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No-Reference Framework for Image Quality Assessment

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Abstract: The technological advances in computer and communication devices have been an important factor in the appearance for the applications of visual communication. Image quality assessment is one of the pillars for these applications. It is a measure to assess the quality of images. There are many degradations in image quality that occur during the reproduction and transmission of the image. This paper aims to introduce a framework of No-Reference Image Quality Assessment. The framework provides a general estimation for three types of image distortions which are sharpness, blackness, and noisiness. Based on this framework, experiments have been conducted by the use of two datasets (LIVE database, CSIQ database). The results of the experiments have shown that we have introduced a more precise framework of No-Reference Image Quality Assessment.

Keywords: *IQA, NR-IQA, BIQA, LIVE database, CSIQ database.*

1. INTRODUCTION

The need for an effective image quality assessment (IQA) metrics has become an essential component of visual communication systems and applications of digital image processing. The IQA metrics act to resolve the degradations in these systems. The methods of IQA are classified into three types which are Full-Reference (FR), Reduced-Reference (RR), and No-Reference (NR). Actually the FR uses a target image, named as a reference image, which typically degraded from an original perfect image.

In the RR, a reference image is partially available to assess the quality of the distorted image. The NR is referred to as blind image quality assessment (BIQA) because it doesn't have a reference image to be used in the assessment. Therefore, it is the most difficult scheme among these methods. The NR-IQA might be a more realistic the research problem. In the absence of reference image, NR-IQA methods are used to classify and predict quality of images, so it is the best method to be used during the reproduction and the transmission of the images.

Blurring and noisy are two distortions which degrade the image textures. Blockiness is a type of image distortion which caused by the independent processing of individual blocks that involved in the Block-based compression. Sharpness refers to an image's overall clarity which based on resolution and acutance. Images which lack sharpness can appear blurry and lacking in detail. The higher the resolution of the image the more pixels it has—the sharper it can be. The acutance subjective measure of the contrast at an edge, so edges which have more contrast appear to have a more defined edge to the human visual system.

This paper proposes a pseudo reference image (PRI) based framework for BIQA. The framework can be used to estimate the general distortion of the invoked images. To perform its function, the framework assembles and utilizes five components.

The rest of this paper is organized as follows. Section II gives the literature review of the study. Section III describes the methods Which we will use for the study. Results and discussion are given in section IV. Finally, section V concludes the paper.

2. Literature Review

Because of image improvement and the increasing interaction of Multimedia technologies, visual data which recorded by pictures Has become the primary source of knowledge acquisition. Many quality aspects (e.g., image quality, color quality, video quality, and so on) has been utilized in our everyday life. Generally, quality is defined as a measure of distinction. The ISO (International Organization for Standardization) has defined the image quality as "overall merit or excellence of an image as a perceived by the observers" [4]. Image quality may be exposed to many degradations during processing, transmission of images. Furthermore, some artifacts or noise, which degrade the visual quality, may occur in images. Therefore, The IQA is a field of study which act to resolve these degradations and artifacts. IQA involves two categories of methods: subjective methods and objective methods [5].

Subjective Methods: These methods depend on the image features which assessed by perceptual human observers. The methods estimate the image quality as a linear quality scale. The scores which provided by multiple people are later averaged to acquire the mean opinion score or difference mean opinion score (DMOS). Due to the multiple people who work to estimate the quality in a controlled test environment. The methods of subjective quality have been characterized as accurate and costly method [7].

Objective Methods: These are quantitative methods where the intensity of images and many types of image distortions are utilized to compute the image quality. The objective methods can estimate the quality through computer algorithms. The methods are further classified into three categories: Full-Reference (FR), Reduced-Reference (RR), and No-Reference (NR).

1) Full-Reference (FR): It is a FR-IQA which uses a target image that named as a reference image, which typically degraded from an original perfect image (See Fig 1). The mean absolute error (MSE) and the peak mean square error **(**PSNR) are commonly used in the FR-IQA to predict the blind quality [5]. This quantity is estimated by contrasting distorted image and the unique reference image[5].

