INTRODUCTION

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. In general, measurement of image quality usually can be classified into two categories, which are subjective and objective quality measurements [2].

Human visual system (HVS) is well adapted for this purpose as the main function of human eye is to extract structural information from the viewing field [3]. Therefore, the perfect method of quantifying image quality is through subjective evaluation. To evaluate this type of measurement, a number of observers are selected, tested for their visual capabilities, shown a series of test scenes and asked to score the quality of the scenes [4]. Nevertheless, subjective evaluations are time-consuming and expensive which makes them impractical for real-time applications.

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

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is to design algorithms that are able to predict the quality of an image automatically and accurately. Objective IQA can be classified into three categories according to the availability of a reference image [4].

The approaches are known as:

i. Full-reference: A complete reference image is available.
ii. Reduced-reference: The reference image is not fully available. Instead, some features of the reference image are extracted as side information in order to evaluate the quality of the test image.
iii. No-reference: The reference image is not available.

1.1 Image Quality Assessment

In general, measurement of image quality usually can be classified into two categories which are:

i. Subjective measurement: A number of observers are selected, tested for their visual capabilities, shown a series of test scenes and asked to score the quality of the scenes. It is the only "correct" method of quantifying visual image quality. However, subjective evaluation is usually too inconvenient, time-consuming and expensive.
ii. Objective measurement: These are automatic algorithms for quality assessment that could analyze images and report their quality without human involvement. Such methods could eliminate the need for expensive subjective studies.

Objective image quality metrics can be classified according to the availability of an original (distortion-free) image, with which the distorted image is to be compared. Most existing approaches are known as:

i. Full-reference (FR): meaning that a complete reference image is assumed to be known.
ii. No-reference (NR): In many practical applications, however, the reference image is not available, and a no-reference or "blind" quality assessment approach is desirable.
iii. Reduced-reference (RR): In a third type of method, the reference image is only partially available, in the form of a set of extracted features made available as side information to help evaluate the quality of the distorted image. The work in this paper is based on the design of full-reference category.

2. DATA SET AND PERFORMANCE METRICS

TID2008 database is downloaded to be implemented during the evaluation of the selected IQA metrics. This database contains 1700 test images (25 reference images, 17 types of distortions for each reference image) [5]. TID2008 is intended for evaluation of FR IQA metrics. It allows estimating how a metric corresponds to mean human perception. Three commonly applied performance metrics are used for calculating the prediction monotonicity which are:

i. Spearman rank- order correlation coefficient (SROCC)
ii. Kendall rank-order correlation coefficient (KROCC)
iii. Pearson linear correlation coefficient (PLCC

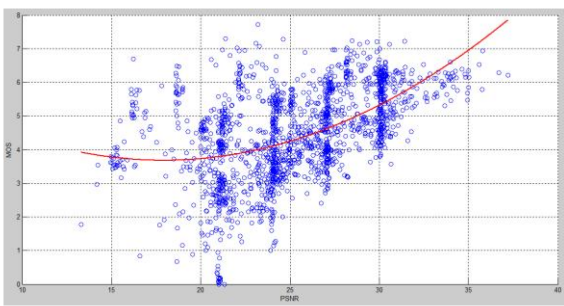
3. EVALUATION RESULTS AND DISCUSSION

3.1 Evaluation of Prediction Performance

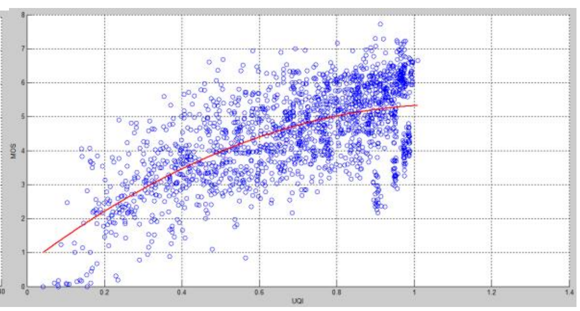
Initially, then, a comparison has been done between the five IQA metrics by simulating them using MATLAB software. The five FR IQA metrics are:

i. Peak Signal-to-Noise Ratio (PSNR)
ii. Universal Image Quality Index (UIQI) [6]
iii. Structural Similarity Index (SSIM) [7]
iv. Multiscale Structural Similarity Index (MSSIM) [8]
v. Wavelet Structural Similarity Index (WSSI) [9]

