

FR IQA Classification and Evaluation

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ABSTRACT: Image quality assessment plays a vital role in various image processing applications such as medical imaging technology, forensic Science, fake biometric detection, image enhancement, etc. Image quality is defined as the integrated set of perceptions of the overall degree of excellence of the image. Image quality assessment methods are used to evaluate image quality, its measure the degradation in digital images in order to improve the quality of the image for various image processing applications. There are two types of IQA methods, the subjective methods are costly process and it needs experts for evaluating image quality. Now a days many objective IQA methods image are available for finding the quality of images. These are mainly based on the properties of human visual system. In this paper give an idea about the classification of full reference image quality assessment and their evaluation. In this paper give the performance evaluation six IQA metrics.

KEYWORDS: Classification, FR IQA, Human visual system, Image quality assessment, no-reference IQA. Reduced-reference IQA,

I. INTRODUCTION

Digital images are subject to a wide different types of distortions during acquisition, processing, compression, storage, transmission and reproduction, any of which may result in a degradation of image quality. So IQA methods are used to measure the degradation in digital images in order to improve the quality of the image for various image processing applications.[1]. Image quality assessment methods are two types Subjective method and Objective method [1], For applications in which images are ultimately to be viewed by human beings, the only correct method of quantifying visual image quality is through subjective evaluation. In subjective evaluation, human being to evaluate the quality of an image. But the main drawbacks of subjective methods are time consuming and expensive, because subjective results are obtained through experiments with many observers and also it cannot be incorporated into real time applications such as image compression, and transmission, etc. Their results depend heavily on the subjects physical conditions and emotional state and also depends on other factors such as display device and lighting conditions of subjective experiments. In order to overcome the disadvantages of subjective methods, objective image quality assessment is to develop. It is a quantitative measures that can automatically predict perceived image quality. Three main categories of the objective IQA are No-reference image quality assessment(NR-IQA)[5], Reduced-reference image quality assessment (RR-IQA)[4] and Full-reference image quality assessment(FR-IQA). In NR-IQA[5]the reference image is not available and the quality evaluation is solely based on the test image. In RR-IQA[4], the reference image is not fully accessible. Instead, a number of features are extracted from the reference image. In FR-IQA metrics, the perfect quality reference image is fully available for quality prediction process. In this paper explain briefly about the FR IQA classification and their evaluation.

II. FULL-REFERENCE IMAGE QUALITY ASSESSMENT (FR-IQA)

In FR IQA the distorted image is compares with the original or an undistorted version of that image. Here the perfect quality reference image is fully available for quality prediction process.

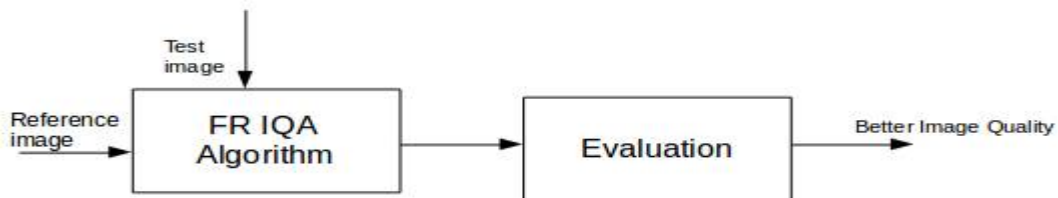


Fig.1 Full Reference Image Quality Assessment

Now a days there are lot of IQA metrics available for the image quality evaluation process. In order to evaluate the performance of existing IQA metrics, you need to conduct experiments on the available image databases. Normally, in such a database, there are a lot of reference images and for each image, there exist several distorted images. For each distorted image, there are several subjective evaluations by human beings. In order to evaluate an IQA metric, you need to compute objective scores for all the distorted images in the database using the selected IQA metric. Then, you can evaluate kinds of correlations between the obtained objective scores and the subjective scores provided by the database. By such a process, the performance of IQA metrics [2] can be used. The Pearson linear correlation coefficient (PLCC), Spearman rank order correlation coefficient (SROCC), Kendall rank correlation coefficient (KRCC), are performance IQA metrics used for the evaluation.

The Pearson's correlation coefficient is the linear interdependence between two variables or two sets of data. It is defined as the covariance of the two variables divided by the product of their standard deviations. It measures the linear dependence between two variables, the resulting value having range [-1, 1] where 1 is total positive correlation and -1 is total negative correlation and 0 indicates there is no correlation among the variables. The Spearman's correlation coefficient is used when both the variables are in ranked order data type called ordinal data. The maximum value of correlation coefficient is 1 which gives the maximum positive association between the ranks and the minimum value is -1 which denotes a maximum negative association between the ranks. The value of zero shows no association between the ranks. Similar to Spearman rank correlation coefficient, Kendall rank correlation coefficient is used to evaluate the association between two ordinal (two ranked variables) variables.

III. FR IQA CLASSIFICATION

In this section we are mainly discussing about the classification of FR IQA metrics. Here Full reference image quality measures could be classified into three classes of objective image assessment measures.

