Efficient Color Image Quality Assessment Using Gradient Magnitude Similarity Deviation

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Abstract
In the present research work, a new objective image quality assessment method based on gradient similarity map and directional derivatives map is presented and called as Efficient Image Quality Assessment (EIQA). It assesses image quality by using different characteristics of human visual system (HVS). Considering directional derivative map (DDM) is important because there exists anisotropic structure in the image and the edges always stretch out in multiple directions. The Gradient Similarity Map (GSM) is employed as the secondary features in EIQA. The proposed EIQA method has been compared with Gradient Magnitude Similarity Deviation (GMSD) and other conventional image quality assessment (IQA) metrics using three widely used databases i.e. LIVE (Laboratory for Image & Video Engineering), TID2008 (Tamper Image Database 2008) and CSIQ (Categorical Subjective Image Quality) . The proposed method yield better performance in terms of correlation coefficients such as Spearman rank-order correlation coefficient (SROCC), Kendall rank-order correlation coefficient (KROCC), Pearson linear Correlation Coefficient (PLCC) and Root Mean Squared Error (RMSE) with the help of MATLAB software.

Keywords
Color Image, Efficient Image Quality Assessment, Gradient Magnitude Similarity Deviation

I. Introduction

Digital image processing is a technique of processing digital image with the use of computer algorithms. Image processing allows various numbers of algorithms to be applied to the input data and to avoid problems such as noise and distortion during processing of image. Digital images that are exchanged and distributed via digital communication networks are subjected to various types of distortion during the acquisition, processing, compression, transmission and reproduction. These distortions may originate in various stages of image processing. Image quality is a characteristic of the image that measures the image degradation "before" and "after" (typically compared to original image) processing. It uses the visual content of an image such as structure similarity, luminance and contrast masking etc. to measure quality of image [1]. Mainly there are two kinds of approaches in image quality measurement: Subjective measurements, Objective measurement. Subjective measurement is a process to determine the quality score of images with the help of number of viewers. In practice; subjective measurement system is generally time-consuming, expensive and cannot be perform in the real time application easily. In order to solve this problem, an objective approach is required. The main purpose of objective measurement system is compute the quality score which are precisely correlate with the quality score given by human viewer. Generally the objectives quality assessment are classified into three categories based on the amount of information required for quality assessment: 1) Full reference (FR) method, in which original and distorted image is required to compute the quality score. (2) No Reference (NR), it only use the distorted image for compute the quality score (3) Reduced Reference (RR), where partial information of the reference image is required [2].Our proposed model is mainly focuses on FR-IQA model shown in fig 1.

Recently, Wufeng et al [3] proposed a method for measurement of image quality which involves the HVS that is highly suitable for extracting structural information. There are few metrics based on human perception such as the Feature Similarity Index (FSIM) [4], SSIM, NQM, IFC [5] and the wavelet based visual signal to noise ratio (VSNR) [6]. Researchers observations till today has proved that the performance of the SSIM, MS-SSIM VIF and IFC metric based on HVS offers statistically better performance than the MSE VSNR and PSNR The conventional metrics such as or Peak Signal to Noise Ratio (PSNR) or Mean Square Error (MSE) do not properly correlates with human perception, and researchers have been showing much efforts in developing advanced accessible field driven IQA models [7]. Based on above specifics, we proposed an IQA model called Efficient Image Quality Assessment (EIQA). The major issue in multimedia applications is the complexity of implemented IQA models increasing as the resolution of the image rapidly increasing which required large memory and time. The proposed EIQA model is much faster and compared with than other start-of-the-art FR-IQA models. The gradient map of image is important feature in IQA model, because most of the information of the basic primitives is carried by the edge locations where zero crossing occur [7].

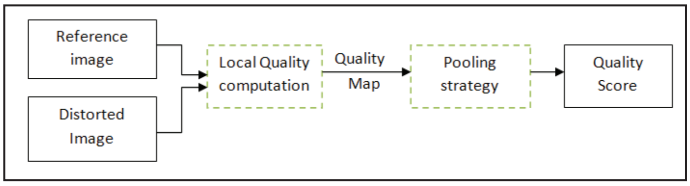

Fig. 1: The Flowchart of Two-Step FR-IQA Models

The two main strategy used with FR-IQA method. The first strategy lies on the basis of bottom up frame work provides help in stimulating human visual system including contrast sensitivity ,visual masking effect The second strategy is differ from first it is basically based on top-down framework. Different IQA models tend to share a general two step framework as shown in Fig.1.Firstly LQM is generally evaluated by comparison of distorted image and with reference image by using similarity function. Then overall quality score is computed with the help of LQM via using some pooling strategy [3]. The simple and broadly used pooling strategy is average pooling, i.e. with the help of pooling strategy we find the average of all available local quality values, and so with these we predict the overall quality score. The local quality values can be weighted according to the available data to produce the final quality score. Example weighting strategies include distortion based weighting, visual attention, content-based partitioning, assumed visual fixation, and local measures of information content. When we compared weighted pooling strategy with average pooling, weighted pooling strategy can give

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more accuracy at some extent for improvement IQA method [7]. The main drawback of weight strategy is it become costly when computes the weights. Besides that weighted pooling make the pooling process complicated and predicted quality scores become more nonlinear with respect to the subjective quality scores (as shown in fig. 1)

II. Proposed image Quality Assessment Method

This section presents design and implementation steps involved in development of proposed EIQA model for image quality assessment (IQA). Conceptual framework is provided to understand the working of entire system. Development of IQA system consists of two steps: First, a Local Quality Map (LQM) is computed by locally comparing the distorted image with the reference image via some similarity function. Then a single overall quality score is computed with standard deviation. The goal is to predict the quality of images without human viewers. To evaluate quality of images the following steps are followed:

Step 1: Transform the Reference (IR) and Distorted (ID) images into 8-bit gray scale as shown in fig. 2

