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A Survey on Image Quality Assessment Techniques, Challenges and Databases

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ABSTRACT
Growth in digital image processing technologies have completely change our way of life. In our day-to-day life, we are using a number of image processing applications knowingly or unknowingly. Many times image gets distorted somehow during the acquisition, processing, transmission, storing or sharing. So the evaluation of image quality is essential component for many image processing applications.Such image quality assessment techniques are the state-of-the-artresearch area. This paper provides a detailed survey on various image quality assessment methods.This review isprimarily focussed on three objective quality assessment methods viz. (full reference image quality assessment (FR-IQA), reduced reference image quality assessment (RR-IQA), and No reference image quality assessment (NR-IQA). An extensive review on various publically available research databases has been presented.

General Terms
Image processing, Machine learning.

Keywords
Image Quality Assessment, FR-IQA, RR-IQA, NR-IQA, Databases etc.

1. INTRODUCTION
Image quality is a characteristic of an image that measures image degradation by comparing it with the ideal or perfect image. Image may be distorted by different degradations like frequency distortion, noise and blocking artefacts, Blurring, fading. Due to these distortions image quality gets degraded entirely. Image degradation occurs while image acquisition, processing, compression, transmission, storage, reproduction, decompression, display, printing etc. Quality assessment of image content is achievable either through subjective tests or through objective matrix. Hence image quality assessment has classified into two parts viz. a) subjective quality assessment b) objective quality assessment.

Image quality assessment by human observeris known as subjective quality assessment. The meanopinion score (MOS), is a subjective quality measure which requires a number of human observers for assessmentpurpose, MOS is considered as the best method of image quality measurement. Subjective quality assessment is a traditional method for measuring the quality of the image in which group of people are involved who have to rate for the quality of a medium in a controlled test environment. Ratings may be different for each person. Result gets finalised by statistical processing. It can provide accurate result but it is very slow for real-world applications and expensive for practical use [1, 2]. In objective quality assessment, image or video quality of an image can be evaluated by means of a machine. It is further classified in three ways according to the availability of an original image.

(1) Full-reference image quality assessment (FR-IQA)

(2)Reduced-reference image quality assessment (RR-IQA)

(3) No-reference image quality assessment (NR-IQA)

2. FULL REFERENCE IMAGE QUALITY ASSESSMENT (FR-IQA)
Heredistorted image is compared with the original or undistorted version of that image. Which is usually captured using a high quality device. Fig 1 illustrates FR-IQA.

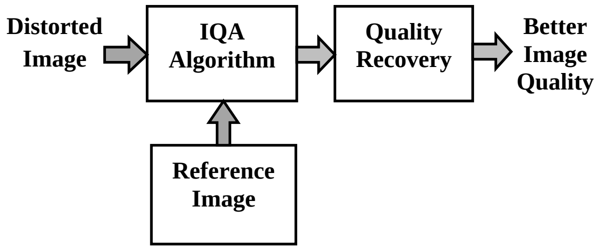

Fig.1 Full-Reference Image Quality Assessment

There are different approaches towards FR-IQA based on different parameters. Some of them are discussed below.

For FR-IQA based assessment, MSE and PSNR are generally used to predict the visual quality by comparing distorted image with original reference image which is usually calculated as in (1) and (2),

$$MSE = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [f(i,j) - g(i,j)]^2 \qquad (1)$$

Where $f(i,j)$ and $g(i,j)$ are reference image and distorted image respectively [3].

$$PSNR = 10 \log\left(\frac{(2^B - 1^2)}{MSE}\right) dB \qquad (2)$$

Where, B is number of bits per pixel of the image. Both MSE and PSNR are simple and widely used metrics but it gives poor correlation with subjective test and Human Visual System (HVS) [4].

Damera Venkata et al. [5] developed a model which is based on degradation.They Developed Distortion (DM) and a Noise Quality Measure (NQM) to specify the impact on HVS of frequency distortion and noise injection in image restoration while processing NQM, the perspective like variation in contrast interaction between spatial frequency, variation in the local luminance mean, contrast interaction between spatial frequency, contrast masking effect are considered, NQM can be calculated as below in (3),

$$NQM = 10\log_{10}\left(\frac{\sum_i \sum_j f^2(i,j)}{\sum_i \sum_j (f(i,j) - g(i,j))^2}\right) \quad (3)$$

Where, $f(i,j)$ is model restored image and $g(i,j)$ is restored degraded image. Zhou wang et al. [6] proposed an algorithm which computes universal quality index of distorted image which is calculated as in (4).

$$Q = \frac{4\sigma_{\bar{i}\bar{j}}\bar{i}\bar{j}}{\left(\sigma_i^2 + \sigma_j^2\right)[\bar{i}^2 + \bar{j}^2]} \quad (4)$$

Where i and j are mean luminance, σ_i and σ_j are standard deviations of image. Q lies in between -1 and +1 and best value for Q is $i = j$ [7]. To enhance the traditional algorithm, MSE and PSNR structural similarity (SSIM) metric is introduced [8]. It is a milestone of development using FR-IQA model. SSIM is the function of luminance comparison (L), contrast(C), and structural comparison(S). It is written as follows,

$$SSIM[f(t)g(t)] = L[f(t), g(t)]C[f(t), g(t)]S[f(t), g(t)] \quad (5)$$

Where $f(t)$and $g(t)$ are the image patches. It measures the similarity between the two images and its value lies between 0 and 1.