A. VISIBILITY CHARACTERISTIC BASED METHODS

Some Visibility characteristic based method is listed below

1. Perceptual Image Distortion (PID)

A Perceptual distortion measure that predicts image integrity far better than mean-squared error. This perceptual distortion measure is based on a model of human visual processing that fitting empirical measurements of the psychophysics of spatial pattern detection. [15].

2. Noise Quality Index (NQM)

The NQM, which is based on Pelis contrast pyramid, by using the features like Variation in contrast sensitivity according to distance, spatial frequency, image dimensions, Variation in the local luminance, Contrast interaction between spatial frequencies and the Contrast masking effects.

3. Maximum Difference (MD)

MD is the maximum of the error signal that is difference between the reference signal and test image. Maximum Difference can calculate by

$$MD = \text{MAX} |X(I,J) - Y(I,J)|$$

4. Average Difference (AD)

AD is simply the average of difference between the reference signal and the test image and it is given by the equation

$$AD = \frac{1}{MN} \sum \sum (x(i,j) - y(i,j))$$

AD

5. Visual Signal-to-Noise Rati(VSNR)

The visual signal-to-noise ratio(VSNR), is a two-stage approach. In the first stage, contrast thresholds for detection of distortions in the presence of natural images are computed. If the distortions are below the threshold value, the distorted image is deemed to be of perfect visual fidelity and no further analysis is required. If the distortions are above the threshold, a second stage is applied which operates based on the low-level visual property of perceived contrast, and the mid-level visual characteristic of global precedence. These two properties are modeled as Euclidean distances in distortion-contrast space of a multiscale wavelet decomposition, and VSNR is computed based on a simple linear sum of these distances.

6. Most Apparent Distortion (MAD)

MAD operates by using both a detection-based model and an appearance-based model[13]. For detection, we employ a simple spatial-domain model of local visual masking, which takes into account the contrast sensitivity function, and luminance and contrast masking with distortion-type-specific adjustments. Detection-based quality is then estimated based on the mean-squared error between the original and distorted images .

B. CONTRAST/STRUCTURE FEATURE BASED METHODS

Following metrics are based on contrast and structural based metrics

1. SSIM

The structural similarity index is a method for measuring the similarity between two images. It compares two images using information about luminous,contrast and structure. The SSIM metric is designed to improve on traditional methods like PSNR and MSE and this is calculated on various windows of an image.

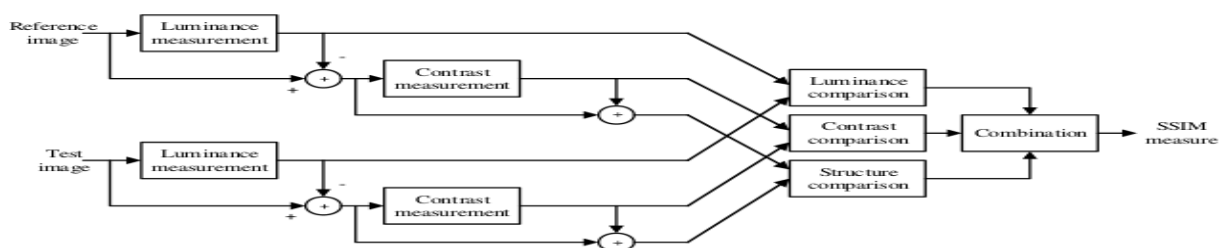


Fig 2: SSIM block diagram

2. Multiscale SSIM (M-SSIM)

In multiscale SSIM the image is decomposed in to different scales. The overall SSIM evaluation is obtained by combining the measurement at different scales [12].

3. Information content weighted SSIM (IW-SSIM)

Information content weighted structural similarity measure (IW-SSIM)[9] is an extension of the structural similarity (SSIM) index by taking the idea of information content weighted pooling. The same idea can also be applied to PSNR, leading to an information content weighted PSNR (IW-PSNR). By combining information content weighting with multiscale SSIM, information content weighted SSIM measure (IW-SSIM) is defined.

4. Gradient Similarity based method (GSM).

Variations of contrast/structural information based on gradient magnitudes in image signals are important in perceived visual quality. The Mean Structural Similarity Index (SSIM) fails in measuring the badly blurred images, an improved evaluation of quality assessment; called Gradient-based Structural Similarity (GSSIM) is proposed. It is based on the edge information as information of most significant image structure. The Gradient Similarity based FR-IQA method (GSM) which uses four directional high-pass filters to capture the change of contrast/structural information in images.

5. Riesz transform based Feature Similarity (RF-SIM)

The Riesz transform based Feature Similarity (RF-SIM) [8] index by adopting first and second-order Riesz transforms to characterize local structures in images. visual quality scores are calculated only for edge pixels obtained by the Canny edge operator. This is made based on an assumption that edge information is essential for evaluating visual quality scores. The RFSIM is computed by comparing Riesz transform features at pivotall locations between the reference image and a distorted image. The 1st order and 2nd order Riesz transforms are used because in order to extract several types of low-level features of image effectively and efficiently in a unified theoretic framework.

