BLIND IMAGE QUALITY ASSESSMENT MODEL VIA PATCH BASED LEARNING FRAMEWORK

AMALINA ASHILA BINTI ALIAS

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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This report is submitted in partial fulfilment of the requirements for the degree of Bachelor of Electronic Engineering with Honours

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I hereby declare that I have read this report and in my opinion this report is sufficient in terms of scope and quality for the award of Bachelor of Electronic Engineering with Honours.

Signature	:	RedzuanAbdulManap
Supervisor Name	:	Dr Redzuan bin Abdul Manap
Date	:	1 June 2022

DEDICATION

I dedicated this report to my wonderful parents, who have been a source of inspiration and strength for me when I've felt like giving up, and who keep on going to provide moral, spiritual, emotional, and financial support. To my supervisor, thanks for the help, advice, valuable time and wise words.

ABSTRACT

The project focuses on an image quality assessment (IQA) model that estimates the quality of an image without the presence of reference information. Most well-known blind image quality assessment (BIQA) models usually follow a two-stage framework whereby various features are first extracted and then used as input to a regression algorithm. The regression algorithm models human perceptual measures based on a training set of distorted images. However, this approach requires an intensive training phase to optimise the regression parameters. This project attempts to overcome this limitation by proposing an alternative BIQA model that predicts image quality using nearest neighbour methods with virtually zero training cost. The project also proposes a learning framework that operates at the patch level. This enables the model to provide local image quality estimation, a property that can be useful for further local processing stages.

ABSTRAK

Projek ini memberi tumpuan kepada model penilaian kualiti imej (IQA) yang menganggarkan kualiti imej tanpa kehadiran maklumat rujukan. Kebanyakan model penilaian kualiti imej tanpa rujukan (BIQA) biasanya menggunakan rangka kerja dua peringkat di mana pelbagai ciri imej diekstrak di peringkat pertama dan kemudian digunakan sebagai input kepada algoritma regresi. Algoritma regresi membuat permodelan ukuran persepsi manusia berdasarkan set latihan imej terherot. Walau bagaimanapun, pendekatan ini memerlukan fasa Latihan yang intensif untuk mengoptimumkan parameter regresi. Projek ini cuba mengatasi kelemahan ini dengan mencadangkan model BIQA alternatif yang meramalkan kualiti imej menggunakan kaedah jiran terdekat dengan kos latihan menghampiri sifar. Projek ini juga mencadangkan rangka kerja pembelajaran yang beroperasi pada peringkat tampalan imej. Ini membolehkan model menyediakan anggaran kualiti imej global anggaran kualiti imej tempatan, satu ciri yang berguna untuk peringkat pemprosesan tempatan selanjutnya.

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LIST OF SYMBOLS AND ABBREVIATIONS

AGGD	:	Asymmetric Generalized Gaussian Distribution
BIQA	:	Blind Image Quality Assessment
CNN	:	Convolutional Neural Network
DCT	:	Discrete Cosine Transformation
DMOS	:	Differential Mean Opinion Score
DS	:	Distortion-Specific
FF	:	Fast Fading
GB	:	Gaussian Blur
GGD	:	Generalized Gaussian Distribution
GM	:	Gradient Magnitude
gMAD	:	Group Maximum Differentiation
HVS	:	Human Visual System
I2C	:	Image-2-Class
IQA	:	Image Quality Assessment
JAN	:	Joint Adaptive Normalisation
JP2K	:	JP2000
KNN	:	k-Nearest-Neighbour
LCC	:	Linear Correlation Coefficient

LOG	:	Laplacian of Gaussian
LT	:	Label Transfer
MOS	:	Mean Opinion Score
NDS	:	Non-Distortion-Specific
NSS	:	Natural Scene Statistic
RMSE	:	Root Mean Square Correlation Coefficient
SIFT	:	Scale Invariant Feature Transform
SROCC	:	Spearman Rank-Order Correlation Coefficient
SVM	:	Support Vector Machine
SWT	:	Stationery Wavelet Transform
VSI	:	Visual Saliency Index
WN	:	White Noise

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CHAPTER 1

INTRODUCTION

1.1 Introduction

We can observe an increase in digital images as our country's technology progresses. Any digital image processing digital image can cause distortions, which cannot be prevented. Image quality is affected by distortion, contrast noise, sharpness, vignette, dynamic range tone reproduction, exposure accuracy, colour accuracy and other factors. In several Image acquisition and machine learning software, image quality has become increasingly important. It is important to have dependable ways for assessing the image quality. Image quality assessment (IQA) is a technique for determining the visual quality or overall distortion of an image. IQA predicts image quality as observed by human observers using metrics. IQA metrics based on human perspective are widely known as the gold standard for assessing perceptual image quality. These subjective measures are frequently produced from image quality assessments that enable people to contribute their opinions on image quality. A mean opinion score (MOS) or differential mean opinion score (DMOS) is calculated by averaging the ratings of all observers (DMOS). The MOS/DMOS is an IQA statistical measure that is subjective. These subjective measurements are time-consuming, complex, and unsuited for most practical uses since they require human observers. An IQA model that can provide objective measurement comparable to MOS/DMOS is preferred.