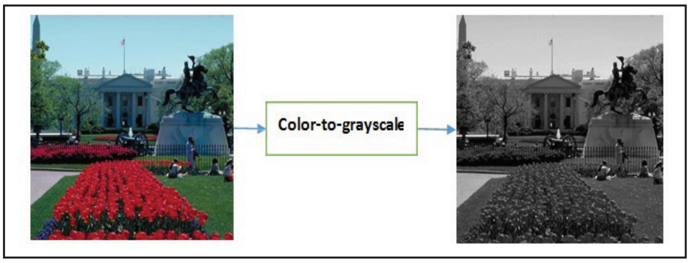

Fig. 2: Color Image to Grey Scale Conversion

Step 2: Compute the Directional Derivatives Similarity (DDS). The directional derivatives are computed by convolving the reference (RI) and distorted (DI) image with the filters K^j, $j = 1,2,3,4$, which are given below.

$$K^H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & -3 & 0 & 3 & 0 \\ 0 & -10 & 0 & 10 & 0 \\ 0 & -3 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad K^V = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 10 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & -3 & -10 & -3 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad (1)$$

$$K^P = \begin{bmatrix} 0 & 0 & 3 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 & -3 \\ 0 & 0 & 0 & -10 & 0 \\ 0 & 0 & -3 & 0 & 0 \end{bmatrix} \quad K^M = \begin{bmatrix} 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 10 & 0 \\ -3 & 0 & 0 & 0 & 3 \\ 0 & -10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad (2)$$

Convolving K^j, with reference image and distorted images gives you the directional derivatives along horizontal, vertical and diagonals directions. The directional derivatives of IR and ID at location i, denoted by G_R^j and G_D^j, where $j = 1,2,3,4$ are computed as follows.

$$G_R^1 = K^H \otimes RI, G_R^2 = K^V \otimes RI,$$

$$G_R^3 = K^P \otimes RI, G_R^4 = K^M \otimes RI \qquad (3)$$

$$G_D^1 = K^H \otimes ID, G_D^2 = K^V \otimes ID,$$

$$G_D^3 = K^P \otimes ID, G_D^4 = K^M \otimes ID \qquad (4)$$

Here symbol "⊗" denotes the convolution operation. With the directional derivatives images G_R^j and G_D^j in hand, the directional derivatives similarity (DDS) map is define as follows:

$$DDS(i) = \frac{2G_R^j(i)G_D^j(i)+C}{G_R^j(i)^2+G_D^j(i)^2+C} \qquad (5)$$

Where C is a positive constant to stabilize the result and its proposed value is 0.0025.

Step3. Compute the Gradient Magnitude Similarity (GMS). For simplicity of computation, the Sobel filter was utilized to calculate the gradient because it is the simplest one among the 3 ×3 template gradient filters. By using other filters such as the Prewitt and Scharr filters, the proposed method will have similar IQA results. The Sobel filters along horizontal (x) and vertical (y) directions are defined as:

$$I_X = \frac{1}{4}\begin{vmatrix} 1 & 0 & -1 \\ 2 & 1 & -2 \\ 1 & 0 & -1 \end{vmatrix},$$

$$I_Y = \frac{1}{4}\begin{vmatrix} 1 & 0 & -1 \\ 2 & 1 & -2 \\ 1 & 0 & -1 \end{vmatrix} \qquad (6)$$

Convolution I_X and I_Y with reference and distorted images gives the horizontal and vertical gradient images of IR and ID. The gradient magnitude of IR and ID at location i, denoted by G_{IR}(i) and G_{ID} (i), are computed as

$$G_{IR}(i) = \sqrt{(IR \otimes I_X)^2 + (IR \otimes I_Y)^2} \qquad (7)$$

$$G_{ID}(i) = \sqrt{(ID \otimes I_X)^2 + (ID \otimes I_Y)^2} \qquad (8)$$

Here symbol "⊗" denotes the convolution operation. With the help of gradient magnitude images G_{IR}(i) and G_{ID}(i) in hand, the Gradient Magnitude Similarity (GMS) map is define as follows:

$$GMS(i) = \frac{2G_{IR}(i)G_{ID}(i)+C}{G_{IR}^2(i)+G_{ID}^2(i)+C} \qquad (9)$$

Here, C is a positive constant to stabilize the result and its proposed value is 0.0025.

Step 4: Compute the Quality Score with Standard Deviation. Based on the idea proposed in gradient magnitude similarity deviation (GMSD) (Xue and Zhang, 2014), that local quality loss can reflect its overall quality. We apply our quality score measurement method on DDS and GMS map using standard deviation, called as EIQA and define as:

$$DDS_{std} = \left[\frac{1}{N}\sum_{i=1}^{N}(DDS(i) - \overrightarrow{DDS})^2\right]^{1/2} \qquad (10)$$

Where $\overrightarrow{DDS}$ and $\overrightarrow{GMS}$ is:

$$\overrightarrow{DDS} = \frac{1}{N}\sum_{i=1}^{N} DDS(i),$$

$$\overrightarrow{GMS} = \frac{1}{N}\sum_{i=1}^{N} GMS(i) \qquad (12)$$

Where N is number of pixels in the image. With the help of DDS_{std} and GMS_{std} in hand, we calculated overall quality score for EIQA metrics.

$$EIQA_{Quality\ Score} = \text{Min}\ (DDS_{std}, GMS_{std}) \qquad (13)$$

Value of $EIQA_{Quality\ Score}$ reflects the range of distortion in an image. Lower the $EIQA_{Quality\ Score}$ score lower the distortion range.