2) Reduced-Reference (RR): In this category of methods, the reference image is partially available to assess the quality of the distorted image. As shown in Fig 2, the RR-IQA uses parameters which are extracted from a reference image to give reduced information about the reference [5].

3) No-Reference (NR): For the most part, this technique is referred to as blind image quality assessment (BIQA) as the reference image is missing. It is the most difficult IQA methods, where it assesses the nature of image without a reference image (see Fig 3).

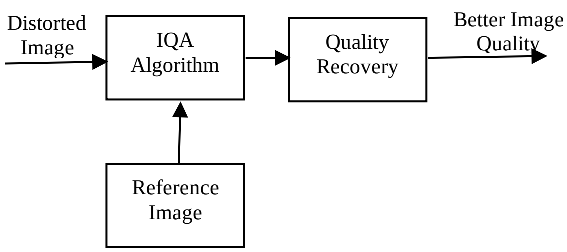

Fig .1. Full Reference Image Quality Assessment

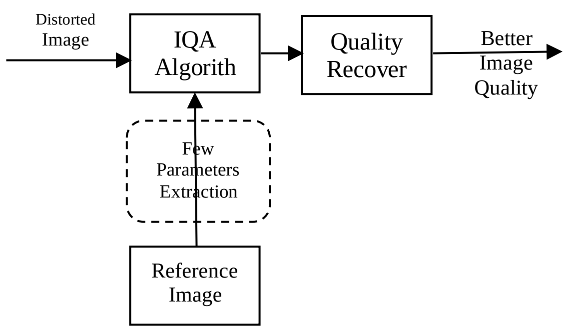

Fig .2. Reduced Reference Image Quality Assessment

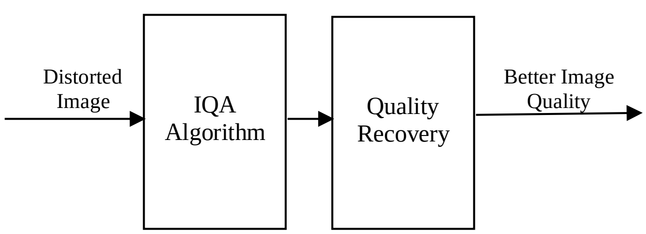

Fig .3. No-Reference Image Quality Assessment

There are many types of image distortions such as blockiness, sharpness and noisiness. Many researchers have developed distortion-specific metrics of FR-IQA, where each of these metrics was devoted to one of the distortions.

The JPEG standard of image and video has embraced the block transform coding. Therefore, the decompressed images and videos display different sorts of distortion artifacts (e.g., blocking, blurring, ringing and noising). H. R. Sheikh et al propose the use of use natural scene statistics (NSS) to blindly measure the quality of images compressed by JPEG2000 (or any other wavelet based) image coder [9]. They train and test an algorithm with data from human subjects, and show that reasonably comprehensive NSS models can help us in making blind, but accurate, predictions of quality. Z. Wang et al develop NR quality measurement algorithms for JPEG compressed images [10]. First, they established a JPEG image database and subjective experiments were conducted on the database. They propose a computational and memory efficient NR quality assessment model for JPEG images. The subjective test was conducted on 8 bits/pixel gray level images. There are 120 test images in the database.

Sharpness estimation is more widely used of blurring distortion in various application. A work based on the notion of just noticeable blur (JNB) was introduced by R. Ferzli and L. J. Karam [11]. In this work, it is shown that the HVS will mask blurriness around an edge up to a certain threshold; this threshold is referred to as the JNB. Nevertheless, the work doesn't include investigate the effect of color on sharpness perception. K. Gu et al propose a model of no-reference (NR)/ blind sharpness metric in the autoregressive (AR) parameter space [12]. The model is established via the analysis of AR model parameters, first calculating the energy- and contrast-differences in the locally estimated AR coefficients in a point wise way, and then quantifying the image sharpness with percentile pooling to predict the overall score. The proposed model to the sharpness assessment of stereoscopic images.

The noise in images is generally known as undesirable information that can distort the image and reduce its clarity. C. Tang et al develop a framework for estimating the noise level of a natural image using two important statistics: 1) high kurtosis and 2) scale invariance in transform domain. They significantly improve the performance of existing denoising techniques that require the noise variance as a critical parameter.