Wang et al. [9] proposed a multiscale extension of SSIM named as MS-SSIM. By using this multiscale method better resultscan produced than its single scale counterpart. Total Image quality MSSIM is gained by computing the average of SSIM values over all windows:

$$MSSSIM = \frac{1}{N}\sum_{i=1}^{N}(SSIM)_i \quad (6)$$

Sheikh and Bovik [10, 11] proposed a frame work known as information fidelity criterion (IFC). In this, Gray Scale Model (GSM) model is used. Fidelity criterion is nothing but the mutual information between reference image and distorted image.IFC was later enhanced to the Visual Information Fidelity (VIF).VIF models the natural images in the wavelet domain using Gaussianscale mixtures (GSMs). Images and videos that are taken from naturalenvironment by using high quality capturing devices operating in visual spectrumare classified as natural scenes. VIFalgorithm consists of three components: source model, distortion model, and HVSmodel. But VIF is very complex for computation

Chandler and hemami [12] presented a Visual Signal to Noise Ratio (VSNR). VSNR is related to wavelet transform in which metric calculated in two stages.

Fengshao et al. [13, 14] proposed Perceptual FR-IQA of Stereoscopic Images by taking into account Binocular Visual Characteristics. In their further research they introduced a stereoscopic images based new FR-IQA by learning binocular reception properties. Their experiment results achieved high consistency validates using five 3D-IQA databases.

Yong et al. [15] proposed a new approach based on statistical local correlation which extracted in wavelet transform and then pooled into quality score. Huanet al. [16] developed an FR-IQA metric in which they have worked on semantic information and luminance differences.

1. REDUCED-REFERENCESIMAGE QUALITY ASSESSMENT (RR-IQA)

In this method the reference image is partially available which helps to evaluate quality of distorted image.Figs 2 describe the method RRIQA.

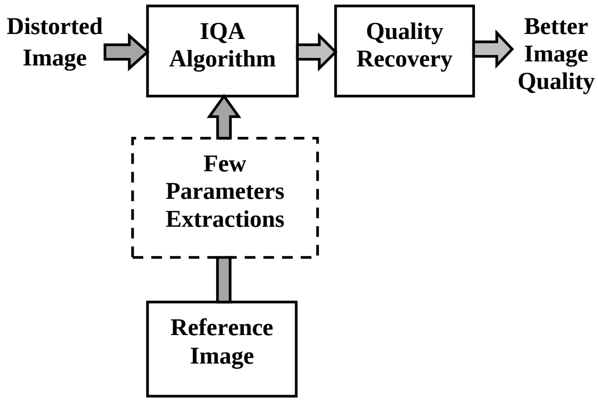

Fig.2: Reduced-Reference Image Quality Assessment

In RR-IQA, parameters are extracted to provide reduced information of the image and it is not directly related to any specific degradation. It required training for distinctive sorts of distortion. Artifacts will occur because of the degradation and it is measured in view of the natural image statistics and training is not more consistent to the visual perception of image quality.There are many different approaches developed by researcherson this area.

Jinjan et al. [17] developed a Reduced-Reference Image Quality Assessment based on visual information fidelity. They have proposed an index and used 30 bit data and achieve high consistency with human perception.

Redi et al. [18] used descriptors based on color correlogram. They have analysed the alternations between the color distributions of an image for RR-IQA. Rehman and Zhou [19] proposed an RRIQA method with the estimation of SSIM, which is mostly utilized by FR-IQA. Soundarajan and bovic [20] studied the problem of RRIQA with respect to changes in image data which are measure between reference and natural image approximation of distorted image.

Lin et al. [21] proposed an RR-IQA by statically modelling the DCT distribution. Experimental analysis determines that only a small number of reduced reference parameters are sufficient to estimate the image quality.

Xu et al. [22] introduced an approach for RRIQA which measures the differences of spatial arrangement between the reference image and distorted image in terms of spatial regularity measured by fractal dimension. Proposed method was evaluated on seven publically available benchmarking databases.

Bhatijaet al. [23] developed an application specific approach for smart cameras in which, performance improvement and robustness can be achieved by intelligent moderation of the parameters both at algorithm and hardware level.

4. NO-REFERENCE IMAGE QUALITY ASSESSMENT (NR-IQA)

Generally this method is known as blind image quality assessment as the reference image is absent. This is most difficult task as it evaluates the quality of an image without reference image. It may be less accurate but more realistic the research problem.

