SUDAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

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A Modified Framework for No-Reference Digital Image Quality Assessment

إطار معدل للتقييم غير المرجعي لجودة الصور الرقمية

A Thesis Submitted In Partial Fulfillment of the Requirement for the Degree of Master in Computer Science

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الايــة

قال تعالى :

(إِنَّ الَّذِينَ آمَنُوا وَعَمِلُوا الصَّالِحَاتِ إِنَّا لَا نُضِيعُ أَجْرَ مَنْ أَحْسَنَ عَمَلًا)

سورة الكهف ، الآية 30

DEDICATION

I dedicate my thesis work to my family and friends. A special feeling of gratitude to my loving parents, Eldaein University (secretary of academic affairs) for sponsoring my studies and their guides. My supervisor Dr. Hozeifa Adam Abd Alshafy for his advice and patient during the research.

I also dedicate this work and give special thanks to my brothers and sisters for being there for me throughout the entire master program. All of you have been my best cheerleaders.

I dedicate this dissertation to my many friends who have supported me throughout the process. I will always appreciate all they have done, for helping and hours of proofreading.

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I would first like to thank Dr. [Hozeifa Adam] who left his office door to be always me open whenever I ran into a trouble spot or had a question about my research.

I also like to thank my fellow master students for their feedback, cooperation and of course friendship. In addition, also I would like to thanks Eldaein University for giving me this master program opportunity.

Last but not least, I would like to thank my family: my parents and to my brothers and sister for supporting me spiritually throughout writing this thesis and my life in general.

ABSTRACT

In light of the information revolution and rapid technological jumps which caused to increase use the digital images to develop large applications in visual communication systems, the target image is typically degraded from an original perfect quality image is called the reference image. Image quality assessment (IQA) is a measure to assess the quality of an image in understanding or in reference to the original image. May occur degradations in image quality during reproduction, transmission. And also the signal transformed might be exposed to various sorts of distortions which degrade the quality of the image. In this research, use a "reference" called the pseudo reference image (PRI) and introduces PRI based on blind image quality assessment (BIQA) framework. Specific-distortion estimated for PRI based blokiness, PRI based sharpness, and PRI based noisiness after preprocessing of all stages of the model. After extracting features (PSS, LSSs, and LSSn) are using these features to train the classifier (NNK) to identify the general distortion. Through 2-stages to estimate the specific-distortion after preprocessing and then integrating distortion identification. The proposed framework (BPRI) is simplifying by abolishing a score alignment. Can be results obtained (quality score) of images using two datasets LIVE and CSIQ. Comparing the results BPRI proposed framework with subjective image test (DOMS standard).

المستخلص

في ظل ثورة المعلومات والتطور التكنولوجي السريع الذي تسبب في زيادة استخدام الصور الرقمية للتطوير تطبيقات كبيرة في أنظمة الاتصالات المرئية ، عادة ما تتدهور الصورة المستهدفة من صورة الجودة الأصلية المثالية تسمى الصورة المرجعية. تقييم جودة الصورة IQA كمقياس محدد لتقييم جودة الصورة في فهم الصورة الأصلية أو الرجوع إليها. قد يحدث تدهور في جودة الصورة أثناء إرسالها اوتخذينها. وكذلك قد تتعرض الإشارة المرسلة إلى أنواع مختلفة من التشوهات التي تؤدي إلى تدهور جودة الصورة. في هذا البحث ، استخدم "مرجع" يسمى الصورة المرجعية الزائفة (PRI) ويقدم PRI استنادًا إلى إطار تقييم جودة الصورة العمياء (BIQA). التشويه النوعي المقدر للشفافية القائمة على PRI ، والحدة القائمة على PRI ، والضوضاء القائمة على PRI بعد المعالجة المسبقة لجميع مراحل النموذج. بعد استخراج الميزات (PSS و LSSs و LSSn) تم استخدام هذه الميزات لتدريب المصنف (NNK). من خلال مرحلتين لتقدير التشويه المحدد بعد المعالجة المسبقة ومن ثم دمج تحديد التشويه. تم تبسيط إطار العمل المعدل (BPRI) من خلال إلغاء محاذاة النقاط. يمكن الحصول على نتائج (نقاط جودة) من الصور باستخدام قاعدتين بيانات LIVE و CSIQ. مقارنة النتائج إطار العمل المعدل(BPRI) مع اختبار صورة عن طريق البشر (معيار DOMS).

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	*Description*
IQA	image quality assessment
FR	Full-Reference
RR	Reduced-Reference
NR	No-Reference
PRI	Pseudo reference image
BIQA	Blind image quality assessment
BPRI	Blind image quality assessment
DMOS	Difference Mean Opinion Score
PSNR	Peak signal-to-noise ratio
MSE	Mean Square Error
SSIM	Structural similarity index metric
NSS	Natural scene statistics
DIIVINE	Distortion Identification-based Image Verity and Integrity Evaluation
SRCC	Spearman rank-order correlation coefficien
CC	Contrast change
pWN	Additive pink Gaussian noise
BRISQUE	Blind/Reference less Image Spatial Quality Evaluator
LIVE	Laboratory for Image & Video Engineering
CSIQ	Computational and Subjective Image Quality

CHAPTER - I

INTRODUCTION

Chapter I

1. INTRODUCTION

1.1. Background

In light of the information revolution and rapid technological jumps which caused to increase use the digital images to develop large applications. These images may have degradation in most visual communication systems for efficient and effective image quality assessment (IQA) metrics which can measure the quality images accurately (Min, 2018). In visual communication systems, the target image is typically degraded from an original perfect quality image is called the reference image. As per the accessibility of the reference image, objective IQA measurements divided into three approaches: Full-Reference (FR) is full depend on the reference image, Reduced-Reference (RR) Use a few parameters that were extracted the features from the reference image, No-Reference (NR) without using the reference image because not available. Classify the objective IQA methods based on the application scope into two methods: the first general purpose methods are unaware of the type distortion-specific, the second specific methods that model for the specific types of distortion (Jaliya, 2017). NR-IQA methods are the difficult task causes absent the reference image we use to classification and prediction the quality of image.

Image quality may occur degradations during reproduction, transmission. Furthermore storage, some artifacts or noise may occur in images. The blurring visual quality on a digital advanced imaging system, the image is caught, moreover, occur it is changed to a digital signal by the sensor. Afterward, the signal transformed might be exposed to various sorts of distortions which degrade the quality of the image (Wang, 2011). NR-IQA methods aim to predict the quality of distorted images with respect to human perception automatically without reference images. Create a pseudo reference image (PRI) in this study. PRI is the worst quality more than the distorted image. Basically, they were derived from the distorted image. Then measure the distance between distorted image and PRI as the quality. PRI-based general-purpose BIQA framework to estimate the general-purpose distortion in 2-stages estimate specific-distortion after preprocessing and then distortion identification.

1.2. Problem statement:

The field of NR-IQA has been a more difficult activity. This is largely due to the fact that NR IQA incudes many challenges which need to solve. This difficulty due to the non-existence of the reference images for evaluation quality of the image (Moorthy, 2010). Many image degradations may occur in the visual communication systems these degradations may happen during reproduction, acquisition, processing, transmission, furthermore storage, some artifacts or noise may occur in images (Min, 2018). These degradations may make a lot of social and economic effects.

The blurring visual quality on a digital advanced imaging system, the picture is caught, moreover, occur it is changed to a digital signal by the sensor. Afterward, the signal transformed might be exposed to various sorts of distortions which corrupt the quality of the image. Such as noise, compression or transmission (Wang, 2011). For instance, in image compression, loss compression schemes present blurring and ringing impacts, which prompts quality degradation. Besides, when signals exceed the transmission bandwidth there will be dropping some information which results in quality degradation of the images.

1.3. Research objectives:

The aim of this study is to introduce a framework of No. This objective is achieved by:

- Investigate and modify the framework of the NR-IQA, which was done by Min and others in the year 2018, so as to enhance the performance of the assessment.
- Introduce an assessment for the general distorted images that by considering the sharp, block, and noise.

1.4. Proposed Solution:

In this study, will be proposed a framework PRI-based BIOA to provide models measure some specific-distortion and integrate to general-purpose BIQA.

1.5. Research Scope:

The importance of Image Quality Assessment (IQA) lies in its developing multidisciplinary themes that generally incorporate image processing and signals, visual psychophysics, computer vision, neural physiology, machine learning, the design of the communication systems, also use in display and image acquisition systems (Rajkumar, 2016).

1.6. Research Hypotheses:

The research hypothesis states what the researcher expects to find – it is the tentative answer to the research question that guides the entire study.

- Can we build a model that optimizes performance in BIQA?
- Can we estimate the quality of images with specific-distortion?
- Can we evaluate the quality of distorted images without a reference image?

1.7. Research Methodology:

In this study, will be proposed a framework PRI-based BIOA to provide models to measure distance between distorted image and PRI as quality. This is done through an estimate blockiness, sharpness, noisiness as specific distortion and integrate to general-purpose BIQA.

1.8. Research Organization:

This research has the following structure: Chapter I contains background, problem statement, Research objectives, Proposed Solution, Research Scope, research methodology, research organization, Chapter II contains some previous studies related to measure IQA, Chapter III we describe the details of PRI based general-purpose distortion BPRI model. The experiment results are given in Chapter IV, and Chapter V it include conclusion, recommendations, and references.

CHAPTER -II

LITERATURE REVIEW & RELATED WORKS

2. LITERATURE .ATED WORKS

2.1 Introduction:

This chapter provide some literature review for IQA technologies and related works.

2.2 Image Quality Assessment Technologies:

With the improvement of imaging and more interact with multimedia technologies, visual data, recorded by pictures has become into the primary source for knowledge acquisition. Quality word is utilized in our everyday life like image quality, color quality, video quality, and so on. It is defined as a measure of distinction. ISO defined the image quality as “overall merit or excellence of an image as a perceived by the observers”(Raijada et al., 2015).