The general purpose BIQA metrics do not require knowing the distortion types, which makes them much more practical and can be applied in various situations. C. Li et al develop a no-reference image quality assessment (QA) algorithm that deploys a general regression neural network (GRNN) [14]. The algorithm is trained on and successfully assesses image quality, relative to human subjectivity, across a range of distortion types. A. K. Moorthy and A. C. Bovik propose an (NR)/blind algorithm named as DIIVINE (Distortion Identification-based Image Verity and INtegrity Evaluation index). The algorithm assesses the quality of a distorted image without need for a reference image. DIIVINE is based on a 2-stage framework involving distortion identification followed by distortion-specific quality assessment. It is capable of assessing the quality of a distorted image across multiple distortion categories, as against most NR IQA algorithms that are distortion-specific in nature.

3. Methodology

This paper proposes a framework of No-Reference Image Quality Assessment. The framework is evaluated by the use of the two LIVE and CSIQ databases. As shown in Fig 4, the model of the framework involves five components which are: preprocessing, PRI based blockiness estimation, PRI based sharpness estimation, PRI based noisiness estimation, and distortion identification.

LIVE Image Quality Database

This database is constructed at Laboratory of Image and Video Engineering (LIVE) in a joint effort with the department of psychology at the University of Texas in Austin. A broad examination was led to get dozens of human subjects distorted images of various types of distortions. The LIVE databases contain images of many distortion types such as white noise and blurring

Gaussian, JPEG and JPEG2000 compression and bit errors in JPEG2000 bit stream. In total, there are 779 distorted images. Many researchers train their algorithms using these images to obtain more useful results [17].

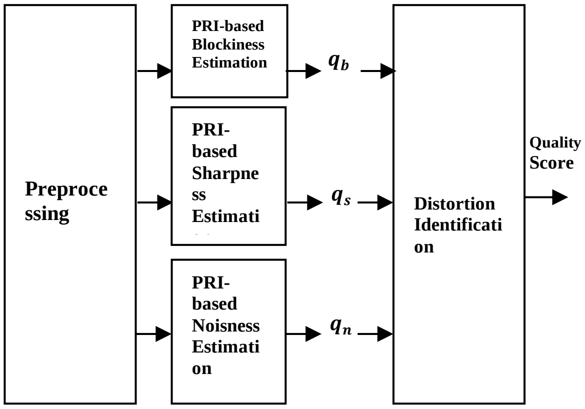

Fig .4. The proposed No-Reference IQA framework

CSIQ Image Quality Database

The CSIQ image database is a famous database for testing the algorithms of image quality assessment algorithms. It contains images of many types of distortions such as noise and blurring Gaussian, JPEG and JPEG2000 compression. The CSIQ image database contains 5000 subjective ratings from 35 different observers were subjectively rated dependent on a linear displacement of the image crosswise over four aligned LCD screens set side-by-side with equal viewing distance to the observer and the ratings are reported in the form of DMOS [18].

Preprocessing

The preprocessing involves a process of image decompression which performed by the use of the SPIHT (Set partitioning in hierarchical trees) algorithm. The SPIHT is one of the most powerful wavelet based image compression techniques [21]. In this process, a good quality of images is obtained by appropriate level of decomposition.

PRI based blockiness estimation

As illustrated in Fig 5, this estimation produces the PSS (pseudo structural similarity) metric based on a PRI image, corners detection, and the JPEG compression.

The distorted image is extensively derived from the PRI. It has been derived as follows.

$$M = JPEG(A, CC) \quad (1)$$

Where M refers to the distorted image, A refers to the invoked image, and CC refers to the decompression factor.

Corners are the most critical features of images. These features are sensitive to various image distortions. Corners are image locations that have large intensity changes in more than one directions. Corners detection can be used to display and describe images structure of the distorted images and PRI image [20].

The PSS is a concept which estimates the similarity between a pseudo structure of distorted images and PRI. The PRI is the pseudo structure of the invoked image. To define the PSS, we have to calculate the overlapping in pseudo structure of distorted images and PRI, as well as the corners in each of the overlapping and the pseudo structure.

