A SURVEY: TECHNIQUES USED FOR IMAGE QUALITY ASSESSMENT IN IMAGE PROCESSING

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ABSTRACT

Image Quality Assessment (IQA) plays an important role in assessing any new hardware, software, image acquisition techniques, image reconstruction or post-processing algorithms, etc. In the past decade, there have been various IQA methods designed to evaluate natural images. In this paper discussed existing methods used for the image quality assessment techniques which assessing the qualities of the images. Paper describes the effects of images are calculated based on their performance using some parameters like quality score, accuracy, sensitivity and peak-signal-to-noise ratio (PSNR). The results of comparative experiment show that although each method has different value to evaluate the images.

Keywords: image quality assessment, image acquisition, quality measurements.

INTRODUCTION

The importance of Image Quality Assessment (IQA) lies in its emerging multidisciplinary topics that widely include image and signal processing, computer vision, visual psychophysics, neural physiology, information theory, machine learning, design of image acquisition, communication and display systems. [1]. Digital images are subject to a wide variety of distortions during acquisition, processing, compression, storage, transmission and reproduction, any of which may result in a degradation of visual quality.

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 [2]. In practice, however, subjective evaluation is usually too inconvenient, time-consuming and expensive. The goal of research in objective image quality assessment is to develop quantitative measures that can automatically predict perceived image quality. Image quality measurement is crucial for most image processing applications. Generally speaking, an image quality metric has three kinds of applications:

First, it can be used to monitor image quality for quality control systems. For example, an image and video acquisition system can use the quality metric to monitor and automatically adjust itself to obtain the best quality image and video data. A network video server can use it to examine the quality of the digital video transmitted on the network and control video streaming.

Second, it can be employed to benchmark image processing systems and algorithms. Suppose we need to select one from multiple image processing systems for a specific task, then a quality metric can help us evaluate which of them provides the best quality images.

Third, it can be embedded into an image processing system to optimize the algorithms and the parameter settings. For instance, in a visual communication system, a quality metric can help optimal design of the prefiltering and bit assignment algorithms at the encoder and the post processing algorithms at the decoder [3].

Measurement of image is a challenging problem in many fields of Image Processing [4]. It is of fundamental Importance to numerous image and video processing applications. In the past years, a vast literature has appeared with many approaches attempting to provide solutions. The goal of image quality assessment (IQA), is to design algorithms that can automatically assess the quality of images or videos in a perceptually consistent manner [5]. The most widely used full-reference image quality and distortion assessment algorithms are peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which do not correlate well with perceived quality [4].

IMAGE WITH DIFFERENT TYPES OF DISTORTIONS

Original Image Impulsive Salt-Pepper Noise

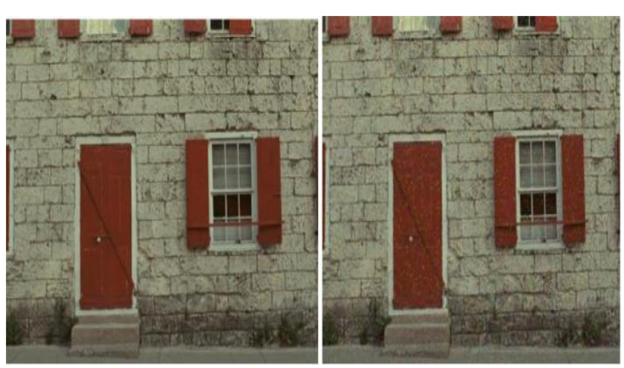
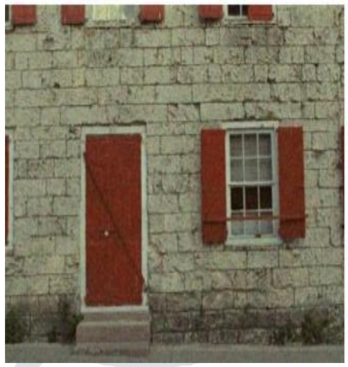