Image quality may occur degradations during processing, transmission. Furthermore storage, some artifacts or noise may occur in images which degrade the visual quality. Image quality assessment can be characterized as to survey or to gauge the nature of image in understanding or in reference to the original image. Image quality assessment (IQA) can be defined as to assess or to gauge the quality of an image in understanding or in reference to the original image. The quality of an image in different types of distortion a method is required to assess quality. Image quality assessment can be evaluated in two method(Yogita and Patil):

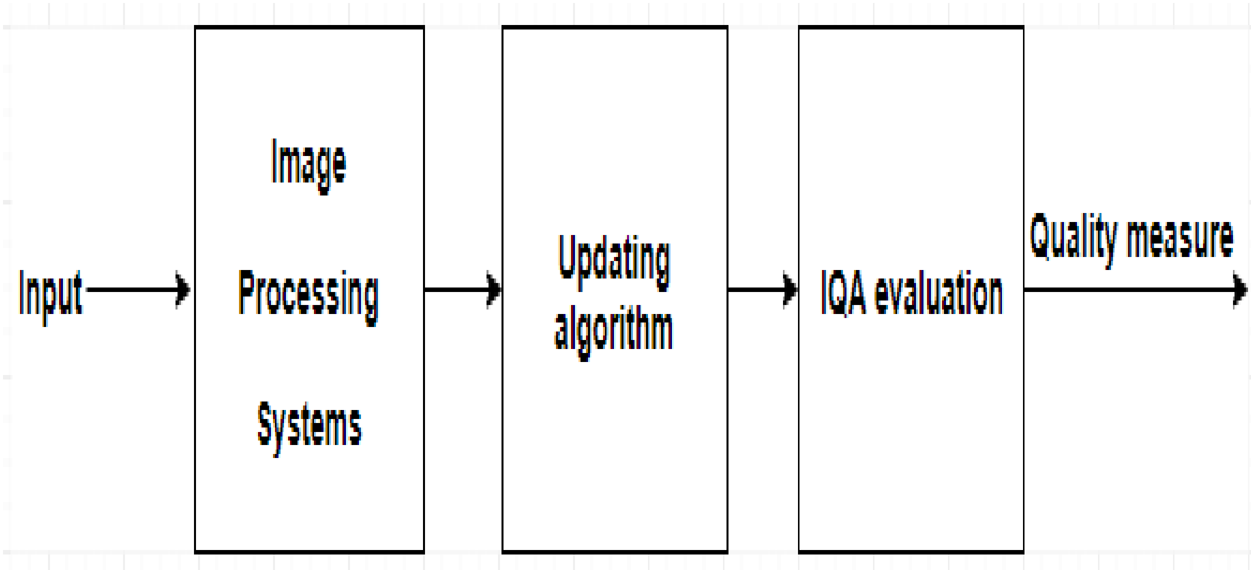


Figure (2.1): Diagram for IQA(Eerola et al., 2014)

A) Subjective Methods: depend on the perceptual human observer's assessment of the features of an image or set of images. The subject assesses the quality of the test images on a linear quality scale without the source as a kind of perspective. The scores assessed by multiple people are averaged for each test image to acquire the mean opinion score or difference mean opinion score (DMOS). The best technique for subjective image quality estimation are given in Table 2.1. Subjective quality assessment is a traditional method for estimating the image quality in which multiple people are included who work an estimate the quality of a medium in a controlled test environment. Subjective quality assessment results accurate but costly(ECE and Mullana, 2011).

Table 2.1: Difference Mean Opinion Score Classes

-1	0	1
Low Quality	Medium Quality	High Quality

B) Objective Methods: This is a quantitative method where the intensity of two images, reference, and type distortion in the image are utilized to compute a number which demonstrates is the image quality. The objective Image Quality Assessment (IQA) can estimate the quality through algorithms and can be classification into three approaches. IQA based on the availability of the reference image.

(1) Full-Reference (FR): The images is generally captured utilizing an excellent-quality device. Compare the distorted image with the original image. See figure (2.2) FR-IQA.

For FR-IQA based appraisal, mean absolute error (MSE) and peak mean square error **(**PSNR) are commonly used to predict the blind quality by contrasting distorted image and the unique reference image which is generally determined as in eq. (1) and eq.(2) (Yogita and Patil).

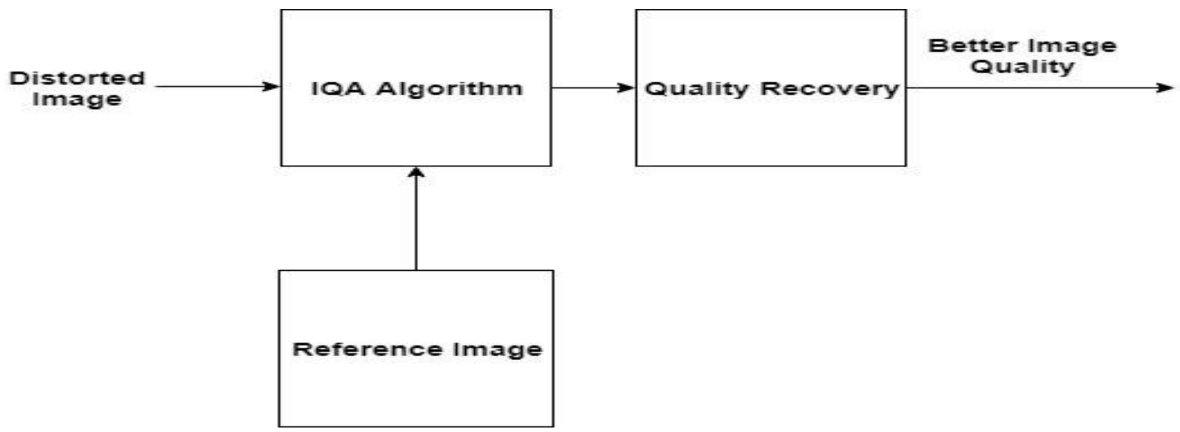


Figure (2.2): Full-Reference Image Quality Assessment(Yogita and Patil)

- **Mean Absolute Error (MAE):** MAE is average of absolute difference between the reference signal and test image. It is given by the equation

$$MSE = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(a_{i,j} - b_{i,j}\right)\hat{}2 \text{ \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ } (1)$$

Where ai, and bi, are reference image and distorted image respectively.

- **Peak Mean Square Error (PMSE):** It is given by the following equation $PSNR$=10 log10 $\frac{255\hat{}2}{MSE}$ ____________________________________ (2)

Where 255 is the maximal possible value the image pixels when pixels are represented using 8 bits per sample, and MSE (mean square error) is the Euclidian distance between the original and the degraded images.

(2) Reduced-Reference (RR): In this method, the reference image is partially available which assesses the quality of the distorted image. Portray the technique RR-IQA. In figure (2.3) illustrates RR-IQA, parameters are extricated to give reduced information of the image and it isn't specifically identified with a particular degradation.

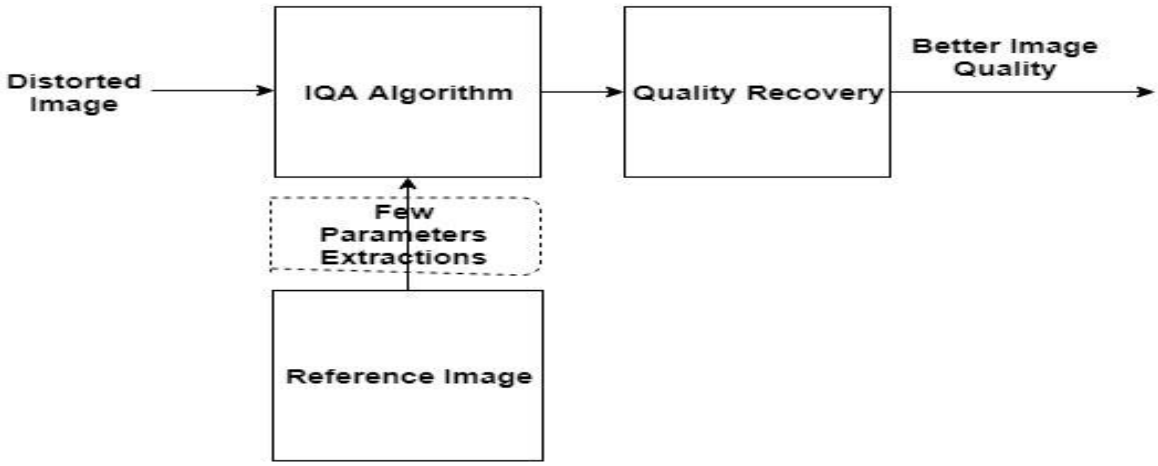


Figure (2.3): Reduced-Reference Image Quality Assessment(Yogita and Patil)

(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. This is the most difficult undertaking as it assesses the nature of image without a reference image illustrates in figure (2.4) NR-IQA. It might be less exact however more realistic the research problem.

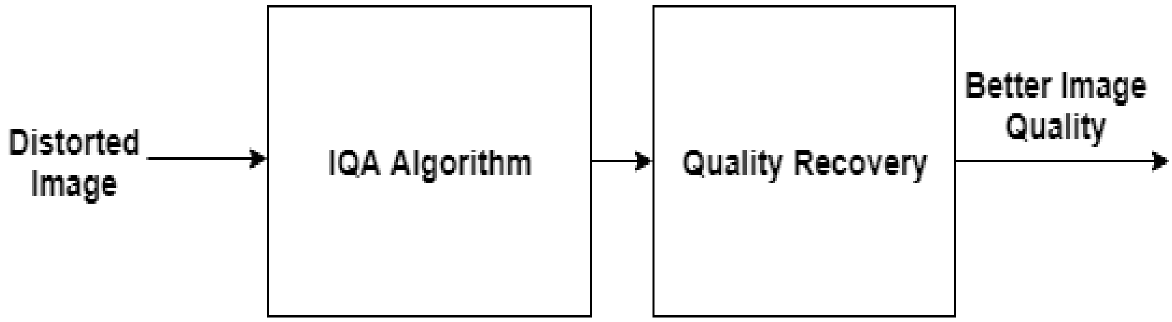


Figure (2.4): NO-Reference Image Quality Assessment(Yogita and Patil)

2.3 Image Quality Assessment Metrics:

- The structural similarity index metrics (**SSIM**): SSIM metrics is single scale method used to measure the similarity between two images apply in full reference metric.
- Edge-based structural similarity (**ESSIM**), can be defined as an edge-based structure between the distorted image block and the original one, and replace the structure comparison.
- **MS-SSIM:** is multi scale method used to measure similarity structural between two images.
- F**SIM:** feature-similarity (FSIM) index for full reference IQA is proposed based on the fact that human visual system (HVS) understands an image mainly according to its low-level features instead of high level features(Raijada et al., 2015).

2.4 Specific-distortion BIQA Metrics:

2.4.1 Blockiness Estimation: Block transform coding has been broadly embraced in numerous present images and video compressions standards, for example, JPEG, H.261 and MPEG-4. In the request to accomplish low bits rates, quantization is typically utilized during encoding to block the transform coefficients. Accordingly, the decompressed image and video display different sorts of distortion artifacts, for example, blocking, blurring, ringing and noising (Wang, 2002).

Sheikh et al have proposed a no-reference image quality metric utilizing natural scene statistics (NSS) of JPEG-2000 compressed images. JPEG-2000 pressure bothers the nonlinear dependencies which are seen in the original image. Wavelet coefficients' extents and sizes of the straight forecast of coefficients in four sub-groups are utilized as factual features (Sheikh, 2005). (Wang, 2002) evolved NR quality estimation algorithms for JPEG compacted images or blurred images. First. Built up a database of JPEG image and experiments of subjective were directed on the database. Demonstrate that Peak Signal-to-Noise Ratio (PSNR). Assumed that NR IQA algorithms that look to estimate the goodness of JPEG/ JPEG2000 compressed images.

The algorithm is prepared to utilize the mean opinion score (MOS) provided with the LIVE database (H.R. Sheikh, 2005). Wang et al have evolved NR quality estimation algorithms for JPEG compacted images or blurred images (Wang, 2002).