The following formulas explain the estimation method of the PSS.

$$P_0 = P_d \times P_p \quad (2)$$

Where P_0 is overlapping in pseudo structure of distorted images and PRI, P_p refers to the structure of the PRI, P_d to denote the structure of distorted image.

$$PSS = \frac{N_0}{N_m+1} \quad (3)$$

Where 1 is constant added for equation stability, N_m refer to the Number of pseudo corners in P_p, and N_0 refer to the number of pseudo corners in P_0 .

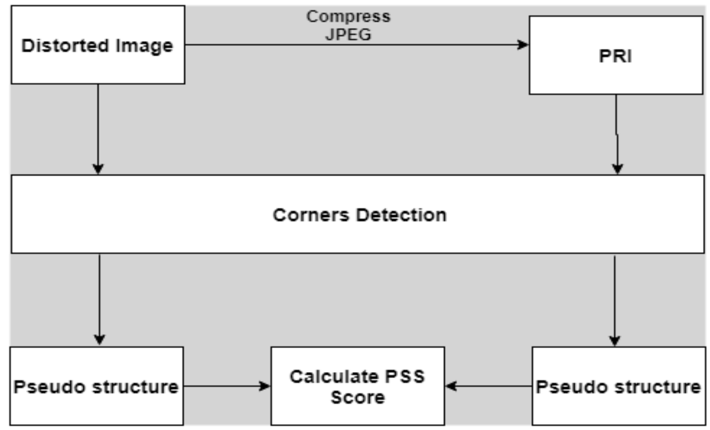

Fig. 5. The PRI based blockiness estimation

PRI based sharpness estimation

This estimation uses a PRI image and the LBP (Local Binary Pattern) so as to generate the LSS_s (Local Structure Similarity for sharpness) which estimates the image sharpness (see Fig 6). The distorted image here is a blurring image.

To get the LBP a filter, which is a vector of horizontal and vertical motions, is applied to the invoked image. The filter performs multidimensional filtering using convolution. The default Len of the vector is 9 and the default theta vector is 0.

The LBP is the most critical features of images. These features are sensitive to the various types of image distortions [20].

The algorithm which construct the LBP feature vector can be defined as follows:

i. Divide the inspected window into cells (e.g. 3x3 pixels for every cell).

ii. For every cell, the pixel in the center of the cell is contrasted to its neighborhood pixels (i.e., the let neighbor pixel, the right neighbor pixel, the top neighbor pixel, the bottom neighbor pixel, and the corner neighbor pixels).

iii. In this contrast we replace each neighborhood pixel with “1” if it is less than or equal the cell center pixel, otherwise it is replaced by “0”).

iv. The binary digits of the neighborhood pixels are combined to form a decimal number that conformed to the cell.

v. Lastly, the LBP feature vector is constituted by the decimal numbers those conformed to the cells.

The formula number (2) is used to produce P_0 which is the overlapping in the blurring image and the PRI. Such that P_d refers to the blurring distorted image and P_p refers to the structure of the PRI.

The LBP algorithm is applied to each of P_0 and P_p so as to get their LBP feature vectors. Then LBP feature of P_0 and P_p are respectively used to generate N_0 and N_m. Ultimately, LSS_s is calculated by the following formula.

$$LSS_s = \frac{N_0}{N_m+1} \qquad (4)$$

PRI based noisiness estimation This estimation produces the LSS_n (Local Structure Similarity for noisiness) based on the PRI image, Gaussian noise, and image edges detection (see Fig 7).

The Gaussian function is added to the PRI so as to generate a noisy image. Such that P_d denotes the noisy image and P_p denotes the PRI. The formula number (2) is used to produce P_0 which is the overlapping in the nosy image and the PRI.

Edge detection plays an important role in many computer visual systems by identifying points of intensity discontinuity in an image. The locations of these intensity discontinuities usually reflect underlying discontinuities in the geometry of surface reflectance of a scene and thereby discount the effects of varying illumination and imaging parameters.