III. Results and Analysis

A. Results on Laboratory for Image & Video Engineering (LIVE)

LIVE is a standard database, which contains a set of images which can be used for validation of image quality assessment algorithms. The database contains both types of images, reference and its distorted versions. There are 29 reference images, which are distorted by 5 types of distortions with different degradation levels. The database is provided with a file, which contains the Differential Mean Opinion Score (DMOS) of each image present in the database. DMOS is the mean of quality scores given by different human observers. This score is considered as a standard quality score with which output of different FR-IQA algorithms is to be compared.

1. Correlation Coefficients (CC) Observations on LIVE database

The performance evaluation of different FR-IQA can be done using correlation coefficients. In this chapter, LIVE database is used to get output of an algorithm and then the output is compared with DMOS. The two variables in the correlation formula are the quality scores of images in LIVE database calculated by FR-IQA algorithm under test and the DMOS. SROCC, PLCC, KROCC, RMSE are used to compare the performance of different FR-IQA algorithms. A better objective IQM should have higher PLCC, SRCC, and KRCC while lower RMSE values. Table 1 lists the four correlation coefficients results of EIQA and other seven IQMs on the LIVE database. The best results across the seven IQMs are highlighted in boldface. From Table 1, it can be seen that EIQA performs the best on the Live database.

Table 1: Performance of proposed EIQA model by using GMSD and other competing FR-IQA modelsa in term of PLCC, KROCC, SROCC and RMSE on the live data base.

IQA MODELS	LIVE DATA BASE (779 images)			
	Correlation coefficients			
	PLCC	KROCC	SROCC	RMSE
EIQA	0.961	0.8291	0.9612	7.5571
GMSD	0.960	0.826	0.960	7.621
FSIM	0.9597	0.8337	0.9634	7.6780
MSSIM	0.9430	0.7922	0.9445	9.0956
SSIM	0.9449	0.7963	0.9479	8.9455
IFC	0.9248	0.7540	0.9234	10.392
VSNR	0.9231	0.7616	0.9274	10.506
PSNR	0.872	0.6864	0.8755	13.361

2. Plots of different IQA Algorithms Versus Subjective MOS and DMOS

The output of objective scores obtained by proposed algorithm and the Subjective MOS and DMOS can be plotted on same graph using scatter plot. Scatter plots are obtained for quality score given by different FR-IQA and the actual quality score of an image as shown below in fig. 3. (a),(b),(c),(d),(e),(f),(g),(h).

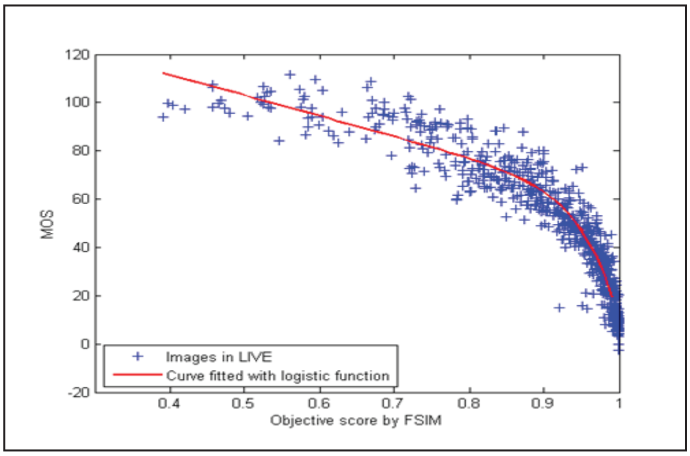

Fig. 3(a):

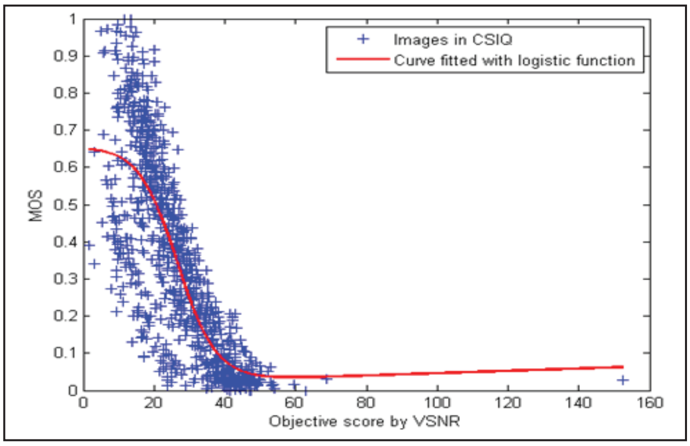

Fig. 3(b):

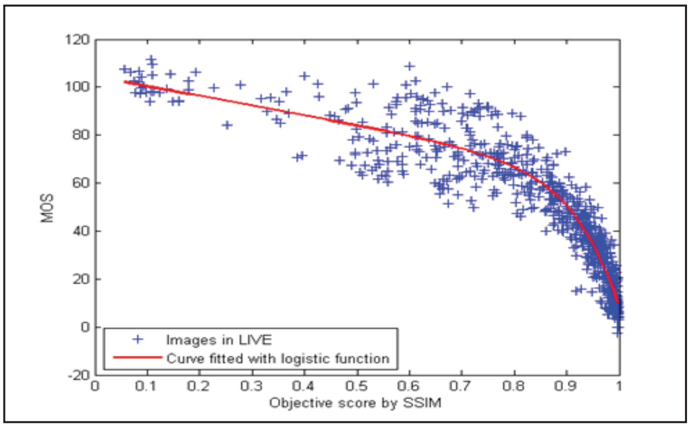

Fig. 3(c):

