



Faculty of Engineering

**Full-Reference Edge-Based Objective Quality Assessment of Natural and
Screen Content Images**

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**Doctor of Philosophy
2022**

Full-Reference Edge-Based Objective Quality Assessment of Natural and
Screen Content Images

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A thesis submitted

In fulfillment of the requirements for the degree of Doctor of Philosophy

(Signal and Image Processing)

Faculty of Engineering
UNIVERSITI MALAYSIA SARAWAK

2022

DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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ACKNOWLEDGEMENT

First and foremost, my great appreciation to my supervisor Associate Prof. Ir. Dr. David Bong Boon Liang for his excellent guidance, encouragement and advices throughout the entire duration of this project. His wide knowledge and logical way of thinking have provided excellent value for me. He had taught me a lot of things to consider especially when preparing this thesis and this helped to release some of my burden in preparing this thesis.

I would like to express appreciation to Universiti Malaysia Sarawak for providing Zamalah Siswazah UNIMAS (ZSU) Scholarship during my period of study. The allowance enables me to focus on my study without worries about living expenses. I would also like to thank the Ministry of Higher Education Malaysia for supporting my work under the Fundamental Research Grant Scheme, project code: FRGS/1/2020/TK0/UNIMAS/02/14, UNIMAS grant number: F02/FRGS/2024/2020.

I wish to express my deepest gratitude to my beloved family members especially my parents who had given their outmost encouragement throughout this research. They had also given me support physically and mentally when I was busy in preparing the thesis and carrying out other activities associated to this research.

Lastly, I would like to thank my friends for exchanging ideas, discussing problems and sharing useful information together. They had helped me a lot by giving advices and ideas that help to finish the research in a better manner. Without the help and supports from them, my project would not have been successful.

ABSTRACT

Nowadays, screen content images (SCIs) are gaining popularity other than natural images (NIs). Quality assessment (QA) methods are needed for these two types of images for better quality of experience. In this thesis, two generalized objective QA methods are proposed for NIs and SCIs, i.e. Curvelet based Method (CurM) and Edge Magnitude and Direction Method (EMaD). The modelling of a generalized QA method that works for both types of images is complicated since NIs and SCIs have dissimilar statistical properties. Moreover, some properties of NIs and SCIs are conflicting to one another and this makes the modelling more challenging. The proposed methods assess the perceptual quality of an image based on gradient information. For the CurM, the gradient information is extracted through Curvelet transform. The coefficients from Curvelet transform denote the gradient information in terms of magnitude and direction. Different from the usual practice, CurM considers the gradient direction in 360 degree. On the other hand, EMD filters the images with Prewitt kernel to obtain the edge information and direction. Through the filter results, the image is classified into low and high gradient regions. For the high gradient regions, they are filtered again with bigger kernel size. After extracting the gradient information from the two methods, the gradient information extracted from reference and targeted images are compared to compute a similarity score. This score indicates the quality of the targeted image compared to the reference image. From the performance comparison, it is shown that the proposed methods could assess the perceived quality of NIs and SCIs with high accuracy where CurM and EMaD achieve the weighted average of 0.9063 and 0.9124 respectively in Spearman correlation coefficients for LIVE, SIQAD, and SCID databases.

Keywords: Quality, natural image, screen content image, gradient, Curvelet transform

Penilaian Kualiti Imej Kandungan Semula Jadi dan Skrin

ABSTRAK

Pada masa kini, imej kandungan skrin (SCI) semakin popular selain daripada imej semula jadi (NI). Kaedah penilaian kualiti (QA) diperlukan untuk kedua-dua jenis imej ini untuk kualiti pengalaman yang lebih baik. Dalam tesis ini, dua kaedah QA umum dicadangkan untuk NI dan SCI, iaitu Kaedah dasar Curvelet (CurM) dan Kaedah Magnitud dan Arah kecerunan (EMaD). Pemodelan kaedah QA umum untuk kedua-dua jenis imej itu sukar dan rumit kerana NI dan SCI mempunyai sifat awasan yang berbeza. Di samping itu, beberapa sifat NI dan SCI saling bertentangan. Sifat-sifat ini menjadikan pemodelan lebih mencabar. Kaedah yang dicadangkan menilai kualiti persepsi imej berdasarkan maklumat kecerunan. Untuk CurM, maklumat kecerunan diekstrak melalui transformasi Curvelet. Pekali dari transformasi Curvelet menunjukkan maklumat kecerunan dari segi awasan dan arah. Berbeza dengan kaedah lain, CurM mempertimbangkan arah kecerunan dalam 360 darjah. EMD menyaring imej dengan kernel Prewitt untuk mendapatkan maklumat dan arah kecerunan. Melalui hasil saringan, imej diklasifikasikan sebagai awasan kecerunan rendah dan tinggi. Selepas itu, awasan kecerunan tinggi disaring lagi dengan ukuran kernel yang lebih besar. Setelah mengekstrak maklumat kecerunan dari dua kaedah yang dicadangkan, maklumat kecerunan yang diekstrak dari imej rujukan dan imej sasaran dibandingkan untuk mengira skor kesamaan. Skor ini menunjukkan kualiti imej sasaran berbanding dengan imej rujukan. Dari perbandingan prestasi, dua kaedah yang dicadangkan dapat menilai kualiti NI dan SCI dengan ketepatan yang tinggi di mana CurM dan EMaD masing-masing mencapai purata wajaran 0.9063 dan 0.9124 untuk pekali korelasi Spearman dalam pangkalan data LIVE, SIQAD, dan SCID.

