No-Reference Image Quality Analysis-An Overview

Krishnendu M.
PG Scholor
Electronics and Communication Engineering
College of Engineering Kidangoor
Kerala,India

Priya M.
Assistant Professor
Electronics and Communication Engineering
College of Engineering Kidangoor
Kerala, India

Joby James
Assistant Professor
Electronics and Communication Engineering
College of Engineering Kidangoor
Kerala,India

***Abstract*: This paper discusses No reference image quality assessment (NR-IQA) approach. We also compare its results to those of other IQA methods. We can show that the BRISQUE model outperforms the FR-IQA approaches in terms of peak signal to noise ratio and structural similarity index, and that it is a strong competitor to the widely used distortion-generic NR IQA model.**

Keywords—No reference image quality assessment; spatial domain; BRISQUE; BLIINDS; DIIVINE

I. INTRODUCTION

Determining image quality with automation is a vital furthermore a difficult task in the image process field. The target of image quality assessment (IQA) is to supply quality measures within the image process systems. Image quality degrades in seconds from capturing to displaying to the observer. A picture is subjected to completely different distortion throughout acquisition, transmission, compression, restoration, and process. Completely different ways are designed to judge the standard of distorted pictures. IQA ways are often divided into subjective and objective ways [1].

The Subjective method supports human perception and so they're inconvenient, time intense. The image processing system is not automated with this technique. When images are analyzed by humans and the visual image quality is quantified by subjective evaluation, subjective methods might be used. They cannot, however, be easily implemented in real-time circumstances, and so cannot be integrated with automated systems. The goal of objective picture quality evaluation is to change quality characteristics that can predict the image's perceived quality of the image [2]. This type of evaluation method can be categorized primarily based on the availability of an authentic distortion-free image to compare the distorted image to.

In No-reference (NR) image quality assessment (IQA) is the automatic quality assessment of images where the only information available to the algorithm is the distorted image whose quality is being evaluated. The Full-Reference (FR) algorithms, on the other hand, analyze the distorted image using both the deformed image and a reference image. Some of the popular Full Reference IQA techniques are Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE), Structural similarity index (SSIM), Mean structural similarity (MSSIM).Aside from the deformed image, reduced-reference (RR) approaches own techniques have some information about the reference image, but not the real image. The availability of a non-distorted image or any other information is of low, the evaluation of the practical application of these algorithms is limited. Similarly, in real-world circumstances, where only basic information is usually available, is limited. Furthermore, because the FR and, to a large extent, the RR approaches evaluate fidelity relative to a reference image, it is possible to argue that they are not true quality measurements[3]-[4]. Moreover, it is difficult to get a 'clear' reference image, since all images are apparently distorted.

This paper thoroughly evaluates the performance of NR-IQA methods, and statistically compare its performance to different FR-IQA approaches. The paper is organized as follows: Section 2 introduces the existing generic NR-IQA algorithms. Section 3 presents performance evaluation of these algorithms and discuss the results. We conclude the paper in section 5 The following is how the paper is structured: The present general NR-IQA algorithms are introduced in Section 2. Section 3 discusses the findings of the performance evaluation of these methods. Section 5 draws a conclusion. 5

II. NO-REFERENCE IMAGE QUALITY ASSESSMENT

No-Reference metrics attempt to assess an image's quality in the absence of a reference image. As a result, it is the most difficult IQA approach. Natural images have a specific regular statistical feature, which primarily changes owing to aberrations, according to NR IQA. The following are some NO-IQA methods:

A.BRISQUE

Blind/reference less image spatial quality evaluator BRISQUE is a model that uses only pixels in an image, to calculate properties. As in the model for pair wise products of coefficients, BRISQUE uses the Natural Scene Spatial Statistics (NSS) model in the spatial domain with locally normalized brightness coefficients. [5]. BRISQUE algorithm can be described as follows.

1. Image Pixel Normalization

Given a distorted image, we calculate locally normalized luminance through local mean subtraction and divisive normalization, we calculate the locally normalized brightness for a distorted image. Equation (1) can be used to generate an intensity image I (i, j) from a given intensity image I (i , j).:

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + c} \tag{1}$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l}[\,I(i+k,j+l) - \mu(i,j)]^2} \tag{2}$$

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} \omega_{k,l}\, I(i+k,j+l) \tag{3}$$

where I(i, j) denotes the gray value of the original image, c is a small constant that prevents the calculated values from becoming unstable as the denominator approaches zero. μ(i,j) and σ(i, j) are weighted mean and variance. ω is a circularly symmetric Gaussian weighting function in two dimensions. The MSCN (Mean Subtracted Contrast Normalized) coefficients are the normalized brightness value of I I (i, j).

2. Spatial Feature Extraction.

The noises in the image can damage the regularity between the adjacent MSCN coefficients. Generalized Gauss distributions, correlation of the neighbouring coefficients are the properties of the normalized coefficients[5].