1.2 Problem Statement

The interest in developing the objective blind IQA (BIQA) model has increased in the last few years. Various BIQA models have been developed and proposed for image processing applications. Most models use a two-stage approach, with several features retrieved first and then used as input to a regression algorithm. Based on a training set of distorted images, the regression algorithm employs human perceptual metrics. However, in order to maximise the regression parameters, this method necessitates an intensive training phase. In addition, these models commonly perform their feature extraction at the image level. Thus, they are only capable of providing estimated global quality scores.

This project aims to overcome these two issues by first providing an alternative BIQA model that uses nearest neighbour methods to predict image quality with virtually no training cost. Second, the project proposes a learning framework for patch-level learning. This allows the model to provide both global and local image quality estimations, which might be useful for later stages of local processing.

1.3 Objective

The project aims to develop a new BIQA model that performs its feature extraction process at the patch level instead of commonly used image-level extraction. The model also proposed to learn its quality prediction via an alternative nearest neighbour method rather than the typical regression method. This aim can be achieved by fulfilling the following objectives:

- To extract relevant quality predictive spatial domain image features at the patch level.
- To develop a quality prediction model utilising the extracted features using nearest neighbour methods.
- 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.

1.4 Scope of Work

The BIQA will be the focus of this project. Based on previous knowledge of the distortion type, BIQA algorithms can be classified as distortion-specific (DS) or non-distortion-specific (NDS). The image distortion is quantified in the DS BIQA, where it is measured separately from other factors. In contrast to DS NR-IQA, NDS BIQA algorithms do not use previous recognition of the different types of distortion consideration. The quality score is determined by assuming that the image for evaluation has the same distortion as those in the training database.

In terms of the spatial domain, the project follows a five-stage framework. Unlike many previous BIQA models, it predicts image quality directly from a set of labelled patches using the nearest neighbour method. This is because the cost of learning for this technique is virtually zero, as the training procedure only includes storing feature vectors and labels from training images. It also extracts its features at the patch level, allowing for local quality estimation level, which was previously unavailable in most BIQA models.

In this project, statistical features of an image's GM and LOG operations are used to extract quality predictive information in the spatial domain. The normalised GM and LOG feature joint statistics are appropriate for the BIQA task while using an adaptive technique to normalise the GM and LOG features. To build image semantic structure, the essential elements GM and LOG are usually used. They are also reliable indicators of local image quality.

The LIVE IQA Database [1] is used in this project. The LIVE database contains 982 images and 779 distorted images that were created by processing 29 original images with five levels of distortion. JPEG2000 compression (JP2K), JPEG compression (JPEG), additive white noise (WN), Gaussian blur (GB), and simulated fast fading (FF) Rayleigh channel are among the distortions used in the LIVE database Visual impairments that cause these distortions include edge smoothing, block artefacts, image distortions, and additive random noise.

1.5 Report Layout

There are five chapters in this report. The project overview is briefly given in Chapter 1 to provide the reader with an understanding of the project area, including the problem statement, objective and scope of work.

Chapter 2 analyzes previous BIQA models, including their conception, principles, perspectives, and methods.

Chapter 3 explains the project methodology. This chapter will go through project development methods and approaches, such as mathematical modelling and software development.

The observations, results, and analysis of the model performance are discussed in Chapter 4. The project's result is also included in this chapter.

The summary of the report and project contents is covered in Chapter 5. It also includes project improvement recommendations for future study and its general conclusion.

CHAPTER 2

BACKGROUND STUDY

2.1 Introduction

Over the previous decade, BIQA research has expanded, resulting in various BIQA models. The literature indicates on BIQA models ranging from DS to NDS. This chapter discusses some of the model types related to the proposed project published in academic journals and articles. While there have been a lot of NDS BIQA models developed in the recent decade, only a few of them are presented here. Apart from that, various additional IQA models that have already implemented the visual attention feature are examined to see how this property affects IQA models.

2.2 Non-distortion-specific Blind Image Quality Assessment (NDS BIQA)

A universal model, also known as an NDS model, can access all types of distortion at the same time without any prior understanding of the various types of distortion. Many studies have focused on building NDS BIQA models since they are more widely applicable in real-world situations. Most NDS BIQA models work by analysing and extracting discriminative images that have been distorted with no considering prior knowledge of distortion. The image quality will be evaluated using quantitative measurements of the various types of distortion features. The natural scene statistics (NSS) and learning-based approaches are the two most frequent feature extraction methods for existing NDS BIQA.

2.2.1 Natural Scene Statistics (NSS) Based Models

The majority of prior high-performing blind perceptual image quality prediction algorithms are based on human quality assessment score databases on artificially distorted images. Real-world images are usually made up of complex composites of numerous distortions. The author in [2] focused at the visually important natural scene statistics of genuinely distorted images in various colour schemes and transform domains. They suggest "bag of feature maps," an approach that avoids making conclusions about the type of distortion in an image. However, they concentrate on getting data on the constancy and variability of real-world visuals. They train a regressor to predict image quality using a vast database of indeed altered images, human ratings, and a variety of variables. They use a large database of indeed altered images, human evaluations, and bundles of variables to train a regressor to predict image quality. The authors then test the learned algorithm on a benchmark database and a recently developed distortion-realistic dataset called the LIVE in the Wild Image Quality Database to show that it can improve automatic perceptual quality prediction.