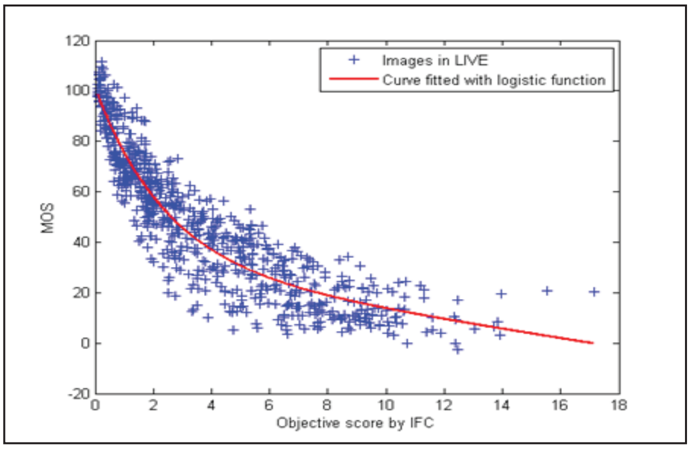

Fig. 3(d):

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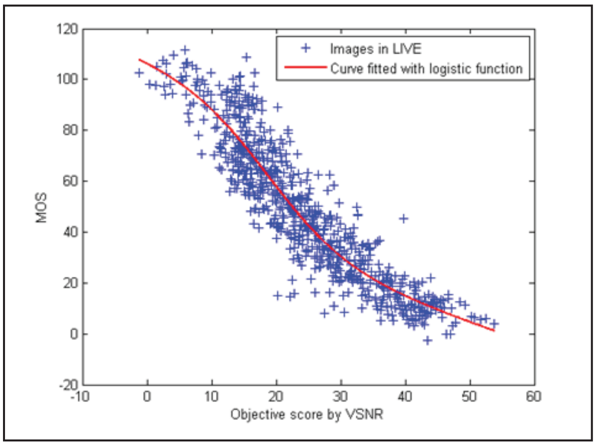


Fig. 3(e):

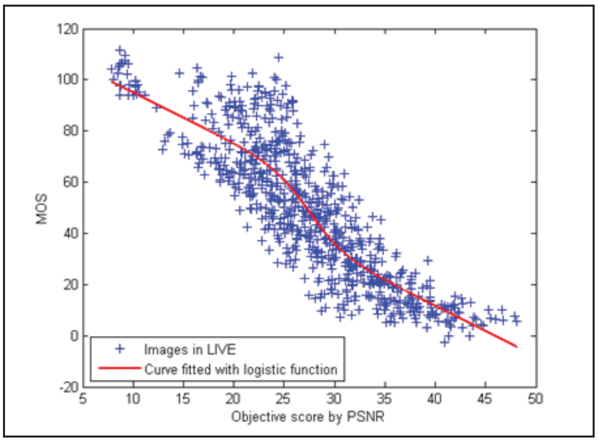


Fig. 3(f):

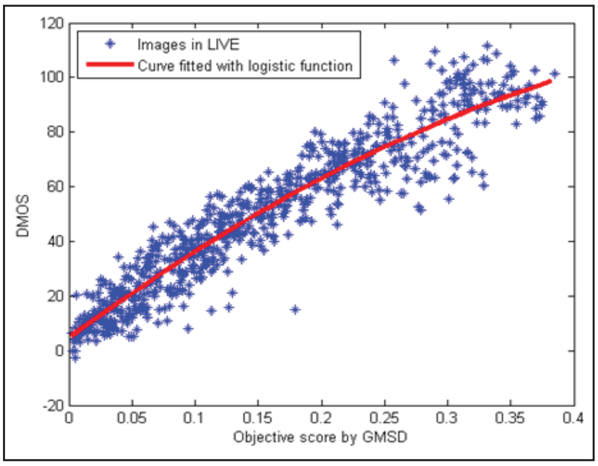


Fig. 3(g):

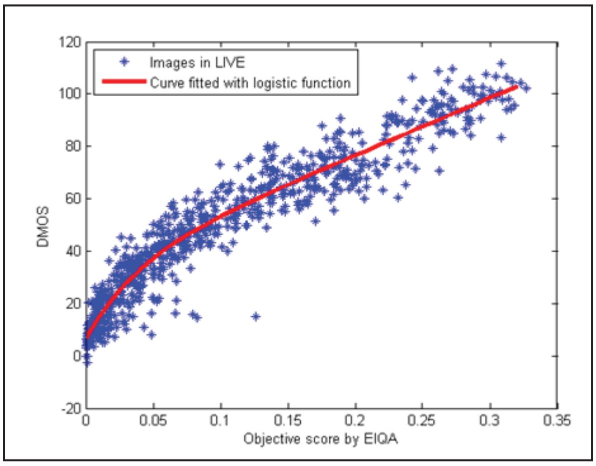


Fig. 3(h):

B. Results on Categorical Subjective Image Quality (CSIQ)

The CSIQ database consists of 30 original images; each is distorted using six different types of distortions at four to five different levels of distortion. CSIQ images are subjectively rated base on a linear displacement of the images across four calibrated LCD monitors placed side by side with equal viewing distance to the observer. The database contains 5000 subjective ratings from 35 different observers, and ratings are reported in the form of DMOS.

1. Correlation Coefficients (CC) Observations on CSIQ database

CSIQ database is used to get output of an algorithm and then the output is compared with DMOS. The two variables in the correlation formula are the quality scores of images in CSIQ database calculated by FR-IQA algorithm under test and the DMOS. SROCC, PLCC, KROCC, RMSE are used to compare the performance of different FR-IQA algorithms. Table 2 lists the four correlation coefficients results of EIQA and other seven IQMs on the CSIQ database. The best results across the seven IQMs are highlighted in boldface. From Table 2, we can see that EIQA performs the best on the CSIQ.

Table 2: Performance of proposed EIQA model by using GMSD and other competing FR-IQA modelsa in term of PLCC, KROCC, SROCC and RMSE on the CSIQ data base.