Kata kunci: *Kualiti, imej semula jadi, imej kandungan skrin, kecerunan, transformasi Curvelet*

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LIST OF ABBREVIATIONS

2D	Two Dimensional
AWN	Additive White Noise
BCIM	Basic Colors and Index Map
BIBS	Blind Image Blur Score
bpp	Bits Per Pixel
CC	Contrast Change
CQD	Colour Quantization With Dithering
CSC	Colour Saturation Change
DCT	Digital Curvelet Transform
DMOS	Difference Mean Opinion Score
DOG	Difference of Gaussian
DSCQS	Double Stimulus Continuous Quality Scale
DSIS	Double Stimulus Impairment Scale
DWT	Discrete Wavelet Transform
ECM	Edge Contrast Map
EDM	Edge Direction Map
ESIM	Edge Similarity
EWM	Edge Width Map
FF	Fast Fading Rayleigh Channel
FR	Full Reference
FSIM	Feature Similarity Index
GB	Gaussian Blur

GFM	Gabor Feature-based Model
GMSD	Gradient Magnitude Similarity Deviation
GMSM	Gradient Magnitude Similarity Mean
GN	Gaussian Noise
GSM	Gaussian Scale Mixtures
GSS	Gradient Similarity Score
HEVC	High Efficiency Video Coding
HG	High Gradient Regions
HVS	Human Visual System
IFC	Information Fidelity Criterion
IQA	Image Quality Assessment
IW-SSIM	Information Weighted Structural Similarity Metric
J2K	Joint Photographic Experts Group 2000
JND	Just Noticeable Difference
JPEG	Joint Photographic Experts Group
LBP	Local Binary Pattern
LIVE	Laboratory for Image and Video Engineering
LG	Low Gradient Regions
LSC	Layer Segmentation-based Coding
MATLAB	Matrix Laboratory
MB	Motion Blur
MDOG	Multi-Scale Difference of Gaussian
MOS	Mean Opinion Score
MSE	Mean Squared Error
MSSIM	Multiscale Structural Similarity Index

NIIs	Natural Images
NR	No Reference
NSS	Natural Scene Statistics
PC	Pearson Linear Correlation Coefficient
PCon	Phase Congruency
PS	Program Segment
PSNR	Peak Signal to Noise Ratio
QA	Quality Assessment
QoE	Quality of Experience
QoS	Quality of Service
QP	Quality Parameters
RMSE	Root Mean Square Error
RR	Reduce Reference
SC	Spearman Rank Order Correlation Coefficient
SCC	High Efficiency Video Coding Screen Content Coding
SCID	Screen Content Image Database
SCIs	Screen Content Images
SDSCE	Simultaneous Double Stimulus for Continuous Evaluation
SFUW	Structure Features and Uncertainty Weighting
SIQAD	Screen Image Quality Assessment Database
SIQM	Structure-Induced Quality Metric
SQI	Screen Content Images Quality Index
SSCQE	Single Stimulus Continuous Quality Evaluation
SSIM	Structural Similarity Index
SVQI	Structural Variation-based Quality Index