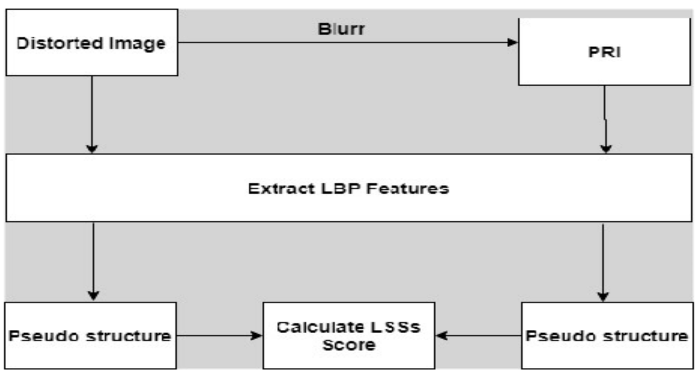

Fig .6. The PRI based sharpness estimation

In the noisiness estimation we use the Canny edge detector algorithm to detect the range of edges in each of the P_0 and P_p.

The LSS_n is calculated as follows.

$$LSS_n = \frac{N_0}{N_m+1} ------ (5)$$

Where N_0 denotes the number of edges in P_0 and N_m denotes the number of edges in P_p.

Distortion Identification

The distortion identification is implemented by a neural network. As illustrated in Fig 8, the neural network is characterized one hidden layer and three inputs (as q_p, $q_s$and q_n). These inputs enact the PSS,LSS_s and the LSS_n which generated by the three PRI based estimations. The neural network output indicates the extent to which the invoked image is distorted.

4. Results and Discussion

We have implemented the proposed BIQA framework by the use of MATLAB. We use both the LIVE database and the CSIQ database to test the framework. Fig 9, 10, and 11 show the sides of some executions which involved in this testing.

The testing gives good results which are values that identify the distorted images. The values show that the invoked images are strongly distorted, and correlation of these values is given by SRCC (Spearman rank-order correlation coefficient). Table 1 shows the SRCC of the proposed framework. The SRCC is 0.995 in the LIVE database, as well as it is 1.000 in each of class pWN and class CC of the CSIQ database.

Table 2 shows comparison performance results. X. Min et al. propose two strategies of BPRI which denoted as BPRI(p) and BPRI(c) respectively [1]. The table reports the SRCCs for the two strategies. These SRCCs measure the performance of the two strategies on the LIVE database as well as class pWN and class CC of the CSIQ. It can be observed that the proposed framework remains top on these databases.

