

**DEVELOPING A BLIND IMAGE QUALITY ASSESSMENT (BIQA)
MODEL BASED ON IMAGE LOCAL CONTRAST FEATURES**

WAN ZAFIRAH BINTI M. ZAIN

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

**DEVELOPING A BLIND IMAGE QUALITY ASSESSMENT
(BIQA) MODEL BASED ON IMAGE LOCAL CONTRAST
FEATURES**

WAN ZAFIRAH BINTI M. ZAIN

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Alamat Tetap: LOT 1662, KG
TERSUSUN
MUHIKBAH
BATU 33, 35350
TEMOH, PERAK

DR. REDZUAN BIN ABDUL MANAP
Senior Lecturer
Faculty Of Electronic & Computer Engineering
Universiti Teknikal Malaysia Melaka (UTeM)
Hang Tuah Jaya
76100 Durian Tunggal, Melaka

Tarikh : 14/12/2018

Tarikh : 14/12/2018

DECLARATION

I declare that this report entitled “Developing a blind image quality assessment (BIQA) model based on image local contrast operator” is the result of my own work except for quotes as cited in the references.

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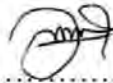
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DEDICATION

I dedicate my dissertation work to my family and many friends. A special feeling of gratitude to my beloved family especially to my loving parents, M. Zain bin Ag. Soh and Zainah binti Shamsudin. Their encouragement and guidance has always be an inspiration to me along this journey of education.

ABSTRACT

This project focuses on image quality assessment (IQA) especially when we have problems on how to assess the quality of an image without presence any of reference information. Blind IQA (BIQA) aims to appraise the perceptual quality of a distorted image without information regarding its reference image. In the past, BIQA models usually predict the image quality by utilizing the transform-based quality predictive features. This approach, however, can be computationally expensive due to the need of image transformation process. This project attempts to alleviate this by developing a transform-free BIQA model that operates based on statistical characteristics of two image local contrast operators namely Gradient Magnitude (GM) and Laplacian of Gaussian (LOG). Relevant quality predictive features were first extracted based on image local contrast operators' statistical characteristics. A quality prediction model was then developed through support vector regressor (SVR) utilising the extracted features. The model's performance was analysed through comparison with several available BIQA models in terms of prediction accuracy, generalisation capability as well as computational requirements.

ABSTRAK

Fokus projek ini adalah berkaitan dengan penilaian kualiti sesuatu imej (IQA) terutamanya bagi situasi dimana penilaian tersebut perlu dilakukan tanpa apa-apa maklumat rujukan. Penilaian kualiti imej tanpa maklumat rujukan (BIQA) bertujuan untuk menilai persepsi kualiti tersebut ke atas kecacatan imej tersebut tanpa maklumat yang berkaitan dengan imej asal. Model-model BIQA terdahulu sering meramal kualiti imej dengan menggunakan ciri ramalan kualiti yang memerlukan proses transformasi. Pendekatan ini bagaimanapun boleh dikira mahal disebabkan oleh keperluan proses transformasi. Projek ini cuba mengatasi masalah tersebut dengan membangunkan sebuah model BIQA tanpa transformasi yang beroperasi berdasarkan statistic dua pengendali kontra tempatan sesuatu imej, iaitu 'Gradient Magnitude' (GM) dan 'Laplacian of Gaussian' (LOG). Projek ini bermula dengan mereka ciri ramalan kualiti berdasarkan statistik pengendali kontra tempatan tersebut. Kemudian, satu model ramalan kualiti dibangunkan melalui 'Support Vector Regression' (SVR) menggunakan ciri ramalan yang direka. Prestasi model dianalisis melalui perbandingan dengan beberapa model BIQA yang ada dalam bentuk ketepatan ramalan, keupayaan generalisasi serta keperluan pengiraan.

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LIST OF SYMBOLS AND ABBREVIATIONS

BIQA	: Blind Image Quality Assessment
BIQI	: Blind Image Quality Indices
BLIINDS- II	: Blind Image Integrity Notator using DCT statistic
BRISQUE	: Blind Referenceless Image Spatial Quality Evaluator
CORNIA	: Codebook Representation for No-Reference Image Assessment
DMOS	: Different Mean Opinion Score
DS	: Distortion-specific
FR	: Full-reference
GM	: Gradient Magnitude
IQA	: Image Quality Assessment
JAN	: Joint Adaptive Normalization
LOG	: Laplacian of Gaussian
NDS	: Non-distortion-specific
NR	: No-reference
NSS	: Natural Scene Statistic
PLCC	: Pearson Linear Correlation Coefficient
RBF	: Radial Basis Function
RMSE	: Root Mean Square Error

RR	:	Reduce-reference
SROCC	:	Spearman's Rank Order Correlation Coefficient
SVM	:	Support Vector Machine
SVR	:	Support Vector Regression
VBIQA	:	Visual Saliency Guided model for Blind Image Quality Assessment

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CHAPTER 1

INTRODUCTION

1.1 Introduction

As the technology in our country is fast developing, we can see there is an increase amount of digital images. It is very important to have reliable methods to evaluate the quality of these images. Image quality assessment (IQA) attempts to determine visual quality or analogically, the total of distortion in a given image. There are factors which determine image quality for examples, noise, dynamic range tone reproduction, colour accuracy, distortion, contrast, exposure accuracy, lateral chromatic aberration, sharpness, vignette, artifacts, etc. The distortions will occur in any digital image processing and it cannot be avoided. (IQA) had become important aspect in various computer vision and image processing application. Application that related with image quality assessment such as image acquisition, transmission, restoration and

enhancement, image search and retrieval, image recognition like an image tagging in the facebook.