TP	Test Presentation
TS	Test Session
VIF	Visual Information Fidelity

LIST OF SYMBOLS

α_1	Relative Importance of Edge Magnitude
α_2	Relative Importance of LG Region
β_1	Relative Importance of Edge Direction
β_2	Relative Importance of HG Region
C	Constant
coe_w	Summed Coefficients
$CurM$	CurM Index
D	Difference Between Objective Score After Nonlinear Transformation and Subjective Score
dif	Difference
$EMaD$	EMaD Index
$EMaD_{reg}$	EMaD Index of A Region
$EMag$	Edge Magnitude
$EMag_{hor}$	Horizontal Edge Magnitude
$EMag_{ver}$	Vertical Edge Magnitude
F	Scale
i	Particular Image
Im	Total Number of Images Being Compared
k	Orientation
Ker_{hor}	Horizontal Kernel
Ker_{ver}	Vertical Kernel
Ker_p	Prewitt Kernel

Ker_p'	Prewitt Kernel of Larger Size
l	Location
N	Total Number of Pixels
Ob	Objective Score
P	Particular Pixel
PC	Pearson Linear Correlation Coefficient
Pre	Result of Mapping Objective Score
$RMSE$	Root Mean Squared Error
S	Similarity
SC	Spearman Rank-Order Correlation Coefficient
Su	Subjective Score
τ	Parameters To Be Fitted
T	Regions
$thres$	Threshold
u	Direction Vector
V	Real Number
\hat{u}	Direction Unit Vector
w_{hor}	Horizontal weight
w_{ver}	Vertical weight

CHAPTER 1

INTRODUCTION

1.1 Overview

According to Oxford Dictionaries (n.d.), an image is defined as a picture of somebody or something seen in a mirror, through a camera, television, or computer. There are two types of images in common. They are natural and screen content images. Natural images (NIs) are the images captured through lenses. Some of the examples are shown in Figure 1.1. In Figure 1.1, the examples of NIs include human portraits, indoor scenes, outdoor scenes, and man-made objects. On the other hand, for screen content images (SCIs), they are usually shown on screen or monitors. Figure 1.2 shows some examples which include posters, brochures and web pages. Most of the research in the past decades focuses on the NIs. Recently, some researches regarding SCIs are proposed too. This is because of the booming of SCIs related applications in our daily life due to the increase of internet connectivity and mobile devices such as smartphones, laptops, and tablets.

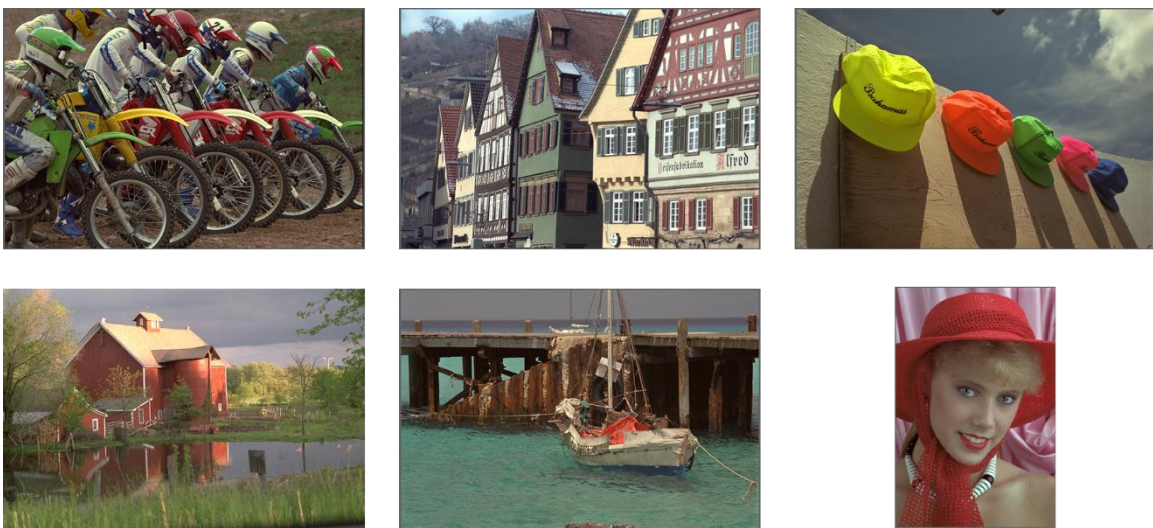


Figure 1.1: Examples of NIs (Sheikh et al., 2005b)