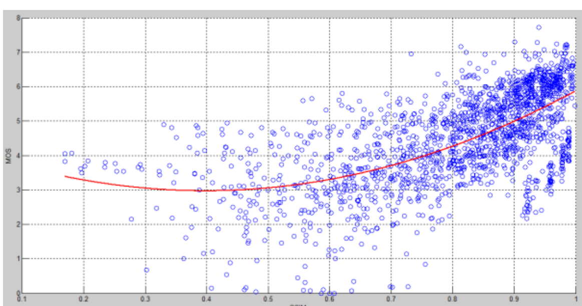
Mean Opinion Score (MOS) is then plotted in a scatter graph against with the scores obtained. The best fit line are plotted so the trends of the graph can be perceived clearly.



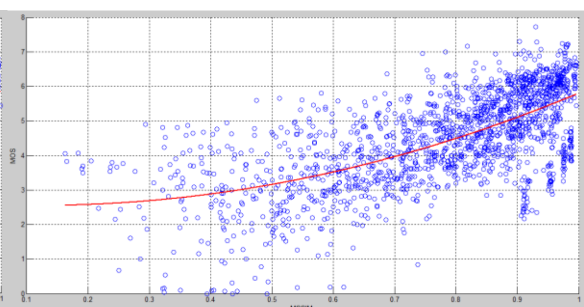
(a) PSNR algorithm



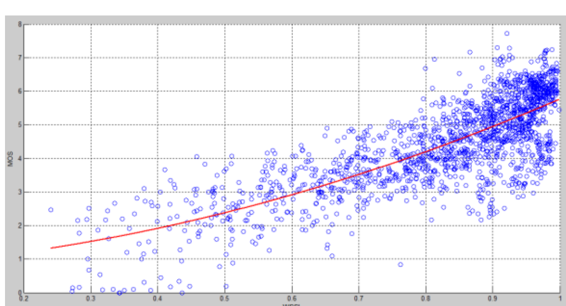
(b) UIQI algorithm



(c) SSIM algorithm



(d) MSSIM algorithm



(e) WSSI algorithm

Figure 1. Plotted graph of MSE vs obtained results for each algorithms. (a) PSNR algorithm (b) UIQI algorithm (c) SSIM algorithm (d) MSSIM algorithm (e) WSSI algorithm.

Table 1: Performance comparison of 5 IQA indices on TID2008 database

		PSNR	UIQI	SSIM	MSSIM	WSSI
TID2008	**SROCC**	0.5229	0.5856	0.6213	0.6332	0.7457
	KROCC	0.3682	0.4259	0.4510	0.4618	0.5605
	PLCC	0.4946	0.6435	0.5998	0.6389	0.7720

Table 2: Overall performance ranking of IQA indices

	SROCC	**KROCC**	**PLCC**
PSNR	5	5	5
UIQI	4	4	2
SSIM	3	3	4
MSSIM	2	2	3
WSSI	1	1	1

4. DISCUSSIONS

The scatter plots of MOS versus model predictions are shown in Figure 1-5, where each point represents one test image, with its vertical and horizontal axes representing its MOS and the obtained quality score, respectively. From Table 1 and 2, it can be concluded that PSNR has the lowest prediction. PSNR is a mathematical formula that measures the image quality based on the pixel difference between reference and distorted image.

Although this metric is simple and easy to calculate, it ignores the features of human image perception.

In 2002, Wang and Bovik proposed UIQI [6]. It breaks the comparison between original and distorted image into three comparisons: luminance, contrast, and structural comparisons. However, it counts only 1st and 2nd order statistic of the original and distorted image. UIQI is considered unstable measure and does not correlate well with subjective assessment.

The same author proposed SSIM as an improvement of UIQI. Similar to UIQI, SSIM separates out the parameters in image which are luminance, contrast and structure. Additionally, this metric is applied locally using sliding window that moves pixel by pixel over the entire image. Computing the average of SSIM values over different windows resulting in MSSIM values.

WSSI has the highest prediction value in this experiment. The reason is that most of the useful image information is concentrated in the first-level approximation sub band.

5. CONCLUSIONS

Image quality assessment plays an important role in various image processing application. A numerous effort has been made by researchers to develop objective IQA metrics. In this experiment, some insights can be seen on why image quality is so difficult to be developed. Many information in an image need to be considered in order to perceived the subjective evaluation.

ACKNOWLEDGMENTS

This research is supported by Fundamental Research Grant Scheme (FRGS) (Pindaan 1/2012).

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