IQA MODELS	CSIQ DATA BASE (779 images)			
	Correlatin coefficients			
	PLCC	KROCC	SROCC	RMSE
EIQA	0.9572	0.8164	0.9598	0.0760
GMSD	0.954	0.812	0.957	0.079
FSIM	0.9120	0.7567	0.9242	0.1077
MSSIM	0.8998	0.7397	0.9138	0.1145
SSIM	0.8613	0.6907	0.8756	0.1334
IFC	0.8381	0.5740	0.7482	0.1432
VSNR	0.8002	0.6247	0.8106	0.1575
PSNR	0.8001	0.6080	0.8057	0.1575

2. Plots of Different IQA Algorithms versus Subjective MOS, DMOS

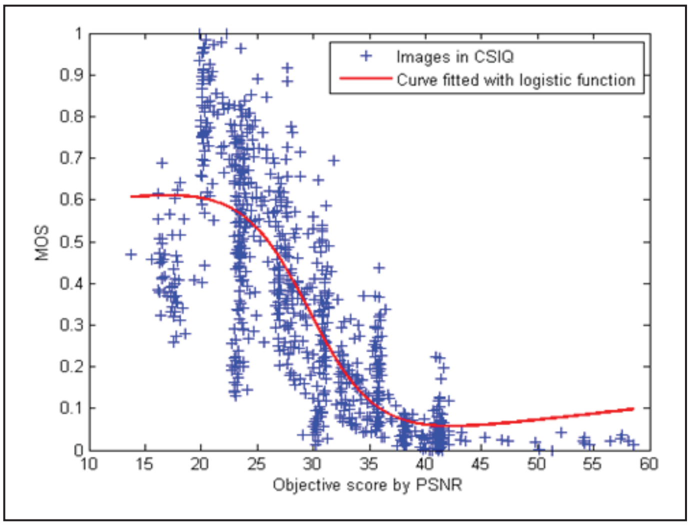


Fig. 4(a):

The output of objective scores obtained by proposed algorithm and the Subjective DMOS and MOS can be plotted on same graph using scatter plot shown in fig. 4 (a,b,c,d,e,f,g,h).

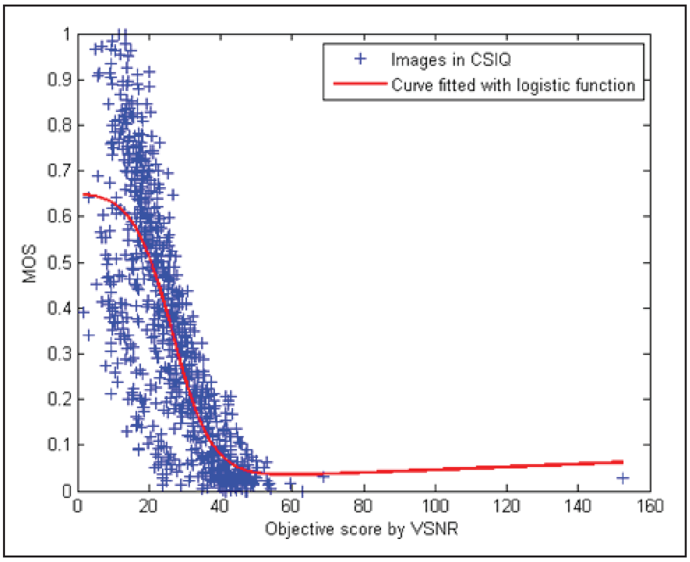


Fig. 4(b):

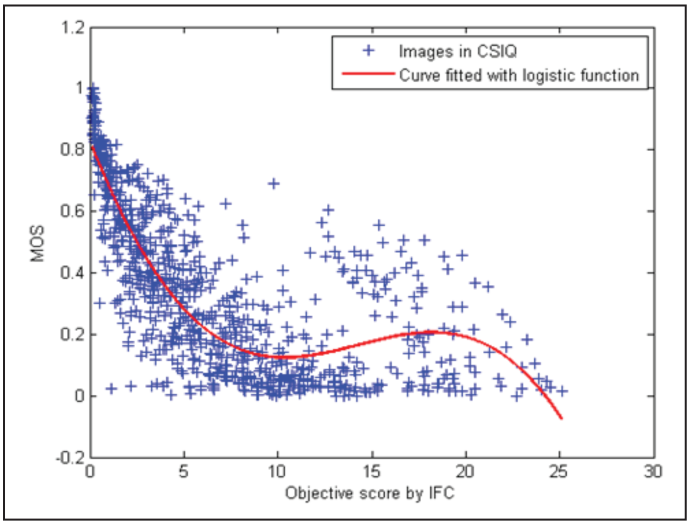


Fig. 4(c):

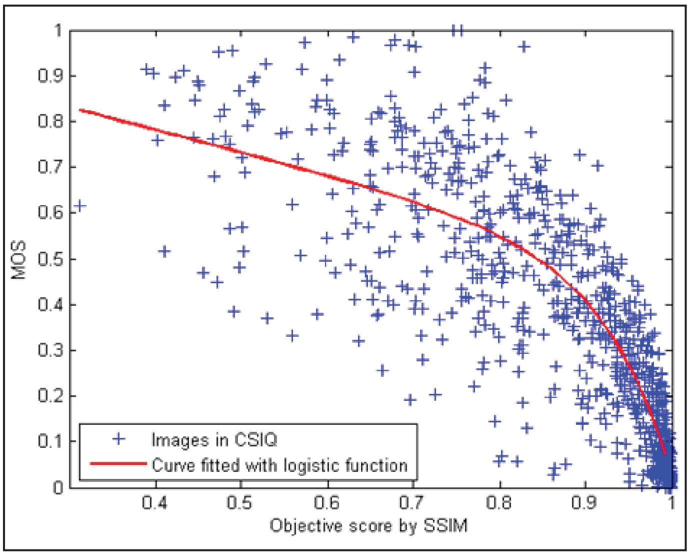


Fig. 4(d):