2.4.2 Sharpness Estimation: Sharpness estimation is more widely used of blurring distortion in various application scenes to reduce the detail of the image by sharpness estimators try to measure sharpness via edge analysis (Min, 2018). Such as image capturing an image/video coding. Introduced the concept of just noticeable blur (JNB) of proposed metric for measure sharpness (Ferzli, 2009). Gu et al proposed a new no-reference (NR)/blind sharpness metric in the autoregressive (AR) parameter space (Gu, 2015).

2.4.3 Noisiness Estimation: Of concepts in image processing techniques. As defined the noise in images is generally known as undesirable information that can distort the image and reduce its clarity. Developed a framework for estimated noise through statistical analysis and noise injection. Utilizing two imperative statistics: high-kurtosis and scale-invariance in the change are (Tang, 2015).

2.5 General-Purpose BIQA Metrics:

A) Distortion Identification-based Image Verity and Integrity Evaluation (DIIVINE):

Bovik, Xiao, and Li have proposed a DIIVINE – divines the nature of image with no requirement for a reference or the advantage of distortion models (Li, 2011). It’s executed by used LIVE IQA database (H.R. Sheikh, 2005). The DIIVINE approach is general distortion since it doesn't calculate distortion-specific properties of quality, however, uses an NSS-based way to deal with quality and in addition the DIIVINE also use a 2-stage framework for blind IQA that initially identifies the distortion type damaging the image and performs particular distortion type quality assessment after distortion identification (Min, 2018).

B) Blind/Reference less Image Spatial Quality Evaluator (BRISQUE):

Mittal has proposed BRISQUE which removes insights of local normalized luminance flags and measures image expectation in view of estimated deviations from an original image (Mittal, 2011). At that point collective distortion-identification with distortion-aware IQA to deliver a showing of the blind impaired image quality index (BIQI) which is of value all alone. BIQI was tried on the LIVE image database (H.R. Sheikh, 2005).

C) Blind Image Quality Index (BIQI): Moorthy and Bovik have used distorted image statistics (DIS) is extension of NSS and utilized this mark to arrange images into distortion classifications. Collective distortion-identification with distortion-aware IQA to deliver a showing of (BIQI) which is of value all alone (Moorthy, 2010). BIQI was tried on the LIVE image database (H. R. Sheikh, 2006) and was appeared to perform well regarding correlation with human perception.

2.6 Summary: in this chapter, we display major concepts for descript image quality assessment and related work. In the year 2018, was presented the proposed model (BPRI) for the evaluation of the quality of digital images.

Table 2.2: Summary of some previous works

Paper Title	Authors	Approach	Advantages	Disadvantages
No-Reference Quality Assessment Using Natural Scene Statistics: JPEG2000(Sheikh et al., 2005)	Sheikh	NSS Approach	Database Specific distortion (JPEG2000 compress)	blur metric was not specifically designed for JPEG2000
No-Reference Image Quality Assessment in the Spatial Domain (Mittal et al., 2011)	Anish Mittal, Moorthy, Bovik, Fellow	NSS Approach	Database general distortion	does not compute distortion-specific features

No-Reference Image Quality Assessment using visual codebooks(Ye and Doermann, 2012)	P. Ye and D. Doermann	Two step framework Based NSS Approach	Distortion Generic	Doesn’t work well for JPEG compression
Blind Quality Assessment Based On Pseudo Reference Image(Min et al., 2018)	Min, Gu, Zhai, Liu, Yang	PRI based BIQA and integrate from specific to general distortion	Distortion Generic	Limit at specific distortion & complex framework

CHAPTER -III

METHODOLOGY

C

3. ME

3.1 Introduction:

This chapter describes the research matters (i.e., LIVE and CAIQ image quality databases) which have been used as an input for our experiments. Moreover, the chapter discuss the components of the proposed model. The components are: preprocessing, PRI based blockiness estimation, PRI based sharpness estimation, PRI based noisiness estimation, distortion identification (see figure (3.1)).

3.2 LIVE Image Quality Database: Is dataset at Laboratory for Image and Video Engineering (LIVE) (in a joint effort with The Department of Psychology at the University of Texas at Austin), a broad examination was led to get dozens of human subjects distorted images of various types of distortion. The LIVE databases contain 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. We can train the algorithm with these pictures to obtain results more useful (H. R. Sheikh, 2006).

3.3 CSIQ Image Quality Database:

The CSIQ image database is a famous database for testing image quality assessment algorithms and different works of image quality. It is contain many types of distortions such as noise and blurring Gaussian, JPEG and JPEG2000 compression. Altogether, there are 866 distorted images. 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 (Chandler, 2010).

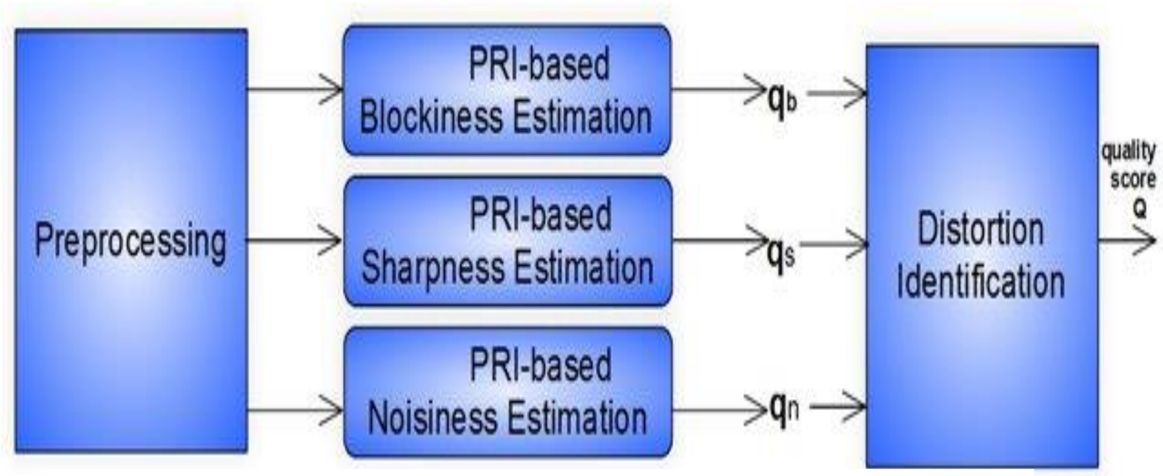


Figure (3.1): Model PRI-based general-purpose BIQA metric

This a proposed model above figure (3.1) will be building a framework PRI-based general-purpose BIQA metric to measure the distorted image's "distance" from PRI as quality by estimate blockiness, sharpness, noisiness as specific-distortion and integrate to general-purpose distortion BIQA**.**

3.4 Preprocessing:

At this stage, remove the compress (decompression) from the images using sphit algorithm as decompression factor as the factor increased the size of the image until we reach the size of the image before the compression.

3.5 PRI based blockiness estimation: as illustrated in figure (3.2) PRI based blockiness estimation contains three operations: PRI, corners detection, the metric (PSS).

1) **PRI:** extensively distorted image. It has been derived as follows: The compression "Quality" parameter, which specifies the compression degree when deriving the PRI.

M=JPEG (A, CC) ____________________ (3)

Where M refer to distorted image, A is PRI and CC is decompression facto

2) **Corners Detection**: Corners are the most critical features of images. These features are sensitive to the various distortions of images. For instance, in block-based image/video compression, dividing based on processing between individual block. The changing the corners the near of the block boundaries compared to the central areas of the blocks. All the more explicitly, the corners is placed near the boundaries of blocks being spaced and the corners in the center block are close from the some. Contrast increases with increasing level of compression. Corners detection can use to display and to describe images structure of the distorted image and PRI image (Min, 2018). If the corners are detected they are spread across all the block boundaries, noting that the block size=8. Otherwise, are detected some ordinary positions see in figure (3.3) and figure (3.4) proposed (minimum eigenvalue) method used to corners detection (Shi, 1993).
3) **Pseudo structure similarity (PSS):** find that there are overlapping in two images pseudo structure by symbolize ($\mathbf{P_0}$) to describe similar between pseudo structures of distorted image $\mathbf{P_d}$ and PRI's pseudo structures $\mathbf{P_p}$.

$\mathbf{P_0}_{i,j}$= ($\mathbf{P_d}_{i,j}$.$\mathbf{P_p}_{i,j}$) h×w ____________ (4)

Where i, j to denote position and h×w refer to row and column

The similarity estimation involves the overlapping (denoted as$\boldsymbol{N_o}$) and the number of pseudo corners in $\mathbf{P_p}$ as $\mathbf{N_m}$. The measure to blockiness estimation name as PSS which stand for pseudo structure similarity.

PSS= $\frac{\mathbf{N_o}}{N_{m+1}}$ ________________ (5) 1 is constant added for equation stability

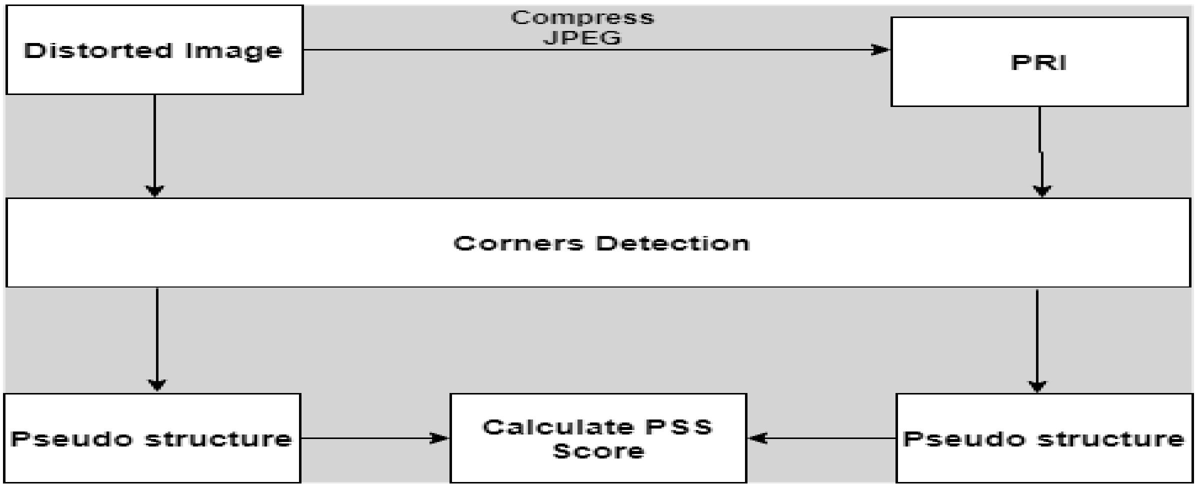


Figure (3.2): PRI based blockiness estimation

Shown in figure (3.2) illustrates the main operations to PRI based blockiness estimation which consist the steps of distorted image to get PRI compression and then detect the corners from two images, finally, calculate pseudo structure similarity (PSS) this measure to existing a similarity between these images.

3.5.1 Analysis the steps for PRI based blockiness estimation:

A) The distorted image: At this stage we can show in figure (3.3) below.