Fig.1 **Fig.2**

Additive Gaussian Noise Multiplicative Speckle Noise



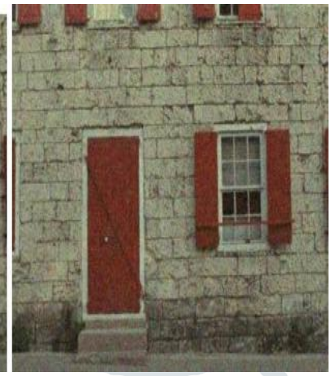


Fig.3 **Fig.4**

Mean Shift Dist Contrast Stretching

Fig.5 **Fig.6**

In image quality Index process the original image is applied, IQA metrics is obtained for distorted image. Mean square error (MSE), Peak signal to noise ratio (PSNR) and Structural similarity index metric (SSIM), are obtained as image quality assessment. Experimental for image the size is 512x384 pixels. The different type of distortion values for image quality metrics for numerous results is summarized within the table. The IQA method for distortion measures provides glorious results. By selecting appropriate metrics worth for SSIM, PSNR and MSE as high as will be achieved.

Type of distortion	SSIM values	MSE values	PSNR values
Salt and Pepper	0.9571	256.30	24.0432
Additive Gaussian noise	0.6908	503.17	21.1136
Multiplicative speckle noise	0.9077	2048.3	15.0167
Mean shift algorithm	0.9736	899.99	18.5884
Contrast Stretching	0.9842	64.942	30.0055
Blurred image	0.5848	506.69	21.0833
Jpeg compressed image	0.8894	263.35	23.9254

Table 1: Image Quality Measurements

The purpose of image quality assessment is to measure the quality of distorted image. It is indispensable to estimate the image quality in such as image compression, transport, display fields [6]. Image quality assessment mainly consists of subjective quality assessment and objective quality assessment. The subjective quality assessment mainly depends on that the observers watch the image directly and give the image score according to a certain image evaluation criterion. Theoretically, the subjective image quality assessment is very accurate and reliable, but it has many drawbacks including the professional background of observers, mental factors and so on. In addition, the subjective quality assessment is time consuming and cannot be applied to the real-time processing.

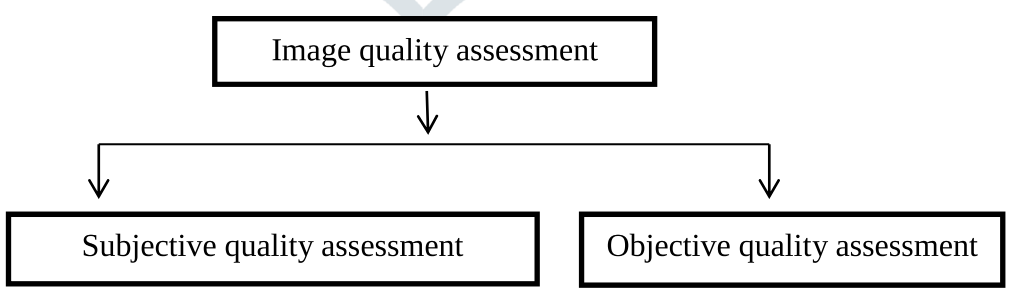


Fig 7 Types of image quality assessment.

The goal of satellite image processing is to identify and isolate the coherent parts of the surface, the atmosphere, and the water bodies. For example, to recognize and detach the urban areas and natural surfaces, the water bodies and terrestrial areas, rock outcrops and soil, the soil and the vegetation, the forests and the meadows, the deciduous and coniferous forests, the healthy and the stressed plants, the storm cells and the clouds, the smoke and the cloud, etc. In other words, our goal is the classification of satellite image's pixels and the creation of thematic layers (maps). This process is called processing of satellite imagery (interpretation), which can be done visually and/or digitally [7].

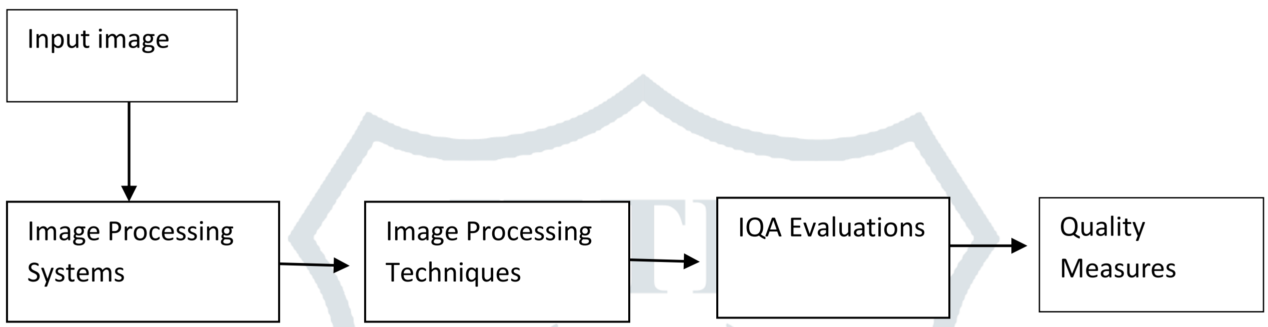


Fig 8 Work flow of image quality assessment.