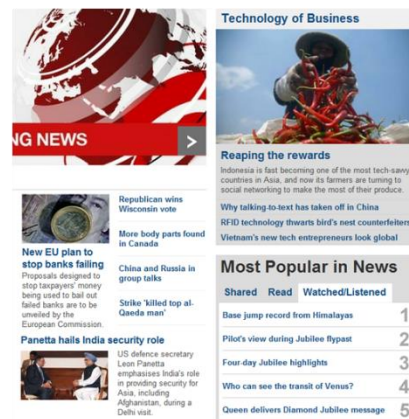
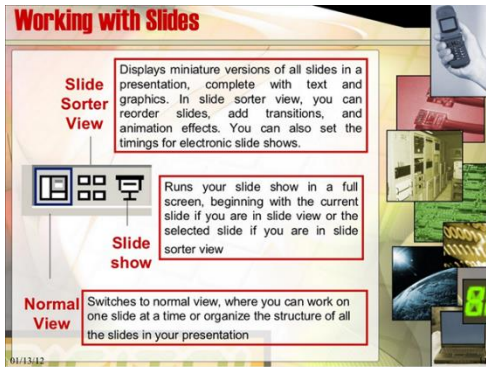


Figure 1.2: Examples of SCIs (Yang et al., 2015)

The popularity of image related activities increases with the rapid growth of internet users. This is due to the ease of accessibility and increasing internet speed, especially for the mobile internet. Figure 1.3 shows the growing number of internet users from the year 2005 to 2018 (DailyWireless, 2019). The number of worldwide internet users in 2019 is over threefold of the number of users in 2005. Besides that, the popularity of the image related activities is also encouraged by the prevalence of social networks. According to Clement, 2019, the number of social network users will reach 3.09 billion in 2021. This number of users is three times larger than the number of users in 2010 as shown in Figure 1.4. Most of the activities on social networks are related to images. For example, over 300 million and 95

million images are uploaded every day to Facebook and Instagram respectively (Dustin, 2019).

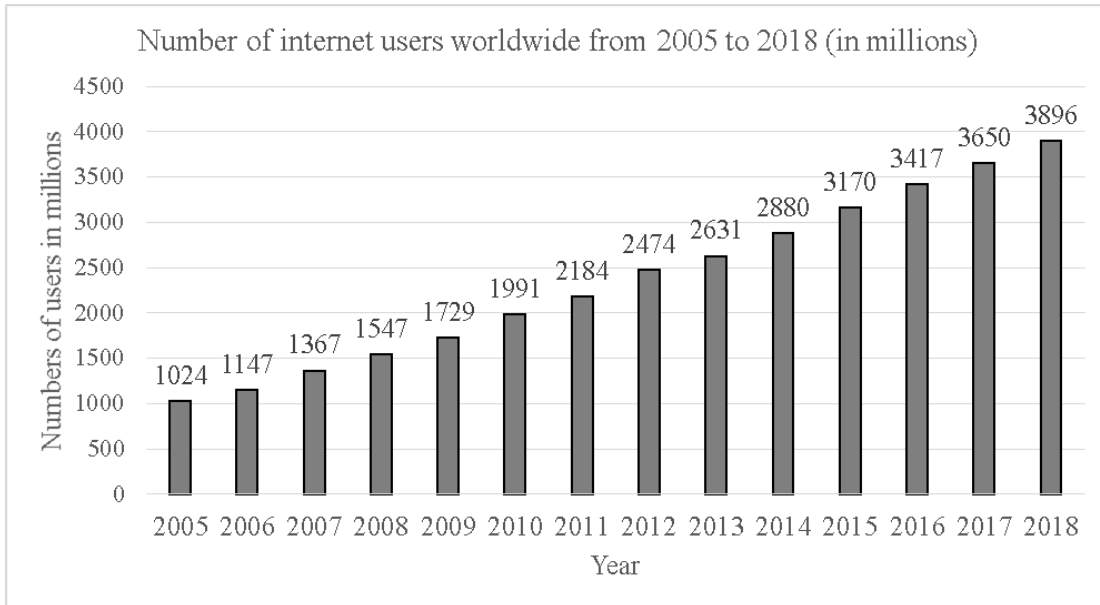


Figure 1.3: Number of internet users worldwide from 2005 to 2018 in millions (DailyWireless, 2019)