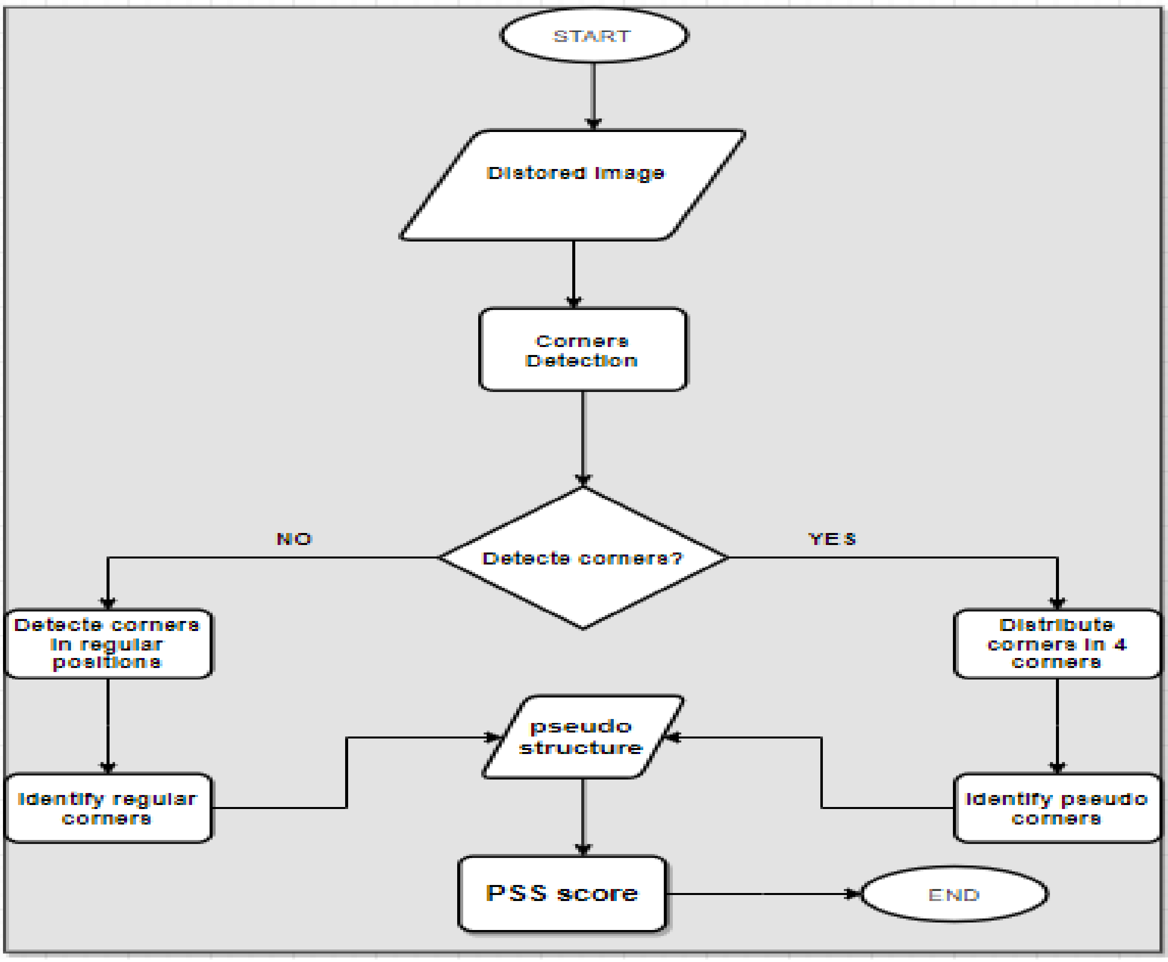


Figure (3.3): Flowchart for extract corners of distorted image

When read the distorted image, detected the corners of distorted image then if the detected corners are distributed at 4 corners of the 8 * 8 block, they are recognized as pseudo corners. Something else, if they are identified at some regular positions, they are taken as ordinary corners.

B) The pseudo reference image:

At this stage we display how to extract a pseudo structure from pseudo image. This stage can show in figure (3.4) below.

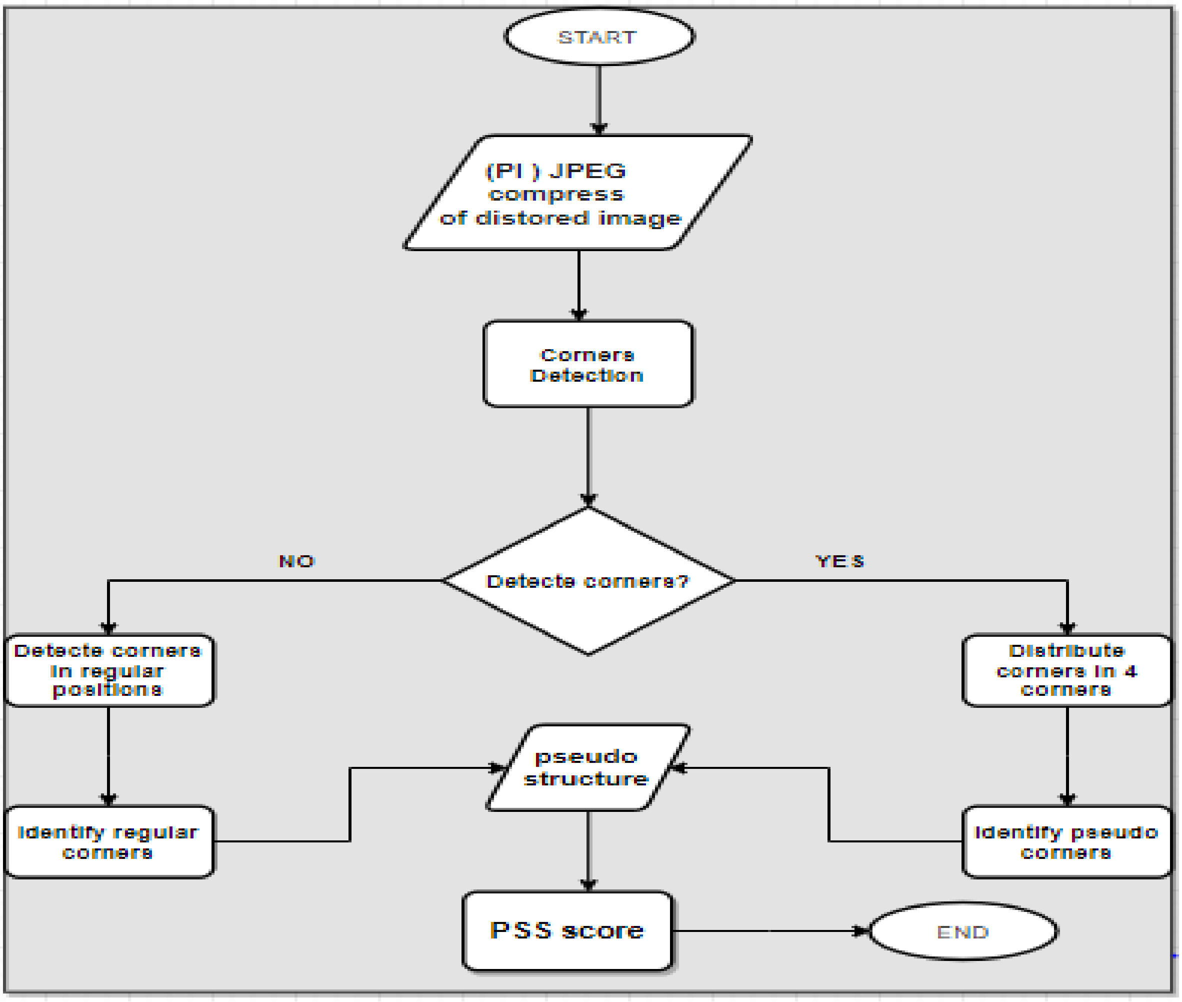


Figure (3.4): Flowchart for extract corners of pseudo reference image (PRI)

When created PRI by compressing the distorted image, then the corner will be detect. The corners is placed near the boundaries of blocks being spaced and the corners in the center block are close from the some. After that pseudo structure was created and they are calculate the structure similarity using PSS metric.

3.6 PRI based sharpness estimation: as illustrated in figure (3.5) PRI based sharpness estimation contains three operations: PRI, local binary pattern, LSSs.

1. **PRI**: derived from a distorted image. The blurring is one of the distortions types, in this section will be applied to blur image as (PRI). There is a filter which a vector for horizontal and vertical motions. The default len vector is 9 and the default theta

vector is 0, which corresponds to a horizontal motion of nine pixels. The filter performs multidimensional filtering using convolution.

2. **Local Binary Pattern**: LBP is the most critical features of images. These features are sensitive to the various types of image distortions (Min, 2018). We applying this to describe pseudo-structure.

The LBP feature vector, in the framework, that way:

- Dividing the inspected window into cells (e.g. 16x16 pixels for every cell).
- For every pixel in a cell, contrast the pixel with every one of its 8 neighbors (to its left side best, left-center, left-base, right-top, and so on.). Pursue the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the central pixel's esteem is more prominent than the neighbor's esteem, state "0". Something else, express "1". This gives an 8-digit binary number (which is normally changed over to decimal for comfort).
- Standardize the histogram (optionally). The histogram can be viewed as a 256-dimensional feature vector.

3. **Local Structure Similarity (LSS):** We find that there are overlapping in two images pseudo structure by symbolize ($\mathbf{P_0}$) we use to describe similar between pseudo structures of distorted image $\mathbf{P_d}$ and PRI's pseudo structures $\mathbf{P_p}$.

$$\mathbf{P_0}_{i,j} = (\mathbf{P_d}_{i,j} . \mathbf{P_p}_{i,j}) \; h \times w \quad \text{\_\_\_\_\_\_} \quad (6)$$

Where i, j to denote position and h×w refer to row and column

The similarity estimation involves the overlapping (denoted as $\boldsymbol{N_o}$) and the number of pseudo corners in $\mathbf{P_p}$ as $\mathbf{N_m}$. The measure to blockiness estimation name as LSS_s which stand for Local structure similarity to estimate sharpness.