LITERATURE SURVEY

Dandawate et al. (2013) Image quality assessment has become an important and challenging task for many applications on Internet and multimedia. Majority metrics developed used gray images and luminance and structural information in it. JPEG images, when compressed undergo change in color information. The color distortion is required in many applications. Author presents a full reference metric which uses Natural Scene Statistics (NSS) in gradient domain computed over different color spaces presenting color information. The metric developed by computing statistical differences presents good correlation with the Human Visual System in comparison with other objective techniques based on square errors [8].

Wang et al. (2013) used SVD as a useful tool to separate content dependent and content independent components in the image. For each design, specific assessment model is used according to its distortion properties. Gradient and contrast similarity between reference and test image is computed for assessment of content dependent part.

PSNR is computed for assessment of content independent part. Results are combined using nonlinear equation to obtain the perceptual quality score. The metric gives HVS consistent results for majority of distortion types available in TID image database [9].

Jadhav et al. (2013) applied structural similarity index metric to colour images after transforming images to HVS consistent colour model. Luminance-chrominance colour models are used in the experimentation and block wise computation of SSIM is applied. Weighted average of calculated values of SSIM in the three planes gives colour SSIM score. Authors have concluded that the metric using luminance-chrominance colour model outperform the metric in other colour models. Results obtained through experimentation in YCbCr, HSI, YUV, YIQ and CIE Lab color space show that when color information is included in quality assessment, quality score of the metric becomes highly consistent with Human Visual System (HVS) [10].

Wu et al. (2009) proposed a method for assessing the amount of blur present in an image. The method uses Sobel operator for edge detection and then applies Radon transform to locate line features. The line spread function and point spread functions are calculated from the located line features. For validation, 13 natural world images are blurred with standard blur levels and then used for testing the algorithm [11]. Effect of increasing image blur on the output of algorithm is used to estimate the performance of algorithm. This metric is designed only for quality assessment of blurred images.

Liu et al. (2010) introduced a metric to measure perceived ringing artifact. In this method, bilateral filtering is used to smooth edges which do not contribute to perceivable ringing. These edges are obtained by Canny edge detector, skeletonizing, edge linking, noise removal and line segment labeling. An extracted perceptual edge map obtained from line segments is used to select edges around which perceivable ringing can occur. Images from "Kodak lossless true color image suit" are used for validation. Pearson's and Spearman's correlation coefficients obtained are 0.868 and 0.85 respectively. This metric can be used for quality evaluation of images which are distorted by ringing artifact only [12].

Shen et al. (2011) presented an image quality assessment algorithm for noisy, blurry, JPEG-2000 and JPEG compressed images. The algorithm is based on hybrid of curvelet, wavelet and cosine transform. It uses the property of natural images which occupy well defined clusters in the transformed space. Image characteristics are expressed by probability distribution of logarithm of the magnitude of curvelet coefficients. Curvelet transform is replaced by wavelet transform and DCT and the same procedure is applied to extract image characteristics. Pearson's correlation coefficient obtained on LIVE database is 0.921. Effect of distortions on statistics of three different transforms is studied in this paper [13].

Chen et al.(2013) proposed and image quality assessment model for static stereoscopic images. In this method, a disparity map is generated from stereo image pair and multi-scale Gabor filter responses are obtained. A cyclopean image is integrated from stereo image pair, disparity map and Gabor filter responses. 2D features are extracted from cyclopean image and 3D features are extracted from the estimated disparity map. These features are then fed to a training model used to predict image quality [14].