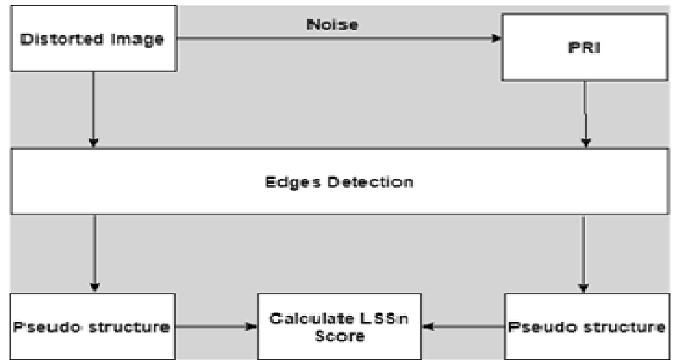

Fig .7. The PRI based noisiness estimation

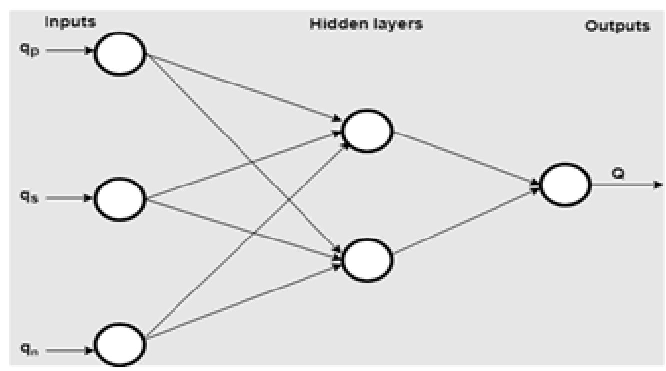

Fig .8. The Neural network of distortion identification

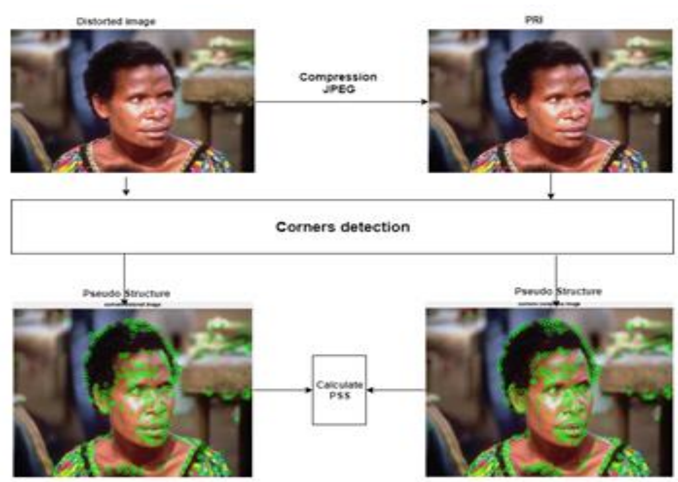

Fig 9. An execution demo for the blockiness side of the proposed framework

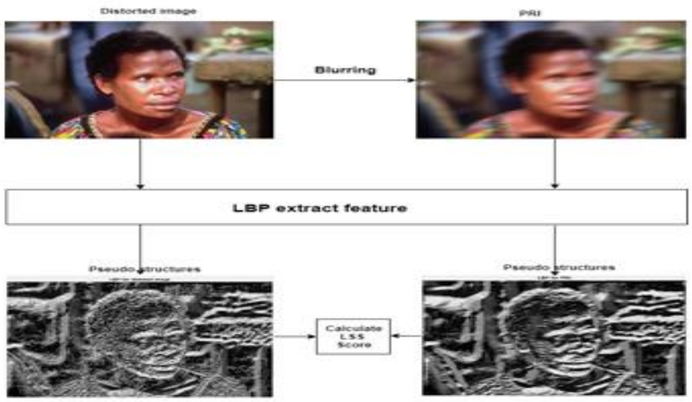

Fig .10. An execution demo for the sharpness side of the proposed framework

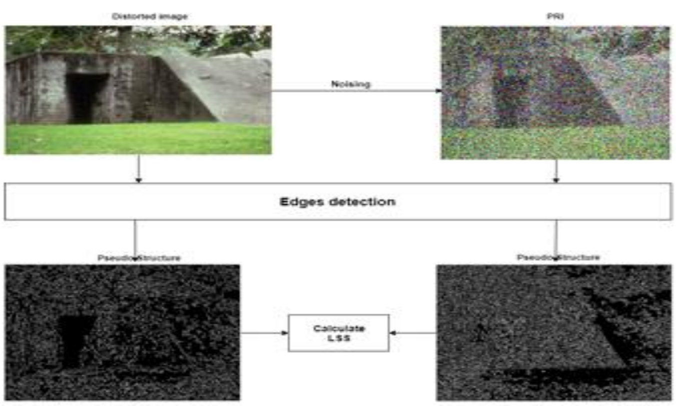

Fig .11. An execution demo for the noisiness side of the proposed framework

Table 1. The SRCC given by the proposed framework

Database / BPRI Method	LIVE	CSIQ pWN	CSIQ CC
The Proposed Framework	0.995	1.000	1.000

Table 2. The SRCC given by the proposed framework

Database / BPRI Method	LIVE	CSIQ pWN	CSIQ CC
BPRI (c)	0.8207	0.3787	0.1076
BPRI (p)	0.8181	03887	0.1563
The Proposed Framework	0.995	1.000	1.000

5. Conclusion

Image quality assessment is one of the main problems in communication systems and applications of digital image processing. So we propose a framework for NR-IQA. The framework is characterized with the preprocessing which involves the SPIHT compression algorithm. The LIVE and CSIQ image databases are used in the testing of the framework. More techniques can be added in the preprocessing so as to enhance the image assessment.

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