$LSS_s = \frac{\mathbf{N_o}}{\boldsymbol{N_{m+1}}}$ _____________ (5) 1 is constant added for equation stability

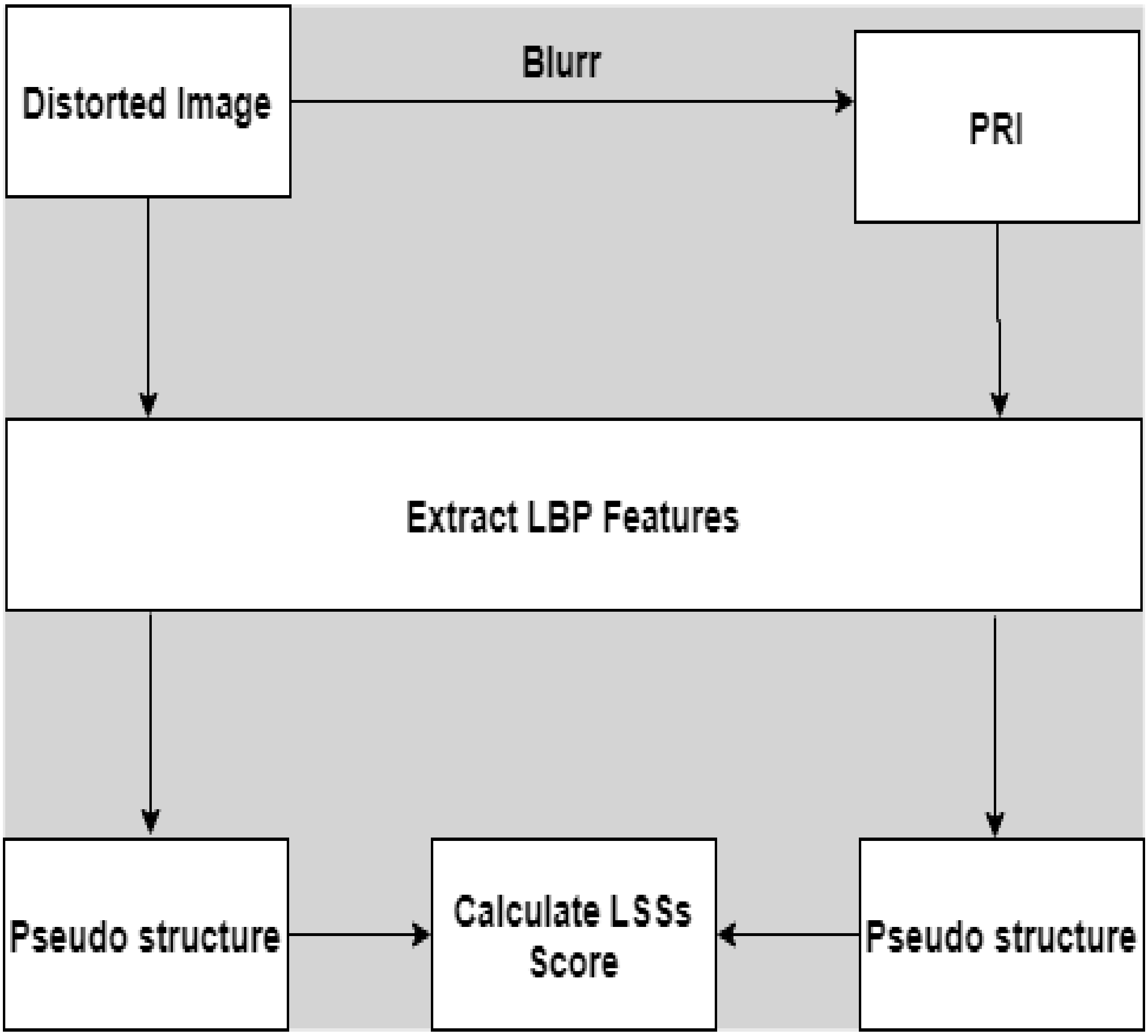


Figure (3.5): PRI based sharpness estimation

The above figure (3.5) illustrates the main operations of the proposed model which consist the steps of a model distorted image to get for a blurred (PRI) and then extract LBP features from two images to describe pseudo structure, finally, calculate local structure similarity (LSS) this measure to existing a similarity between them.

3.7 PRI based noisiness estimation: as illustrated in figure (3.6) PRI based sharpness estimation contains three operations: PRI, local binary pattern, LSSn.

a) **PRI:** derived from the distorted image. In this section will be applied to noisy image (PRI). Use Gaussian noise equal 0.3 knowing that standard Gaussian (0 to 0.5).

b) **Edges Detection:** edges are points between two image districts (boundary) and may include junctions. Besides, some algorithms will then chain high gradient points together form a complete description of an edge and set some constraints on the properties of an edge, such as gradient value and smoothness. The feature detector in detection edges: such as **Canny edge detector** is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. The edges to describe pseudo structure.

Process of Canny edge detection algorithm:

The Canny edge finder is broadly utilized in computer vision to find sharp force changes and to identifier arranges a pixel as an edge if the slope size of the pixel is bigger than those of pixels at the two its sides toward most extreme force change and to discover object limits in an image (Ding, 2001).

a. Apply Gaussian filter to smooth the image in order to remove the noise
b. Find the intensity gradients of the image
c. Apply non-maximum suppression to get rid of spurious response to edge detection.
d. Apply double threshold to determine potential edges.
e. Finalize the detection of edges.

c) Local Structure Similarity (LSS): We find that there are overlapping in two images pseudo structure by symbolize ($\mathbf{P_0}$) we use to describe similar between pseudo structures of distorted image $\mathbf{P_d}$ and PRI's pseudo structures $\mathbf{P_p}$.

$$\mathbf{P_0}_{i,j} = (\ \mathbf{P_d}_{i,j} . \mathbf{P_p}_{i,j}\ )\ h\times w \quad \_\_\_ \ (7)$$

Where i, j to denote position and h×w refer to row and column

The similarity estimation involves the overlapping (denoted as $\boldsymbol{N_o}$) and the number of pseudo corners in $\mathbf{P_p}$ as $\mathbf{N_m}$. The measure to blockiness estimation name as LSS_n which stand for Local structure similarity to estimate noisiness.

$LSS_n = \frac{N_o}{N_m+1}$ ________________ (8) 1 is constant added for equation stability

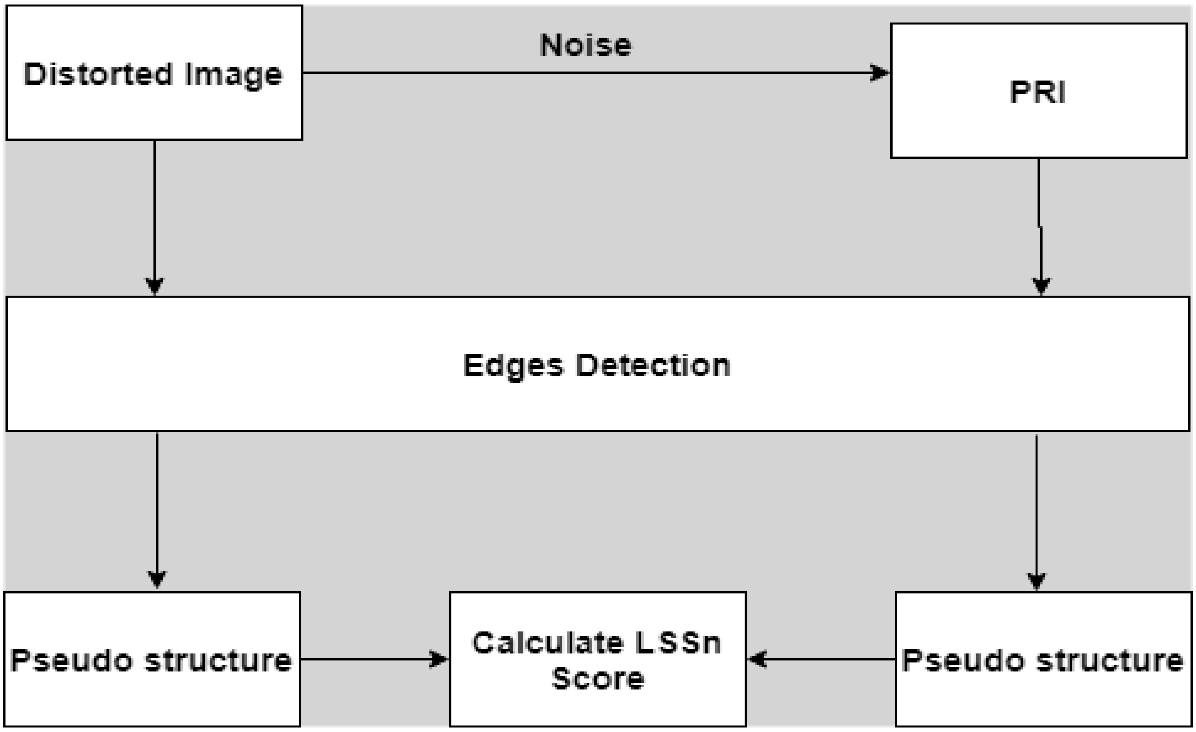


Figure (3.6): PRI based noisiness estimation

The above figure (3.6) illustrates the main operations of the proposed model which consist the steps of a model distorted image to get for a noisy image as (PRI) and then use edges detection from two images to describe pseudo structure , finally, calculate local structure similarity (LSS) this measure to existing a similarity between them.

3.8 Distortion Identification:

The extracted features (i.e., PSS, LSSs and LSSn) in return the same order as q_p, $q_s$and q_n from “PRI-based distortion-specific” has been used these features to train the classifier to identify the general distortion is denoted as quality score (Q). Shown in figure (3.7) employed a neural network tool (NNK) to estimate the quality.

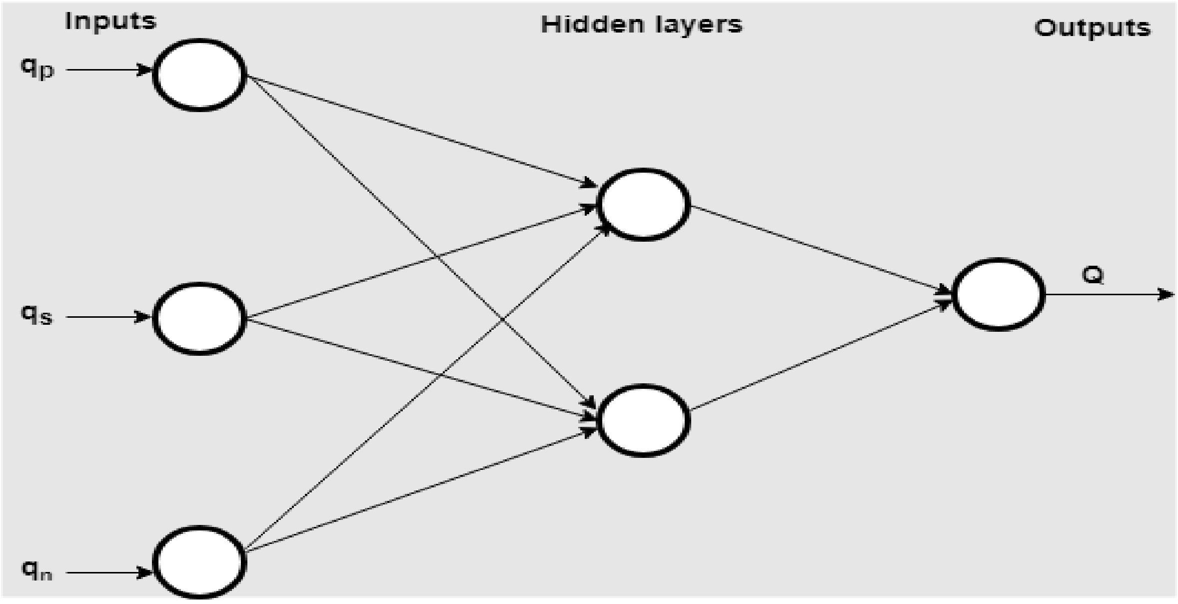


Figure (3.7): ANNK for distortion identification

CHAPTER -IV

RESULTS AND DISCUSSIONS

4. RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter introduces the results which have been conducted through execution of three experiments. The experiments embody on implementation and execution of PRI based blockiness, PRI based sharpness, PRI based noisiness, and distortion identification. Have been used MATLAB R2017a for implementation PRI-based general-purpose BIQA framework. Have taken 35 distorted images and applied the cross-validation technique. This is technique took 30 images as training instances as well as other 5 instances for the testing, then obtained good results in Table 4.1 shows the quality score which gained from our experiment in LIVE database and also used CSIQ database have taken 50 distorted images to obtained good results (Q) also and compare these results with the subjective quality test (DMOS standard) as shown in the Table 4.2.