(2.1) Generalized Gauss distribution characteristics:

The model formula can be expressed as equation

$$f(x;a,\sigma^2) = \frac{a}{2\beta\Gamma(^1/_a)} \exp\left(-\left(\frac{|x|}{\beta}\right)^a\right) \tag{4}$$

where

$$\beta = \sigma\sqrt{\frac{\Gamma(1/a)}{\Gamma(3/a)}} \tag{5}$$

and Γ (·) is gamma function.

The variance is σ^2 and the shape parameter α controls the shape of the modified Gauss model.

(2.2) Correlation of adjacent coefficients:

Correlate the image horizontally, vertically, diagonally, and diagonally with four directions, and use very common statistical distribution (ARG) of the image. Quick setup method for estimating parameters (η, ν σ1, σ2) for each course. Thus, we tend to use sixteen estimates for 4-direction parameters, since correlation is a function of neighboring coefficients. However, due to the multiscale statistical properties of natural images, it is reasonable to distinguish two main distribution features and sixteen related correlation coefficients for the characteristic at two levels.

B. *DIIVIINE*

Distortion Identification Based on Image Identification and Integrity Test (DIIVINE) is an agnostic distortion of NR IQA. This method not only measures the distortion, which is why the image quality, but also suitable for the type of distortion that distorts the image. The DIIVINE indicator uses a two-step framework for the blind IQA that starts by detecting image distortion disturbances and performs direct quality tests. The algorithm for this method is based on natural state statistics (NSS) similarities. Models for natural photos from the NSS Attempt to capture and explain the mathematical links found in unusual images.. The existence of distortions in natural images change with distortion change the mathematical properties of nature, thus giving a ‘non-natural’ image. The NR IQA can be achieved by measuring this 'unnatural' and associating it with tangible quality.

The DIIVINE method for determining the IQA number is as follows: To construct oriented band-pass reactions, the deformed image is evaluated utilizing scale, space, orientation, and degradation (in the broadest sense, wavelet transformations). The resulting sub band coefficients are then used to extract a set of statistics. These symptom statistics can be combined to create a vector that represents the visual distortion statistically. Our goal is to accomplish the following tasks using the feature vector in the images:

1) Determine whether the image is likely to be distorted by one of the many different types of distortion.

2) Map the feature vector to a quality score for each distortion category.

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Construct even if the deformed image has a distinct deformation category, develop a regression model for each distortion category by setting quality parameters, even though the distorted image has a certain deformation category. To achieve the final quality and value for the image, use probabilistic distortion, identify the score, and then combine it with the distortion of a given quality score[6].

C.BLIINDS

BLIINDS (Blind Image Integrity Notator using DCT-Statistics) is a non-distortion specific, blind/no-reference image quality assessment (NR-IQA) technique that performs distortion-agnostic NR IQA utilizing natural scene statistics models and Discrete Cosine Transform (DCT) coefficients. BLINDS use a general model based on NSS, from local coefficients to DCT, and a parameter and function transformation model suitable for evaluating perceptual image quality for predicting the future. DCT feature statistics change naturally and predictably, and image quality can influence them. These features are subjected to a general probabilistic model, which is then utilized to produce probabilistic visual quality predictions. It demonstrates that the procedure is highly correlated with human subjective quality assessments. While many NR-IQA algorithms cause some kind of distortion, the features employed in BLIINDS are derived without regard to the type of image distortion and are applicable to a wide range of distortions. Therefore, it can be used for a wide range of purposes. Because the part works fully in the DCT domain and can be used in the case of platforms that are designed to quickly calculate the DCT transform [7].

III. PERFORMANCE EVALUATION

We used the LIVE IQA database to test NR-IQA's performance, which consists of 29 control images of 779 distorted images arranged in five different distortion categories, JPEG2000 (JP2K) and JPEG compression, adding White Gaussian noise (VN), Gaussian Blur (Blur), and Rayleigh fast-fading channel simulation (FF). Each of the distorted images, includes a difference mean opinion score (DMO), which represents the subjective quality of the image. In Fig. 1, For each of the distortions, we plot the Spearman's rank ordered correlation coefficient (SROCC) between each of these variables and human DMOS from the LIVE IQA database. The plot is to illustrate that each feature captures quality information and to show that images are affected in another way through one-of-a-kind distortions

For analysis, quality assurance, and performance, Spearman's rank ordered correlation coefficient (SROCC) and Pearson's (linear) correlation coefficient (LCC) between the projected score and the algorithm, as well as DMOS) were utilized. In terms of correlation with human opinion, a value of 1 for SROCC and LCC indicates good performance. Tables 1 and 2 exhibit these performance metrics, respectively. The peak signal-to-noise ratio (PSNR), the structural metric (SSIM), and the multiscale structural metric(MS-SSIM) are used to compare the effectiveness of NR-IQA . Although PSNR is a poor indicator of perception quality, it is widely used as a benchmark for algorithm quality. The SSIM and MS-SSIM indexes are popular for their performance.