Moorthy et al. (2011) proposed a blind IQA method based on the hypothesis that natural scenes have some certain statistical properties. In addition, those properties can make the quality of image degeneration. This algorithm was called Distortion Identification- based Image Verity and Integrity Evaluation (DIIVINE) and also was a two-step framework. The DIIVINE mainly consists of three steps. Firstly, the wavelet coefficients were normalized [15]. Then, they calculated the statistical characteristics of the wavelet coefficients, such as scale and orientation selective statistics, orientation selective statistics, correlations across scales and spatial correlation. Finally, the quality of the image was calculated using those statistical features. The method has achieved a good performance on evaluation.

Alain et al 2010, we analyse two well-known objective image quality metrics, the peak-signal-to-noise ratio (PSNR) as well as the structural similarity index measure (SSIM), and we derive a simple mathematical relationship between them which works for various kinds of image degradations such as Gaussian blur, additive Gaussian white noise, jpeg and jpeg2000 compression. A series of tests realized on images extracted from the Kodak database gives a better understanding of the similarity and difference between the SSIM and the PSNR [16].

Yusra A. et al (2012), Measuring the quality of the image is a complicated and hard process since humans opinion is affected by physical and psychological parameters. Many techniques are proposed for measuring the quality of the image but none of it is considered to be perfect for measuring the quality. Image quality assessment plays an important role in the field of image processing. Many studies have been done on image quality measurements based on different techniques such as pixel-difference, correlation, edge detection, neural networks (NN), region of interest(ROI), human visual system (HVS). The good IQM must be accurate and consistent in predicting the quality. Most IQ metrics are related to the difference between two images (the original and the distorted image) [17].

Silpa et al (2012) Various objective evaluation algorithms for measuring image quality like MSE, PSNR, SSIM and PSNR-B are simulated and compared w.r.t. JPEG compression application. Different deblocking filters are used to reduce blocking artifacts and deblocked images are compared through various quality metrics. As the degree of blocking depends on the quantization step, the quality metrics are also simulated and compared by varying the quantization step size. We discussed a new concept called 'Modified PSNR-B' which is under review process that gives even better results compared to the existing PSNR-B which includes the blocking effect factor (BEF) [18].

Fan Zhang (2011) Proposed Practical Image Quality Index**,** full reference quality metric is mainly based on the CSF (Contrast Sensitivity Function). It is having a comparable performance advantages with the other existing image quality measurement algorithms. This algorithm is also based on the texture masking effect. This is a wavelet based method in which the image is divided into different subbands using a wavelet decomposition method. It is based on the assumption that the local distortion and the subband distortion contribute the entire distortion of the image [19].

Goran Ivkovic (2004) presents a new novel algorithm for image quality assessment. First, a simple model of human visual system, consisting of a nonlinear function and a 2-D filter, processes the input images. This filter has one user-defined parameter, whose value depends on the reference image.

In the next step the average value of locally computed correlation coefficients between the two processed images is found. This criterion is closely related to the way in which human observer assesses image quality. In the last step image quality measure is computed as the average value of locally computed correlation coefficients, adjusted by average correlation coefficient between the reference image and error image. This way the proposed measure differentiates between the random and signal-dependant distortion, which have different effects on human observer. Performance of the proposed quality measure is illustrated by examples involving images with different types of degradation [20].

Jie Li et al (2015), Due to the existing image quality assessment algorithm does not take the visual information and the essential features of the image into account and cannot meet the actual need, a new method of objective quality assessment which related to both cases was proposed in this paper. The singular value information of the image shows the essential information of image and human eyes are sensitive to the edge information of image. Theoretically, the algorithm of image quality assessment based on edge information and Singular Value Decomposition is better than traditional methods. The simulation experiment results show the proposed algorithm is more consistent with human subject scores and has greater stability than traditional methods. Through comparison with the time efficiency, the proposed algorithm can basically be able to meet the practical demand, and the algorithm is more usability [21].

Yan Fu et al (2016), propose an efficient general-purpose no reference image quality assessment (NRIQA) method based on visual perception, and effectively integrates human visual characteristics into the NRIQA fields. First, a novel algorithm for salient region extraction is presented. Due to the normalized luminance coefficients of natural images obey the generalized Gauss probability distribution; we utilize this characteristic to extract statistical features in the regions of interest (ROI) and regions of non-interest respectively. Then, the extracted features are fused to be an input to establish the support vector regression (SVR) model. Finally, the IQA model obtained by training is used to predict the quality of the image Experimental results show that this method has good predictive ability, and the evaluation effect is better than existing classical algorithms [22].