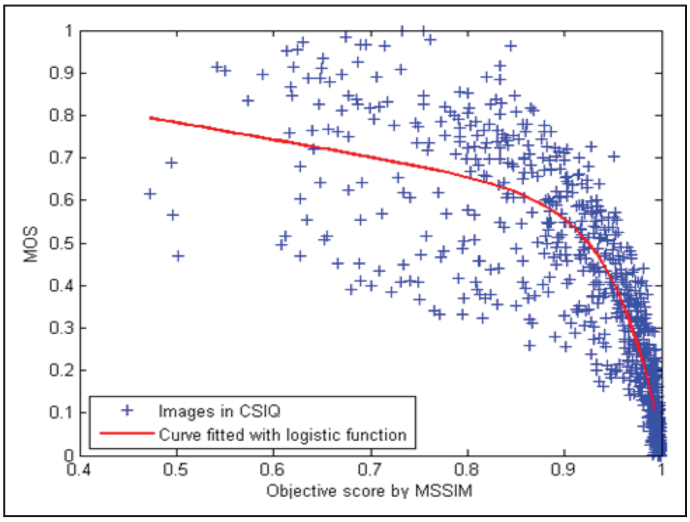


Fig. 4(e):

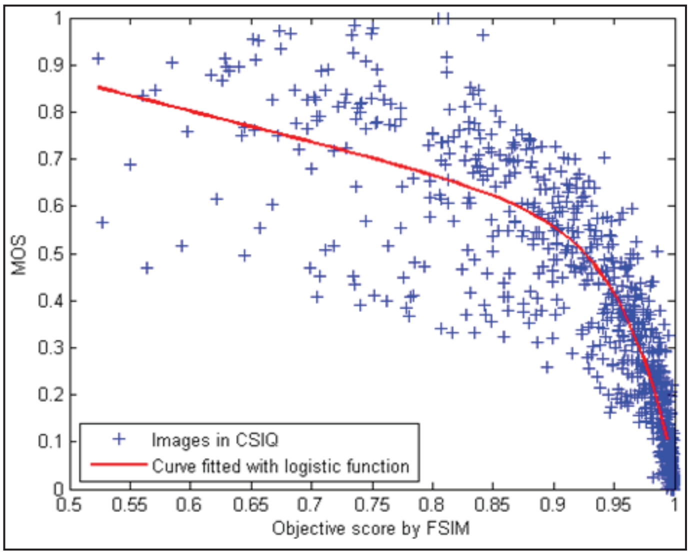


Fig. 4(f):

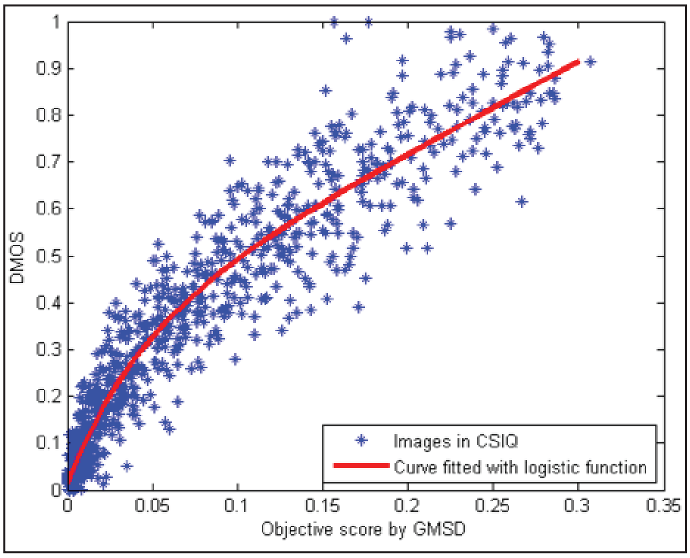


Fig. 4(g):

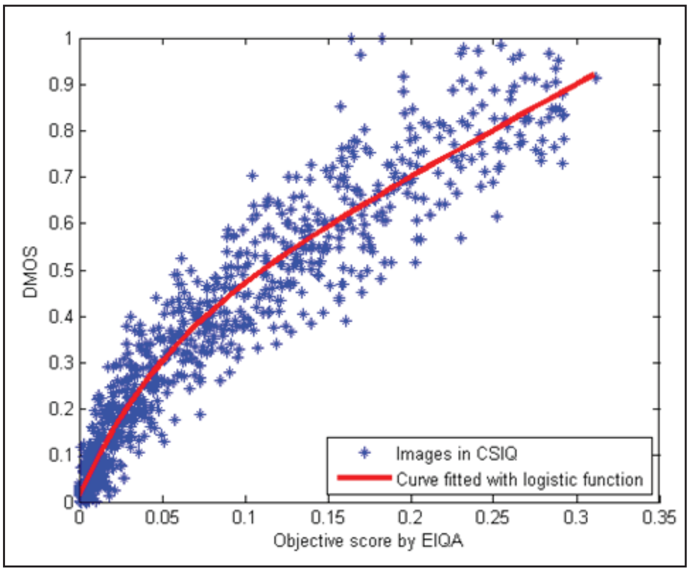


Fig. 4(h):

Fig. 4 shows the scatter plot for different IQMs on CSIQ database

C. Results on Tampere Image Database 2008 (TID2008)

Currently the largest image quality database is available in the public domain both in terms of test images and number of subjects. The TID2008 database contains 1700 images, with 25 reference images and 17 types of distortions over 4 distortion levels. The ratings were obtained from 838 human observers.

1. Correlation Coefficients (CC) Observations

TID2008 database is used to get output of an algorithm and then the output is compared with DMOS. The two variables in the correlation formula are the quality scores of images in TID2008 database calculated by FR-IQA algorithm under test and the DMOS. SROCC, PLCC, KROCC, RMSE are used to compare the performance of different FR-IQA algorithms. Table 3 lists the four correlation coefficients results of EIQA and other seven IQMs on the TID2008 database. The best results across the seven IQMs are highlighted in boldface. From Table 3, we can see that EIQA performs the best on the TID2008.