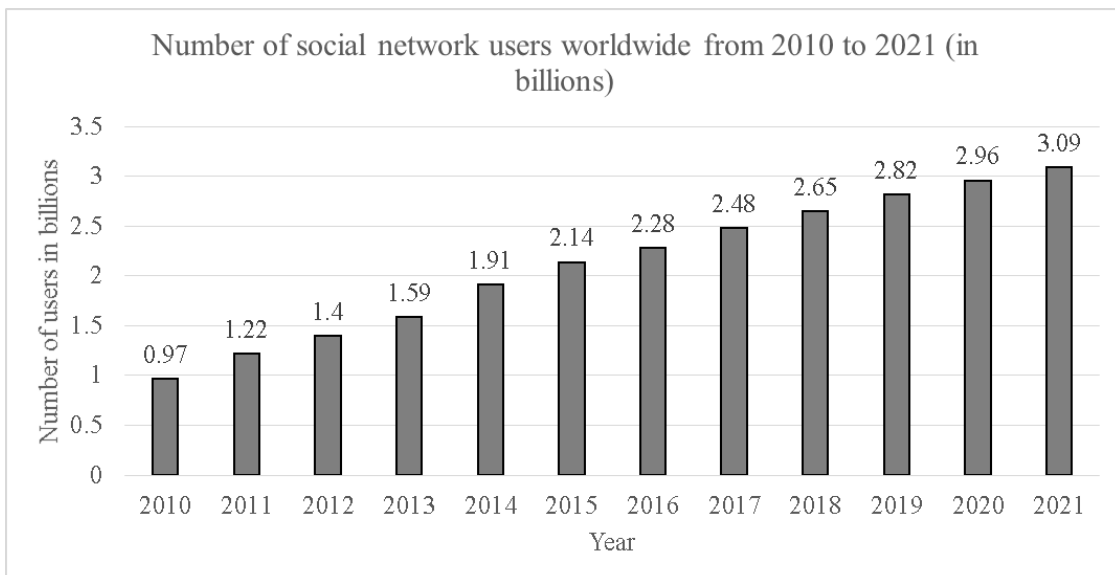


Figure 1.4: Number of social network users from 2010 to 2021 in billions (Clement, 2019)

Since almost all of the activities over the internet involve the displaying of contents on screen or monitors, SCIs are much more related to the interactive activities that enable people to communicate with systems or other people compared to the NIs. Some of the activities that involve SCIs are remote computing, screen sharing, cloud computing and cloud gaming (Baratto et al., 2005; Lu et al., 2011; Yu et al., 2014; Wang et al., 2016). Since these activities involve the transmitting, receiving, and compression of SCIs, the quality of SCIs is essential to be maintained throughout these activities for a better quality of experience for the end users. Quality assessment of an SCI is generally more complex than NI as SCI consists of a mixture of text, graphical contents and natural image. Theoretically, these different types of content have to be assessed separately as they have different image properties.

This thesis presents research works related to image quality assessment (IQA) of NIs and SCIs. IQA method utilizes algorithms to automatically give quality ratings to an image without human intervention. It reduces the effort of getting human evaluators to manually rate the image quality. IQA methods facilitate the examination of the image processing results. For instance, the efficiency of a transmission medium can be evaluated by IQA methods by comparing the quality of an image before and after the transmission. The performance of compression algorithms can also be tested using IQA methods. The IQA value of an image before and after compression can be compared to indicate the efficiency of the compression algorithm. Other than testing compression algorithms, IQA methods can be incorporated into compression algorithms to achieve the highest possible size reduction with minimal impact on perceptual quality (Wang et al., 2004). For instance, JPEG incorporated Mean Squared Error (MSE) for achieving minimal perceptual loss (Hudson et al., 2018).

The booming of image related activities in daily life makes IQA important for enhancing the quality of service (QoS) and quality of experience (QoE) of the end users of these activities (Reiter et al., 2014). The popularity of images is evident with the prevalence of social networks on the internet nowadays. Some of them are Facebook, Instagram, and Twitter. The proposed IQA methods in this thesis are objective quality assessment methods. Computational models are designed for the proposed IQA methods to predict the perceived image quality automatically by algorithms and without human intervention. Quality assessment methods (QA) can be useful. They can be used for testing display devices, evaluating the efficiencies of the compression algorithms, and assessing the efficacies of the transmission networks.

IQA methods are becoming more complicated nowadays. This thesis would like to suggest this could be caused by progressive evolution of images to higher resolutions and the advancement in camera lenses technology. Camera lenses are having higher megapixels and smaller size. For instance, Samsung announced ISOCELL Bright HMX with 108 megapixels to be embedded on smartphones (Samsung Electronics, 2019). Moreover, many of the display devices can display images or videos with very fine resolution. One of the most common examples is the display resolution for smartphones. For example, the display screen for Sony Xperia 1 (Sony Mobile, n.d.) resolves 1644 x 3840 pixels. The increased capability of display screens requires better image quality to be rendered. This is because minor distortions can be easily detected by Human Visual System (HVS).

Images can be affected by many types of distortion. Visual signals have to go through pre-processing stages before presenting to a human subject. These pre-processing stages include transmission, storing, conversion between analogue and digital signals, and