Li Sze Chow (2016) reviews the recent advancement on IQA for medical images, mainly for Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and ultrasonic imaging. Thus far, there is no gold standard of IQA for medical images due to various difficulties in designing a suitable IQA for medical images, and there are many different image characteristics and contents across various imaging modalities. No reference-IQA (NR-IQA) is recommended for assessing medical images because there is no perfect reference image in the real world medical imaging. We will discuss and comment on some useful and interesting IQA methods, and then suggest several important factors to be considered in designing a new IQA method for medical images. There is still great potential for research in this area [23].

Xingang Liu (2016) propose a new full-reference (FR) 3-D IQA method to measure the quality of the distorted images. The properties of the depth component, structure component, and gradient component are taken into account to establish the proposed metric. The experimental results show that the proposed metric is highly consistent with the subjective test scores compared with the existing related metrics. In addition, the main significance of the proposed metric is that it not only could effectively evaluate the quality of 3-D image but also has a satisfied effect for measuring the quality of 2-D image [24].

Yuming Fang (2018) propose a novel no reference quality assessment method by incorporating statistical luminance and texture features (NRLT) for screen content images (SCIs) with both local and global feature representation. The proposed method is designed inspired by the perceptual property of the human visual system (HVS) that the HVS is sensitive to luminance change and texture information for image perception. In the proposed method, we first calculate the luminance map through the local normalization, which is further used to extract the statistical luminance features in global scope. Second, inspired by existing studies from neuroscience that high-order derivatives can capture image texture, we adopt four filters with different directions to compute gradient maps from the luminance map. These gradient maps are then used to extract the second-order derivatives by local binary pattern. We further extract the texture feature by the histogram of high-order derivatives in global scope. Finally, support vector regression is applied to train the mapping function from quality-aware features to subjective ratings [25].

TECHNIQUES USED IN IMAGE PROCESSING FOR IMAGE QUALITY ASSESSMENT

Sl. No.	Title and Year	Methods used	Parameters used			
			Sensitivity	Quality	Accuracy	PSNR
1	Dandawate et al. (2013)	Full Reference with image quality metrics (FR IQM) Natural Scene Statistics (NSS)	0.90	Moderate	74%	5.095
2	Wang et al. (2013)	Singular value decomposition (SVD)	0.94	High	71%	4.654

3	Jadhav et al. (2013)	Structural Similarity Index Metric (SSIM)	0.88	Moderate	75%	5.041
4	Wu et al. (2009)	Blind blur assessment for vision-based applications	0.77	Low	62%	5.012
5	Liu et al. (2010)	a novel no-reference metric for perceived ringing artifacts in compressed images	0.84	High	69%	4.954
6	Shen et al. (2011)	Hybrid no-reference (HNR) model	0.85	High	70%	5.074
7	Chen et al. (2013)	No-Reference Quality Assessment of Natural Stereopairs	0.88	Moderate	78%	4.852
8	Moorthy et al. (2011)	Distortion Identification-based Image Verity and Integrity Evaluation (DIIVINE) Algorithm	0.86	High	65%	4.902
9	Alain Horé, et al (2010)	Objective image quality metrics, the peak-signal-to-noise ratio (PSNR) as well as the structural similarity index measure (SSIM),	0.78	Moderate	69%	4.919
10	Yusra A. et al (2012)	Full-reference image quality matrices Mean Opinion Score (MOS)	0.88	Moderate	78%	4.358
11	Silpa et al (2012)	PSNR-B and Objective Evaluation Algorithm	0.81	Moderate	81%	3.921

12	Fan Zhang (2011)	Practical Image Quality Index**,**	0.79	Low	79%	2.014
13	Goran Ivkovic (2004)	novel algorithm for image quality assessment using Human Visual Syatem (HVS)	0.69	Low	59%	5.174
14	Jie Li et al (2015)	Image quality assessment on the basis of edge information and singular value decomposition	0.91	High	84%	3.021
15	Yan Fu et al (2016)	Novel algorithm for salient region extraction	0.94	High	89%	5.154

Table 2: Summarization of Existing works

CONCLUSION

In the field of image processing, image quality assessment is a fundamental and challenging problem with many interests in a variety of applications, such as dynamic monitoring and adjusting image quality, optimizing algorithms and parameter settings of image processing systems, and benchmarking image processing system and algorithms. The results of comparative experiments show that each image quality metric has its different sensitivity for the different types of distortion image.

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