Table 3: Performance of Proposed EIQA Model by using GMSD and other Competing FR-IQA models a in term of PLCC, KROCC, SROCC and RMSE on the TID 2008 data base.

IQA MODELS	TID 2008 DATA BASE			
	Correlation coefficients			
	PLCC	KROCC	SROCC	RMSE
EIQA	0.8801	0.7100	0.8926	0.6371
GMSD	0.8798	0.709	0.891	0.640
FSIM	0.879	0.6946	0.8805	0.6525
MSSIM	0.8738	0.6543	0.8528	0.7299
SSIM	0.8425	0.5768	0.7749	0.8511
IFC	0.7732	0.4261	0.5692	0.9086
VSNR	0.7359	0.5340	0.7046	0.9815
PSNR	0.6820	0.3696	0.5245	1.1372

2. Plots of different IQA Algorithms Versus Subjective MOS, DMOS

The output of objective scores obtained by proposed algorithm and the Subjective MOS can be plotted on same graph using scatter plot. Scatter plots are used for obtaining the quality score given by different FR-IQA and the actual quality score of an image is shown in below fig. (a) ,(b),(c),(d),(e),(f),(g),(h).

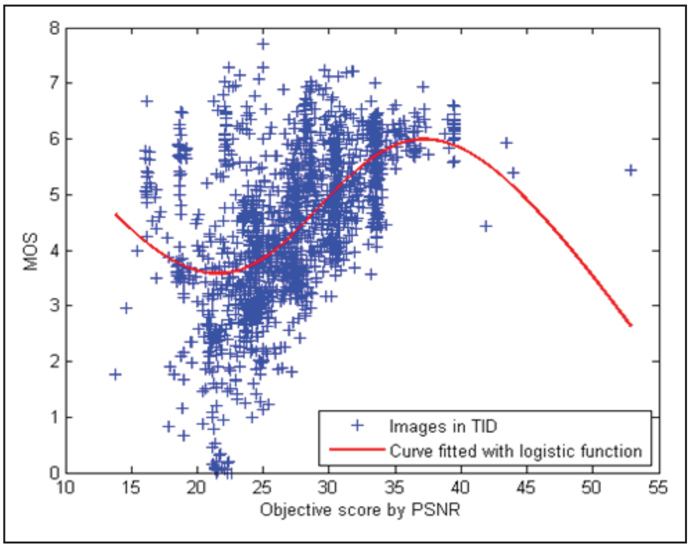


Fig. 5(a):

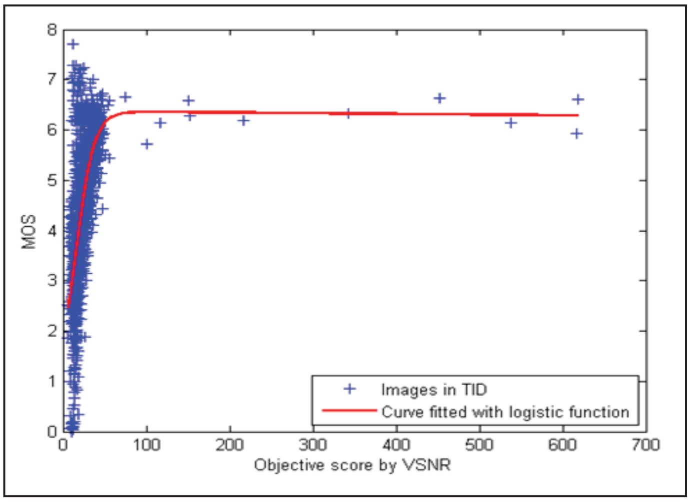


Fig. 5(b):

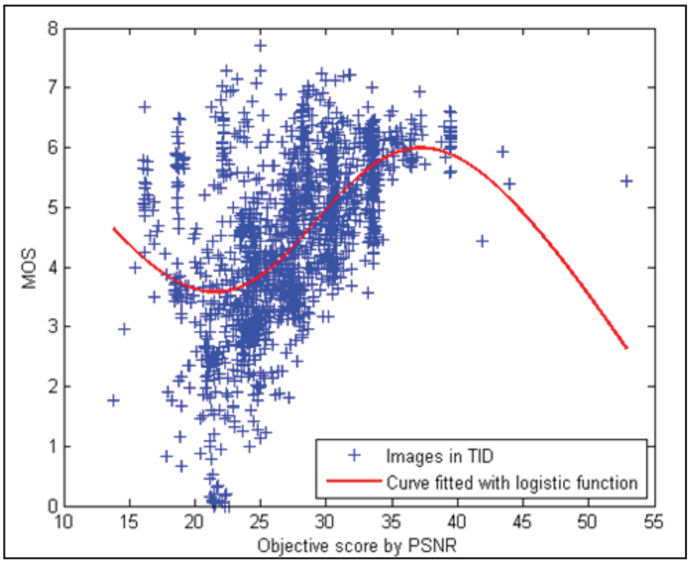


Fig. 5(c):

When EIQA algorithm scatter plot is compared with other scatter plots, EIQA's points are more close to each other, which means that EIQA correlates well with subjective ratings.