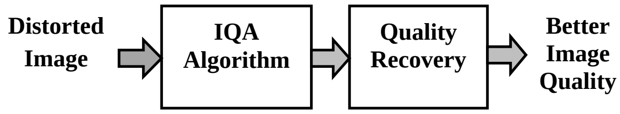

Fig.3: No-Reference Image Quality Assessment

There are various methods used for image quality assessment when original image is absent.

Morthy and Bovic [24] developed an approach in which two step frameworks for NRIQA is presented on natural scene statistics. An algorithm that is proposed here is Blind Image Quality Index(BIQI). Each distortion has its own unique signs and is characterised using DIS and arranges the images into distortion categories at the first stage. Then combine it with distortion aware IQA and obtains the blind image quality index as in (7)

$$BIQI = \sum_{i=n}^{m} p_i q_i \tag{7}$$

Where, $p_i$is the probability of each distortions of the image and q_i is the quality score related to the distortions.

Liu et al. [25] proposed an NRIQA metric for perceived ringing artifacts. For this analysis, Kodak lossless true color image database was used as validation database. Jing Zang and Le [26] presented a new non reference quality metric for JPEG 2000 images. It overcomes the limitations imposed by feature extraction of distorted images. It is uses changing pixel activity along horizontal and vertical directions. This metric is used only for JPEG-2000 compressed images.

Chaofeng et al. [27] proposed BIQA using a general regression neural network in which they expand some features: a) mean value congruency of image, b) entropy of phase congruency image, c) entropy of distorted image d) gradient of distorted image. Here theyevaluatedImage quality byapproximating the function relationship between these features and subjective Mean Opinion Score (MOS) by using LIVE database for training and testing purpose. BIQA is further developed by Xue et al. [28] in which, they proposed a novel BIQA model that utilizes the joint statistics of two types of commonly used localcontrast features: (1) the Gradient Magnitude (GM) map and (2) the Laplacian of Gaussian (LOG) response.

Morthy and Bovic[29] further introduced an algorithm named as Distortion Identification based Image Verity and INtegrity Evaluation (DIIVINE). Evaluation did in two stages, distortion identification and distortion specific quality analysis. For validation of this algorithm they used LIVE and TID2008 databases.

Ciancio et al. [30] presented No-reference IQA algorithm for blur assessment of digital image based on multi-feature classifiers. It used 6000 Blur image from realistic blur image database for testing.

Mittal et al. [31]Proposed NR-IQA in the spatial domain. They proposed a new model named as Blind/Reference less Image Spatial Quality Evaluator (BRISQE). It does not compute distortion specific feature It used Natural Scene Statistics (NSS). Database used for validation is the LIVE database. They further have developed an NR-IQA model which is highly training free and distorted image have certain latent characteristics which are different from those of original image/ natural image.

Saad et al. [32] proposed an algorithm named BLINDS-II. It is an efficient NR-IQA algorithm using NSS model of DCT coefficients. This approach relies on simple Bayesian inference model to predict Image quality score. Peng and Doermann [33] developed a computational model for NR-IQA which is based on visual codebook and itdoes not assumes any specified distortions.

Fenget al. [34]proposed a BIQA for stereoscopic images using Binocular Guided Quality lookup and visual codebook. It simplified the process of binocularquality prediction into monocular feature encoding and binocular feature combination [35].

The performance analysis of various image quality assessment algorithms is presented in Table 1.

Table 1.Performancesof IQA algorithms

Technique	Algorithms	Performance
Full Reference Image Quality Assessment	MSE PSNR	Widely utilized but has poor correlativeness.
	NQM UQI SSIM MS-SSIM IFC VIF VSNR	It is good as that of FR-IQA. But required whole knowledge of the image. Quite complex in the computational point of view.
Reduced-Reference Image Quality Assessment	Application orient	It required prior and sufficient knowledge about distortions of the image. It compensate in between FR and NR approaches in terms of quality prediction accuracy
Non-Reference Image quality Assessment	BIQI BLIND BLIND II BRISQUE DIVINE	Meets desired expectation with least available knowledge. It gives better correlative data score as compared to previous techniques.

5. CONCLUSION

Image quality is an attribute of an image which measures subjective and objective image degradations after performing the comparison with the ideal or perfect image/s. Image may be distorted by different degradations like blurring, fading, frequency distortion, noise and blocking artefacts. Image quality assessment has many challenges due to distortions in images. Researchers are trying to develop various methods to assess the quality of an image. Each method has its own advantages and disadvantages. In real time applications, precise and efficient IQA methods help to assess and report the image quality in application like an aerial image, MRI, CT scan images. In this paper, we have summarized the state-of-the-art techniques, challenges and databases for Image Quality Assessment. Although FR-IQA based techniques have good consistency, there are still some issues to be explored in the future. For example, we can review the new image representation technique to reduce the number of feature extraction parameters needed for IQA metrics and also we can propose the technique which can evaluate the quality of the image using no-reference image quality assessment.

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