Table 4.1: Quality score and DMOS Classes by using LIVE database

#	PSS	LSSs	LSSn	Quality Score	DMOS Classes
1	0.89	0.54	0.09	-0.93	LQ
2	0.83	0.43	0.25	0.95	HQ
3	0.73	0.56	0.14	0.03	MQ
4	0.81	0.43	0.26	0.99	HQ
5	0.72	0.47	0.29	0.91	HQ
6	0.70	0.53	0.25	0.04	MQ
7	0.85	0.60	0.14	-0.96	LQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

8	0.75	0.59	0.30	-0.90	LQ
9	0.88	0.52	0.09	-0.99	LQ
10	0.76	0.56	0.16	0.02	MQ
11	0.71	0.62	0.28	0.05	MQ
12	0.82	0.52	0.17	0.03	MQ
13	0.78	0.59	0.32	-0.98	LQ
14	0.66	0.47	0.22	0.91	HQ
15	0.85	0.65	0.19	-0.88	LQ
16	0.72	0.64	0.17	0.03	MQ
17	0.73	0.53	0.18	0.04	MQ
18	0.82	0.46	0.15	0.93	MQ
19	0.71	0.48	0.30	0.07	MQ
20	0.75	0.69	0.17	0.06	MQ
21	0.70	0..67	0.02	0.01	MQ
22	0.75	0.50	0.04	0.05	MQ
23	0.77	0.65	0.05	0.08	MQ
24	0.79	0.53	0.03	0.04	MQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

25	0.70	0.50	0.04	0.09	MQ
26	0.78	0.60	0.04	0.08	MQ
27	0.79	0.53	0.02	0.09	MQ
28	0.69	0.48	0.04	0.99	HQ
29	0.82	0.49	0.03	0.85	HQ
30	0.66	0.50	0.04	0.05	MQ

Table 4.2: Quality score and DMOS Classes by using CSIQ database

#	PSS	LSSs	LSSn	Quality score	DMOS Classes
1	0.67	0.27	0.36	0.92	HQ
2	0.89	0.32	0.43	0.52	HQ
3	0.96	0.37	0.36	-0.448	LQ
4	0.91	0.36	0.40	-0.23	LQ
5	0.96	0.38	0.38	-0.57	LQ
6	0.31	0.33	0.38	0.96	HQ
7	0.91	0.35	0.45	-0.01	LQ
8	0.99	0.25	0.13	-0.78	HQ
9	0.97	0.32	0.27	0.30	MQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

10	0.98	0.39	0.26	-0.42	LQ
11	0.99	0.34	0.22	0.17	MQ
12	0.98	0.30	0.20	0.52	HQ
13	0.95	0.32	0.24	0.48	HQ
14	0.98	0.43	0.16	-0.37	LQ
15	0.98	0.30	0.37	0.47	HQ
16	0.98	0.32	0.34	0.26	MQ
17	0.93	0.33	0.45	0.22	MQ
18	0.91	0.32	0.47	0.42	MQ
19	0.96	0.33	0.45	0.12	MQ
20	0.96	0.40	0.27	-0.52	LQ
21	0.76	0.68	0.08	-0.94	LQ
22	0.94	0.42	0.30	-0.73	LQ
23	0.47	0.68	0.04	-0.78	LQ
24	0.97	0.39	0.36	-0.65	LQ
25	0.97	0.31	0.10	0.61	HQ
26	0.99	0.48	0.05	-0.53	LQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

27	0.97	0.47	0.14	-0.60	LQ
28	0.99	0.36	0.08	0.22	MQ
29	0.94	0.47	0.29	0.88	HQ
30	0.96	0..33	0.48	0.15	MQ
31	0.39	0.75	0.04	-0.88	LQ
32	0.96	0.21	0.22	-0.82	LQ
33	0.96	0.35	0.19	0.26	MQ
34	0.97	0.35	0.43	-0.21	LQ
35	0.96	0.32	0.32	0.30	MQ
36	0.95	0.34	0.33	0.05	MQ
37	0.94	0.34	0.34	0.80	HQ
38	0.91	0.35	0.37	0.59	HQ
39	0.89	0.35	0.41	-0.08	LQ
40	0.95	0.28	0.29	0.62	HQ
41	0.94	0.30	0.30	0.52	HQ
42	0.94	0.31	0.32	0.44	MQ
43	0.93	0.32	0.34	0.35	MQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

44	0.90	0.32	0.37	0.42	MQ
45	0.92	0.49	0.31	-0.91	LQ
46	0.92	0.49	0.32	-0.92	LQ
47	0.89	0.47	0.34	-0.90	LQ
48	0.89	0.45	0.37	-0.88	LQ
49	0.89	0.43	0.40	-0.83	LQ
50	0.97	0.28	0.28	0.59	HQ

Table 4.3: Quality score and DMOS Classes by using CC images existing in CSIQ database

#	**PSS**	**LSSs**	**LSSn**	**Quality score**	**DMOS Classes**
1	0.96	0.2531	0.3384	0.69	HQ
2	0.95	0.2571	0.3100	0.58	HQ
3	0.93	0.2556	0.2314	0.07	LQ
4	0.9320	0.2576	0.2096	0.04	LQ
5	0.932	0.2576	0.2107	0.045	LQ
6	0.95	0.3750	0.3297	0.73	HQ
7	0.9265	0.3696	0.2781	0.38	LQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

8	0.8680	0.3510	0.1727	0.105	LQ
9	0.8276	0.3367	0.1302	0.022	LQ
10	0.8276	0.3367	0.1406	0.028	LQ
11	0.9560	0.3243	0.3358	0.615	HQ
12	0.9405	0.3180	0.2713	0.38	LQ
13	0.8527	0.2953	0.1307	0.01	LQ
14	0.7540	0.2793	0.0721	0.008	LQ
15	0.7540	0.2793	0.0698	0.008	LQ
16	0.9779	0.3134	0.2627	0.78	HQ
17	0.9693	0.3129	0.2573	0.64	HQ
18	0.9582	0.3107	0.2379	0.502	HQ
19	0.0186	0.3354	0.4514	0.56	HQ
20	0.9555	0.3079	0.2125	0.40	LQ
21	0.9555	0.3079	0.2177	0.437	LQ
22	0.9809	0.4011	0.1518	0.44	LQ
23	0.9761	0.4109	0.1172	0.26	LQ
24	0.9158	0.3922	0.0568	0.047	LQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

25	0.8036	0.3758	0.0318	0.008	LQ
26	0.8036	0.3758	0.0275	0.007	LQ
27	0.9635	0.2913	0.3457	0.67	HQ
28	0.9554	0.2870	0.2950	0.41	LQ
29	0.9214	0.2749	0.1954	0.07	LQ
30	0.9031	0.2763	0.1456	0.04	LQ
31	0.9031	0.2763	0.1454	0.04	LQ
32	0.9288	0.3358	0.4094	0.599	HQ
33	0.8998	0.3296	0.3437	0.14	LQ
34	0.8066	0.3111	0.1779	0.027	LQ
35	0.7089	0.2847	0.1103	0.020	LQ
36	0.7089	0.2847	0.1223	0.021	LQ
37	0 0.9594	0.3805	0.2930	0.69	HQ
38	0.9452	0.3808	0.2835	0.61	HQ
39	0.9186	0.3747	0.2413	0.23	LQ
40	0.9076	0.3754	0.2214	0.18	LQ
41	0.9076	0.3754	0.2217	0.18	HQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**

42	0.9400	0.3752	0.3441	0.71	LQ
43	0.9221	0.3718	0.2962	0.46	LQ
44	0.8587	0.3585	0.1823	0.107	LQ
45	0.4178	0.1856	0.0064	0.04	LQ
46	0.4178	0.1856	0.0062	0.041	LQ
47	0.9659	0.2423	0.1070	0.035	LQ
48	0.9595	0.2587	0.0906	0.046	LQ
49	0.9457	0.2109	0.0712	0.022	LQ
50	0.9218	0.2223	0.0485	0.032	LQ

Table 4.4: Quality score and DMOS Classes by using pWN images existing in CSIQ database

#	PSS	LSSs	LSSn	Quality score	DMOS Classes
1	0.95	0.26	0.9979	0.03	LQ
2	0.95	0.28	0.9980	0.02	LQ
3	0.92	0.28	0.9979	0.09	LQ
4	0.90	0.28	0.9978	0.13	LQ
5	0.88	0.28	0.9977	0.15	LQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**
6	0.94	0.36	0.9968	0.14	LQ

7	0.92	0.35	0.9967	0.36	HQ
8	0.89	0.34	0.9967	0.16	LQ
9	0.89	0.32	0.9965	0.14	LQ
10	0.89	0.30	0.9966	0.10	LQ
11	0.95	0.32	0.9973	0.15	HQ
12	0.94	0.32	0.9971	0.21	HQ
13	0.90	0.32	0.9973	0.24	HQ
14	0.90	0.31	0.9972	0.17	LQ
15	0.91	0.29	0.9971	0.16	LQ
16	0.97	0.31	0.9977	0.15	HQ
17	0.96	0.32	0.9977	0.18	HQ
18	0.91	0.32	0.9976	0.30	HQ
19	0.89	0.30	0.9975	0.16	LQ
20	0.89	0.29	0.9974	0.13	LQ
21	0.97	0.27	0.9966	0.22	HQ
22	0.94	0.26	0.9960	0.31	HQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**
23	0.89	0.26	0.9959	0.13	LQ

24	0.85	0.26	0.9963	0.07	LQ
25	0.96	0.24	0.9961	0.28	HQ
26	0.96	0.30	0.9986	0.14	LQ
27	0.95	0.31	0.9986	0.12	HQ
28	0.90	0.31	0.9985	0.01	LQ
29	0.91	0.31	0.9984	0.02	LQ
30	0.91	0.30	0.9981	0.06	LQ
31	0.93	0.33	0.9974	0.21	HQ
32	0.92	0.32	0.9972	0.33	HQ
33	0.91	0.30	0.9972	0.22	HQ
34	0.91	0.29	0.9972	0.18	LQ
35	0.91	0.28	0.9972	0.15	LQ
36	0.95	0.37	0.9978	0.66	HQ
37	0.94	0.36	0.9977	0.24	HQ
38	0.91	0.34	0.9978	0.19	LQ
39	0.90	0.31	0.9977	0.23	HQ
#	**PSS**	**LSSs**	**LSSn**	**Quality Score**	**DMOS Classes**
40	0.90	0.29	0.9977	0.17	LQ

41	0.94	0.36	0.9978	0.28	HQ
42	0.92	0.35	0.9977	0.16	LQ
43	0.91	0.32	0.9977	0.26	HQ
44	0.90	0.30	0.9975	0.19	LQ
45	0.90	0.28	0.9977	0.15	LQ
46	0.95	0.22	0.9948	0.25	HQ
47	0.88	0.23	0.9947	0.13	LQ
48	0.85	0.24	0.9948	0.13	LQ
49	0.84	0.24	0.9952	0.13	LQ
50	0.85	0.24	0.9955	0.09	LQ

In the three stages of the experiment, we obtained three estimates in each of PRI based blockiness estimation (see figure (4.1)), PRI based sharpness estimation (see figure (4.2)) and PRI based noisiness estimation (see figure (4.3)).