Both DIIVINE and BLIINDS-II provide excellent NR IQA results, yet each has its own disadvantages. Because DIIVINE computes such a vast number of features, it may be challenging to do so in real time. Although BLIINDS-II is quicker than DIIVINE, it necessitates nonlinear sorting of block-based NSS features, which considerably slows it down. We find that BRISQUE is extremely competitive with all the reference algorithms tested and is statistically superior to the complete reference algorithms, PSNR and SSIM, based on the data. This is no small effort, given that these measures require extra data in the form of a reference image. This discovery suggests that distortions can be replaced to the extent that they can be taught about. This means that, to the degree that distortions can be learned from, comprehensive reference techniques like SSIM can be replaced with the suggested BRISQUE without losing performance. Figure 2 shows the mean SROCC and performance standard deviations for each of the algorithms studied. It demonstrates that BRISQUE is marginally inferior than the FR MS-SSIM, indicating that there may, in any case, be some opportunity to get better in execution.

	JP2k	JPEG	WN	Blur	FF	All
PSNR	0.8947	0.9191	0.9536	0.8357	0.8964	0.8873
SSIM	0.9461	0.9547	0.9679	0.9321	0.9393	0.9201
MSSIM	0.9632	0.9773	0.9786	0.9607	0.9464	0.9550
BLIINDS-II	0.9270	0.9376	0.9565	0.8902	0.8409	0.9123
DIIVINE	0.9114	0.9213	0.9818	0.9386	0.8372	0.9265
BRISQUE	0.8999	0.9467	0.9849	0.9435	0.8861	0.9314

Table 1. On the LIVE IQA data, the median spearman rank ordered correlation coefficient (SROCC) across train-test combinations.

	JP2K	JPEG	WN	Blur	FF	All
PSNR	0.9044	0.9375	0.8981	0.8490	0.9119	0.8666
SSIM	0.9575	0.9630	0.9887	0.9395	0.9644	0.9110
MSSIM	0.9795	0.9357	0.9919	0.9762	0.9689	0.9529
BLIINS-II	0.9329	0.9386	0.9764	0.8944	0.8665	0.9145
DIIVIINE	0.9225	0.9363	0.9869	0.9383	0.8938	0.9283
BRISQUE	0.9090	0.9551	0.9903	0.9498	0.9148	0.9377

Table 2. Median Pearson's linear correlation coefficient (PLCC) across train-test combination on the LIVE IQA database

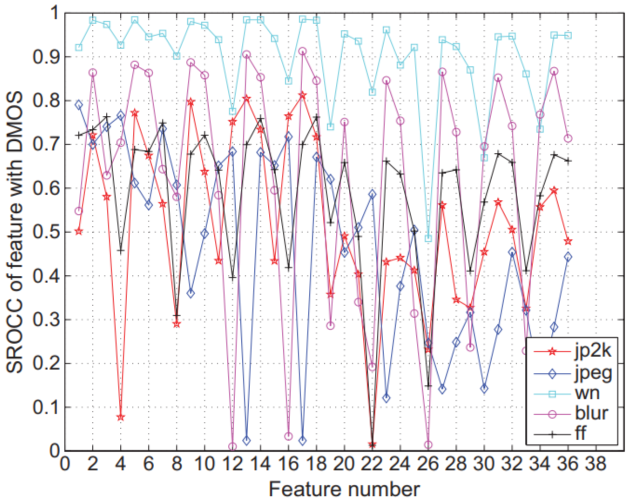

Fig. 1. Correlation of features with human judgments of quality (DMOS) for different distortions

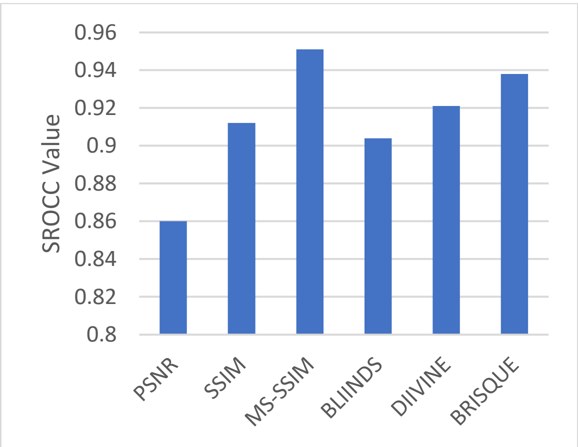

Fig 2 Mean SROCC and the standard deviations of performance across different algorithms

IV. CONCLUSION

As described earlier, the training of IQA algorithms was per- formed As described earlier, the training of IQA algorithms was per-formed As described earlier, the training of IQA algorithms was per-
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As previously stated, the image dataset was subjected to various NR-IQA algorithms. The majority of NR approaches surpassed PSNR, and the top methods, such as the FR-IQA algorithm, have been found to generate good results. The BRISQUE index was then thoroughly analysed in terms of correlation with human perception, revealing that it is statistically superior than FR PSNR and SSIM. It was also demonstrated that BRISQUE is computationally efficient, outperforming alternative distortion-generic techniques to NR IQA, making it a viable option for practical applications such as image denoising.

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