6. Feature Similarity (FSIM)

Her a phase congruency and a gradient magnitude are used as core features to characterize perceived visual quality. The phase congruency and gradient magnitude are calculated by log-scaled values of Gabor filtered coefficients and the Scharr gradient operator, respectively. The FSIM index [7] is designed for grayscale images or the luminance components of color images

7. Visual Saliency-induced Index (VSI)

The Visual saliency (VS) [3] has been widely studied by psychologists, neurobiologists, and computer scientists during the last decade to investigate, which areas of an image will attract the most attention of the human visual system. First, VS is used as a feature when computing the local quality map of the distorted image. Second, when pooling the quality score, VS is employed as a weighting function to reflect the importance of a local region

8. Perceptual-fidelity Aware Mean Square Error (PAMSE)

The Perceptual-fidelity Aware Mean Square Error (PAMSE) is a very simple perceptual distortion metric, The PAMSE is calculated by Gaussian smoothed residuals between two images

9. Gradient Magnitude Similarity Deviation (GMSD)

A very fast FR-IQA method, called GMSD (Gradient Magnitude Similarity Deviation). This is established based on an assumption that image gradients are more vulnerable to image distortions and different local structures in distorted images from different degrees of degradations.

C. INTERNAL BRAIN-MECHANISM BASED METHODS

Internal brain-mechanism based metrics are listed below

1. Visual Information Fidelity (VIF)

Ratio between the total information ideally extracted by the brain from the whole distorted image and the total information conveyed within the complete reference image.

2. Information fidelity criterion index (IFC)

Given a statistical model for the source and the distortion (channel), the obvious information fidelity criterion [11] is the mutual information between the source and the distorted images.

IV. FR IQA EVALUATION

In this section discussing about evaluation of six FR IQA metrics by using three performance metrics. The Pearson linear correlation coefficient (PLCC), Spearman rank order correlation coefficient (SROCC), Kendall rank correlation coefficient (KRCC), are performance IQA metrics used for the evaluation.

If X and Y are considered as two variables and r as a Pearson correlation coefficient, then r is defined as

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

Let X and Y are two variables both of size n, then to determine the Spearman's correlation coefficient ρ, the n raw scores X_i, Y_i are converted to ranks x_i, y_i and ρ is given as.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

where, d_i = x_i - y_i denotes the difference between ranks. Let x_i, y_i be a set of views of the random variable X and Y in a manner that all values of (x_i) and (y_i) are distinctive. The equation for Kendall coefficient, τ is given as

$$\tau = \frac{\sum_{i=1}^n \sum_{j=1}^n \text{sgn}(x_i - x_j) \text{sgn}(y_i - y_j)}{n(n-1)}$$

Here we are using seven publicly available image datasets for evaluating FR IQA metrics. They are TID2008, CSIQ, LIVE, Image and Video Communication Database (IVC).

Dataset	Ref. Images No.	Distorted Images No.	Distortion Types No.	Image Format	Subjects No.
TID2008	25	1700	17	color	838
CSIQ	30	866	6	color	35
LIVE	29	779	5	color	161
IVC	10	185	4	color	15

Table 1: Image datasets for IQA

		SSIM	MS-SSIM	IW-SSIM	IFC	RFSIM	FSIM
TID2008	SROCC	0.7748	0.8541	0.8559	0.5678	0.8682	0.8805
	KROCC	0.5768	0.6568	0.6637	0.4237	0.6780	0.6946
	PLCC	0.7733	0.8453	0.8579	0.9113	0.8645	0.8739
CSIQ	SROCC	0.8756	0.9133	0.9213	0.7671	0.9295	0.9242
	KROCC	0.6084	0.7393	0.7529	0.5897	0.7645	0.7567
	PLCC	0.8000	0.8991	0.9144	0.8384	0.9179	0.9120
LIVE	SROCC	0.8756	0.9513	0.9567	0.9252	0.9401	0.9634
	KROCC	0.6865	0.8045	0.8175	0.7579	0.7816	0.8337
	PLCC	0.8723	0.9489	0.9522	0.9268	0.9354	0.9597
IVC	SROCC	0.9018	0.8980	0.9125	0.8993	0.8192	0.9262
	KROCC	0.7223	0.7203	0.7336	0.7202	0.6452	0.7564
	PLCC	0.9119	0.5029	0.9231	0.9093	0.8361	0.9376

Table 2: Performance comparison

V. CONCLUSION

Now a days image quality measurement is very important for different image processing applications such as recognition, compression, restoration, retrieval, classification, and similar fields. The images may contain different types of distortions like noise, blur, contrast change etc. So it is essential to rate the image quality appropriately. The Subjective quality assessment methods cannot be used in real-time applications. So Objective quality assessment methods are widely used in recent years. In this paper mainly discussed about FR IQA classification and evaluation result of six FR IQA metrics . Overall performance of six FR image quality assessment metrics is compared by using a publicly available image database. The results obtained shows that different metrics perform differently with respect to different correlation method. The FSIM gives the best performance among metrics studied in this paper.

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