A) Framework for PRI based blockiness estimation:

Figure (4.1): A framework of the PRI-based BIQA metric PSS for blockiness estimation to measure similarity for pseudo structures from distorted image and PRI. Circle green denote number of corners.

B) Framework for PRI based sharpness estimation:

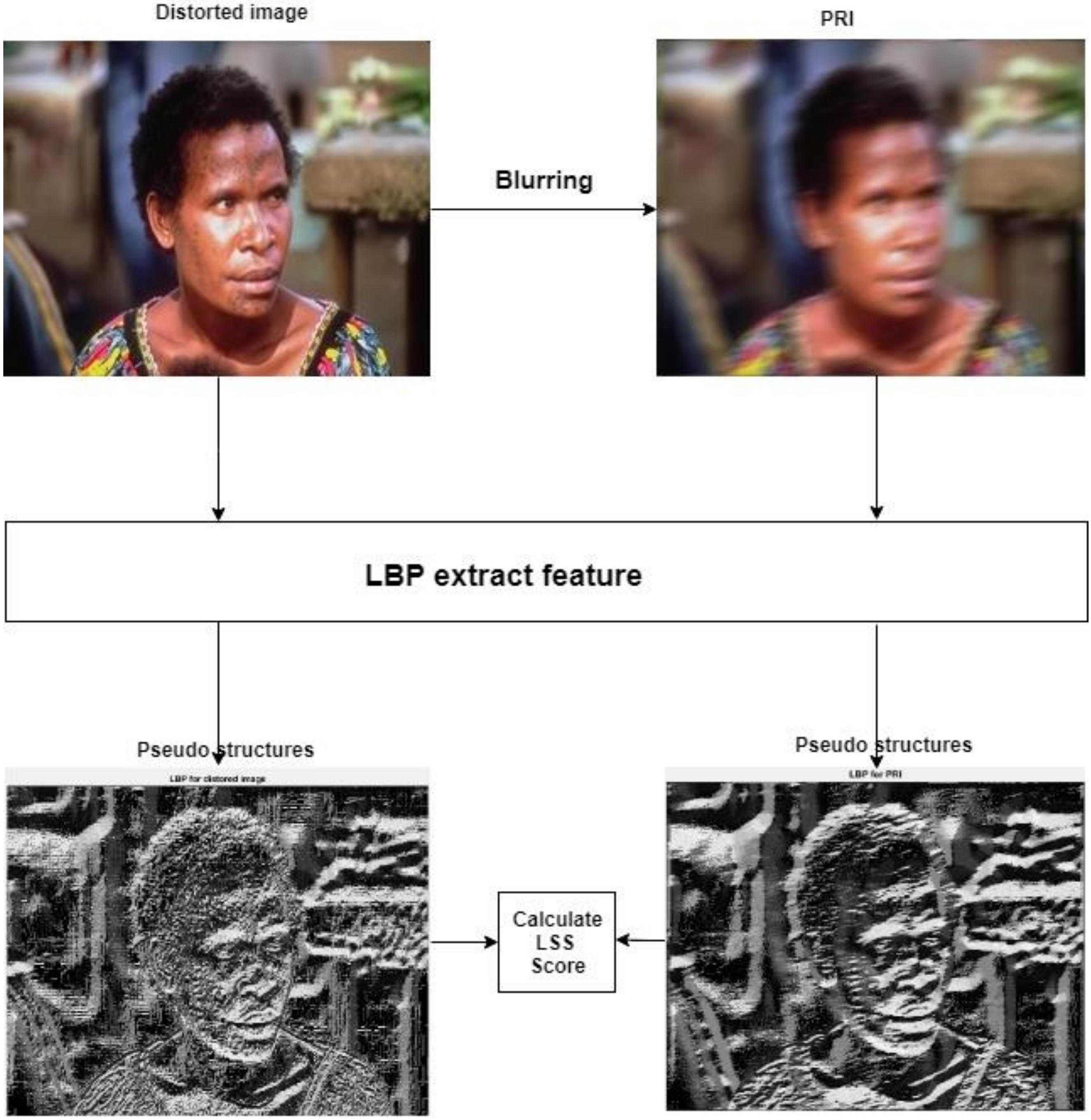


Figure (4.2): A framework of the PRI-based BIQA metric LSSs for sharpness estimation to measure similarity for pseudo structures from distorted image and PRI.

C) Framework for PRI based noisiness estimation:

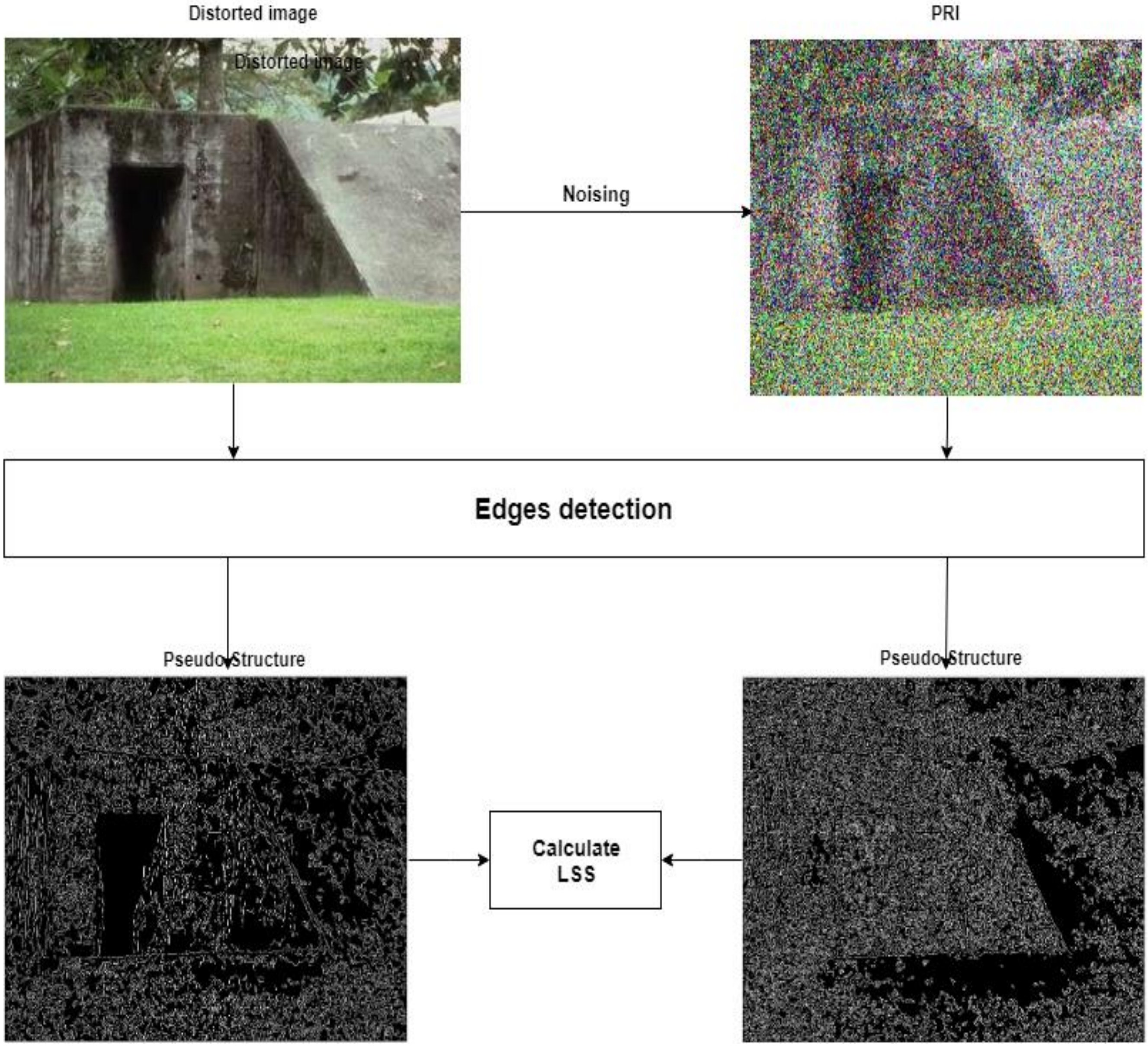


Figure (4.3): A framework of the PRI-based BIQA metric LSSn for noisiness estimation to measure similarity for pseudo structures from distorted image and PRI.

Table 4.5: SRCC performance on non-common of the LIVE and CSIQ

Model	LIVE	CSIQ	CSIQ
	FF	pWN	CC
BPRI (c)	0.8207	0.3787	0.1076
BPRI (p)	0.8181	0.3887	0.1563

Table 4.6: SRCC performance for the LIVE and CSIQ

Model	LIVE	CSIQ	CSIQ
	General-distortion	pWN	CC
Proposed BPRI	**0.995**	**1.000**	**1.000**

4.2 Analyses and Discussions:

Min et al. in the year 2018, described a model (BPRI) for comparing the performance for the BPRI method, both the probability weighting strategy and the hard classification strategy are tested, which are denoted as BPRI (p) and BPRI(c), respectively. Have highlighted the top SRCC (Spearman rank-order correlation coefficient) only report SRCC performance for simplicity. Similar results can be obtained according to other criteria, to find the correlation between these values. Spearman rank-order correlation coefficient values of (r <= +1) mean a strong correlation to (r >= -1) means a strong inverse correlation. Bold values are higher values. Shown in above Table 4.5 lists the performance comparison results. Besides single distortions, we also test on 3 types of distorted images in the LIVE including fast fading (FF) and the CSIQ including contrast change (CC) and additive pink Gaussian noise (pWN). All BIQA models were trained on the LIVE, thus we do not list their performance on the LIVE in Table 4.5 to ensure complete separation of training and testing, thus their performance is excluded on the CSIQ.

The proposed BPRI model can be described as follows:

- Have been used two databases LIVE and CSIQ as standard dataset.
- Check of specific-distortion such as block, sharp and noise.
- Integrate for general-distortion used classifier (NNK) tool.
- Simplify a proposed framework without features alignment from specific-distortion.
- Have been obtained good results of this proposed framework based on no- reference IQA by decompress the data.
- Also use SRCC (Spearman rank-order correlation coefficient) for analysis the results to find the correlation between these values. Spearman rank-order correlation coefficient values of (r) <= +1 mean a strong correlation of (r) >= -1 means a strong inverse correlation. Bold values are higher values. The results see in above Table 4.6.