(IQA) is a basic but quite challenging problem in the field of image processing. Since the Human Visual System (HVS) is a definitive recipient and mediator of the visual substance, subjective assessment speaks to the most dependable quality assessment technique. Since human observer are definitive users especially in most of the multimedia applications, the most precise and also credible way to assessing the quality of images is through subjective assessment. However, subjective assessment is based on human observation mechanism and it take a long time and quite expensive, making it difficult to design in practical applications. Moreover, subjective experiments are more complicated by many factors including viewing distance, display device, lighting condition, subjects' vision ability, and subjects' mood. Therefore, it is important to design mathematical models that are capable of predicting the quality evaluation of an average human observer. Particularly when ongoing calculation is wanted. To beat these restrictions, numerous IQA methods have been proposed over the past years to evaluate the quality of images in agreement with human quality perception automatically.

Numerous IQA model have these objective IQA algorithm are beneficial in condition of repeatability and scalability rather than subjective assessment. The goal of objective IQA is to design mathematical models that can predict the quality of still image accurately and automatically by producing computer program. An ideal objective IQA method should be able to mimic the quality predictions of an average human vision system. So, it is important to design mathematical models that are capable of predicting the quality evaluation of an average human observer.

Existing objective IQA models can be classified into three categories based on the availability of the original (reference) image, which is considered to be distorted-free or perfect-quality image. There are Full-reference (FR), Reduce-reference (RR), and No-reference (NR). Full-reference (FR) model need full information of the reference image to predict the quality of the degraded or distorted images. For example Zhou Wang [1] develop a Structural Similarity Index (SSIM) method to handle color images, predict contrast change and mean shift. This algorithm is based on the concept that human visual system is highly adapted for extracting structural information from an image. So from the available image information in the original and distorted image, a quality measure is constructed.

The (RR) algorithm provides a practical solution for automatic image quality evaluations in various applications where only need partial information of the reference image. In [2], Abdul Rehman developed one of the RR-IQA method based on SSIM that shown to be a good indicator of perceptual image quality. Specifically, they extract statistical features from a multiscale multiorientation divisive normalization transform and develop a distortion measure by following the philosophy in the construction of SSIM.

The last classification of IQA is No Reference IQA or Blind IQA (BIQA) where there is no need of any information of the reference image. In many practical applications, information that related with the reference is unavailable, and thus BIQA algorithm are highly desired. For example Peng Ye [3] have propose BIQA model approach using visual codebooks. A visual codebook consisting of Gabor-filter-based local features extracted from local image patches is used to capture complex statistics of a natural image. This method does not assume any specific types of distortions.

However, when evaluating images with a particular type of distortion, it does require examples with the same or similar distortion for training.

1.2 Objectives

The aim of this project is to develop a BIQA model that operates on the image spatial domain in order to predict the quality of an image consistent with human perceptual measures. The aim can be achieved by fulfilling the following objectives :

- i. To extract relevant quality predictive features based on image local contrast operators' statistical characteristics.
- ii. To develop a quality prediction model through support vector regressor (SVR) utilising the extracted features.
- iii. To analyse the model's performance through comparison with several available BIQA models in terms of prediction accuracy, generalisation capability as well as computational requirements.

1.3 Scope

This project will focus on the BIQA. In general, BIQA algorithms can be classified into two categories which are distortion-specific (DS) and non-distortion-specific (NDS), depending on the previous knowledge of the distortion type. Distortion that affects the image is assumed to be known in the DS BIQA, where it is quantified in isolation of other factors. Opposite to DS NR-IQA, the previous knowledge of distortion type is not considered by NDS BIQA algorithms. The quality score is given through assumption that the image to be assessed has similar distortion type to those in the training database. The project focus on NDS BIQA.

This project will use quality predictive features extracted in spatial domain derived from statistical properties of GM and LOG operators of an image. Using an adaptive

procedure to jointly normalize the GM and LOG features, and to show that the joint statistics of normalized GM and LOG features have desired aspect for the BIQA task. GM and LOG features are basic element that are commonly used to form image semantic structure. They are also strong features to predict image local quality.

This project uses LIVE IQA Database [4] to train the model. The LIVE database consists of 982 images and 779 of the images is distorted images, generated from 29 original images by processing them with 5 types of distortions at various levels. The distortions involved in the LIVE database are JPEG2000 compression (JP2K), JPEG compression (JPEG), additive white noise (WN), Gaussian blur (GB) and simulated fast fading Rayleigh channel (FF).

Regression learning for this BIQA model is done by using Support Vector Regression (SVR). SVR is used because it is the simplest SVR and also can get the good performance. To assess the performance of a BIQA method, three scores that measure the consistency between the results of a BIQA model and the subjective DMOS/MOS scores are generally used which are Spearman rank order correlation coefficient (SRC), which measures the prediction monotonicity while the Pearson correlation coefficient (PCC) and the root mean squared error (RMSE), which measure the prediction accuracy.

1.4 Problem statement

Previous BIQA models often utilize transform-based quality predictive features to perform their quality prediction. This approach, however can be computationally expensive due to the need of image transformation process. Transform-based quality prediction is more complicated since it requires a lot of process. It also taking a lot of time to complete this process. So, this project attempts to alleviate this by developing