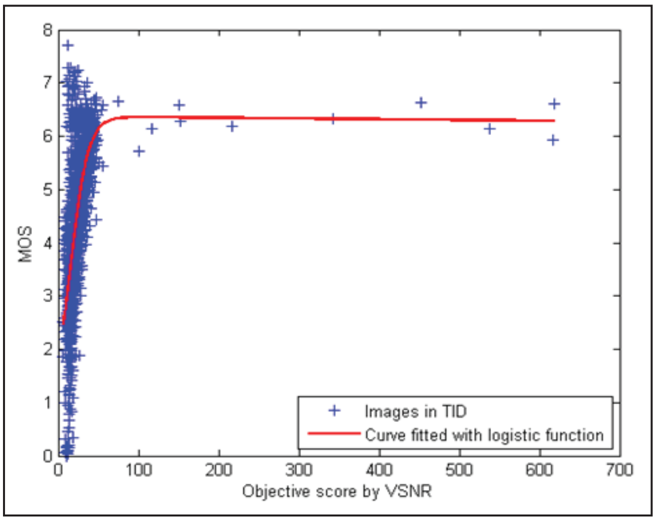
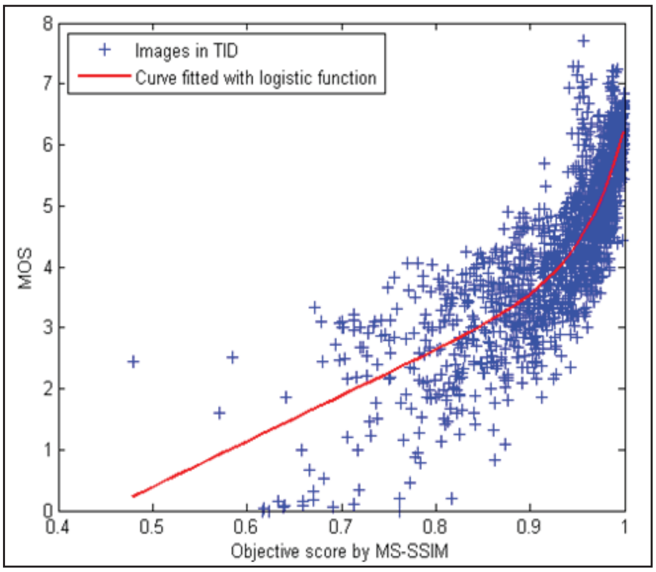


Fig. 5(d):



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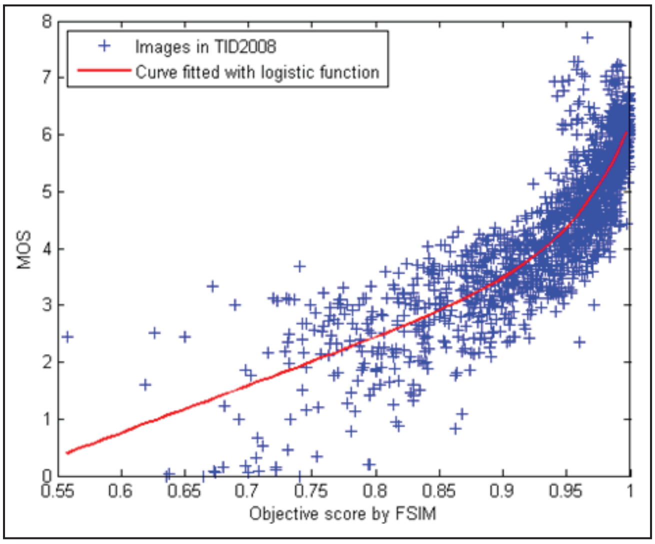

Fig. 5(f):

Fig. 5 Shows the scatter plot for different IQMs on TID2008 database

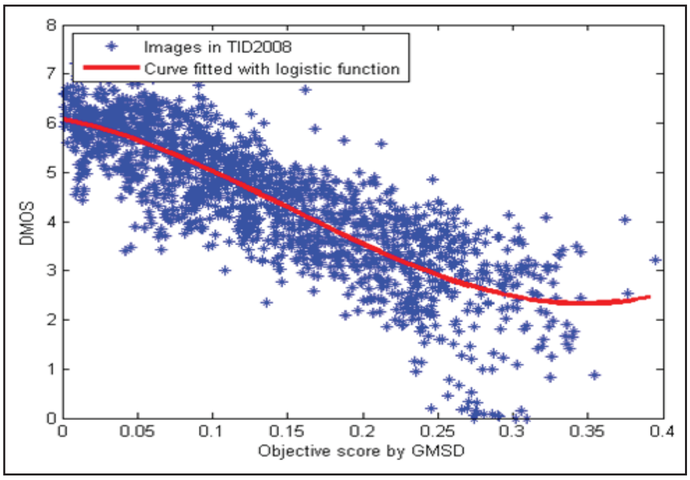

Fig. 5(g):

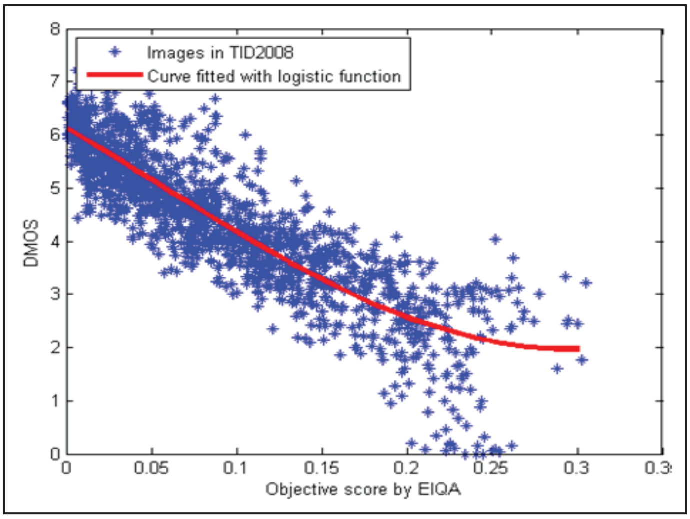

Fig. 5(h):

Fig. 5 Shows the scatter plot for different IQMs on TID2008 database

IV. Conclusion

The proposed IQA algorithm is compared with the existing FR-IQA algorithms. Experimental results on three databases show that none of the state-of-the-art FR-IQA models has better correlation coefficients with the proposed model. Scatter plots demonstrate the performance of the proposed algorithms.

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