4.3 Comparison using MATLAB plots:

MATLAB plots data, not symbols. To plot: generate a vector of inputs (i.e., images 1-50 denoted X horizontal); create a vector of outputs (i.e., experiment result and DMOS standard denoted Y vertical); using PLOT command. See figure (4.4) and figure (4.5).

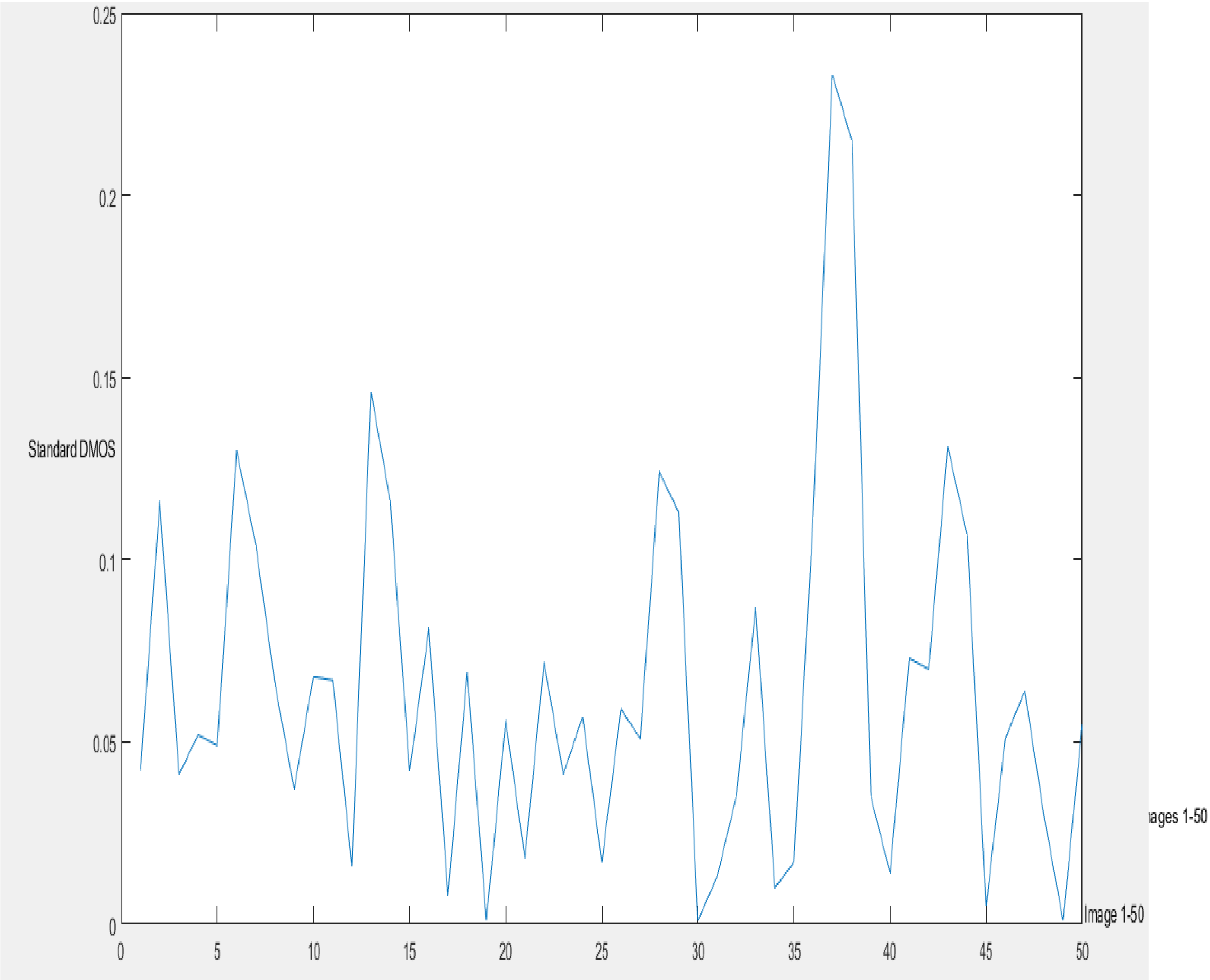


Figure (4.4): Represents a standard DMOS

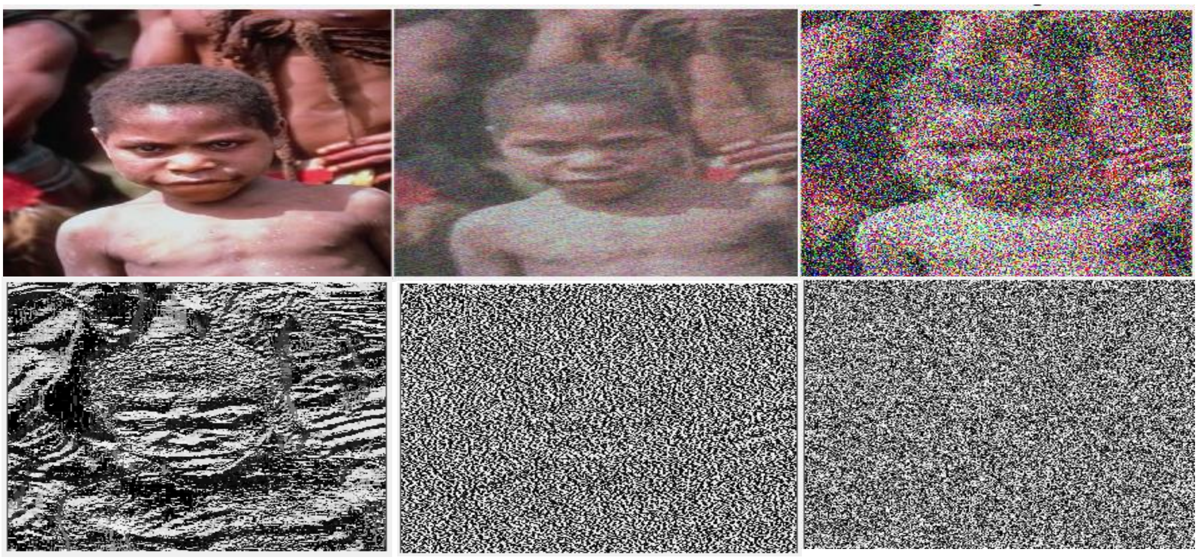
Figure (4.5): Represents experiment results

4.4 Comparison three features (PSS, LSSs, and LSSn) of LIVE database image in different distortion levels according to DMOS:

A) PSS with DMOS:

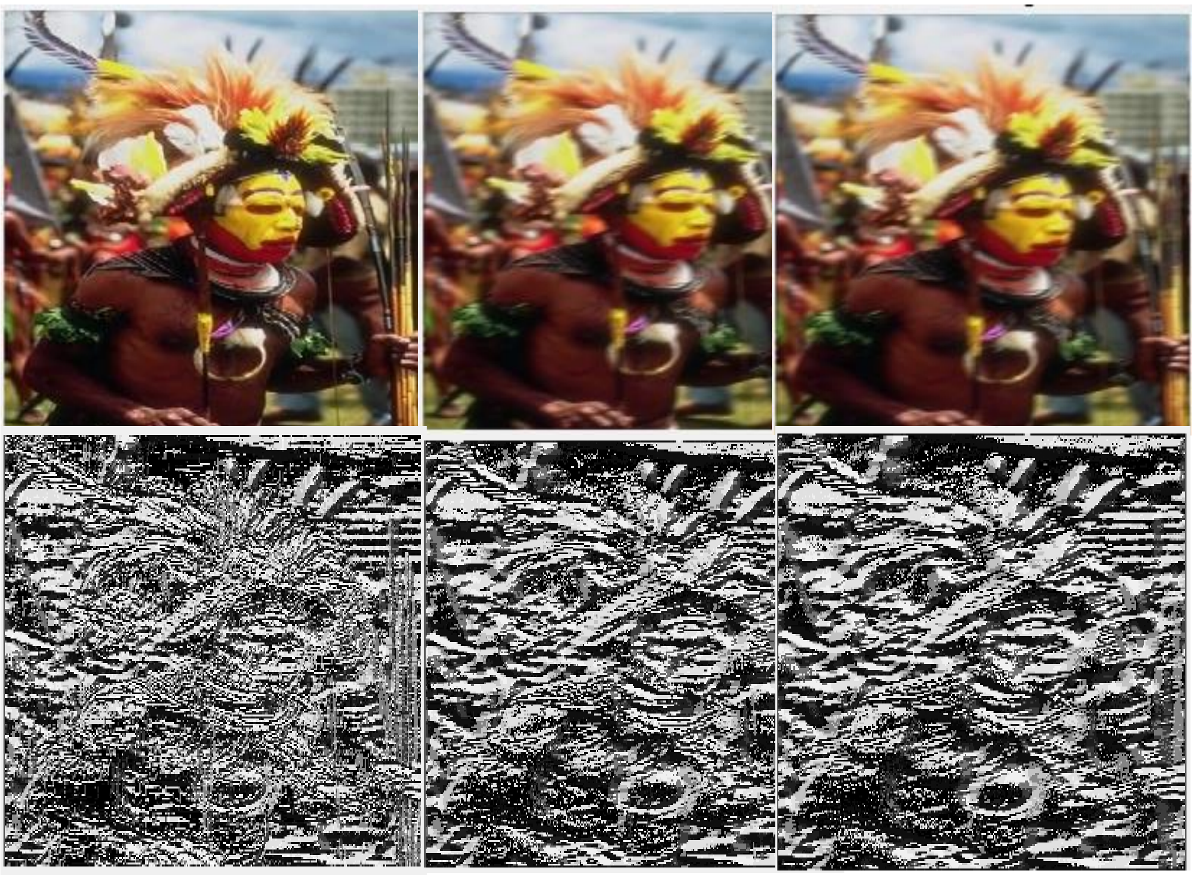
DMOS=37, PSS=0.82 DMOS=39, PSS=0.83 DMOS=42, PSS=0.97

B) LSSs with DMOS:



DMOS=27, LSSn=0.08 DMOS=29, LSSn=0.17 DMOS=30, LSSn=0.24

C) LSSn with DMOS:



DMOS=27, LSSs=0.60 DMOS=30, LSSs=0.65 DMOS=45, LSSs=0.87

CHAPTER -V

CONCLUSION AND RECOMMENDATIONS

Chapter V

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

There is an observable limitation in IQA metrics. In this thesis presented PRI-based general-purpose BIQA metric to measure the distance between the PRI images of the distorted image and applied this experiment to specific types of distortion blockiness, sharpness, noisiness. The preprocessing stage was used in our proposed model. This stage contributes to providing a more simplified and effective model corresponding with other models. This proposed model can compute the quality score in the rate of 82%. Can be apply the proposed model in another specific-distortion type.

5.2 Recommendations

This model shows three distortion- specific type estimation the quality of images. So use a types of distortion is recommend. The researcher recommends that it necessary to find a metric to deal use this issue. As follows:

- This framework can be applied in other approaches such as (FR, RR).
- A multiple types of distortion leading to deterioration of image quality.
- Attention to general-purpose distortion.

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