



UNIVERSITI PUTRA MALAYSIA

***SCENE ILLUMINATION CLASSIFICATION BASED ON HISTOGRAM
QUARTERING OF CIE-Y COMPONENT***

MOHAMMAD HESAM HESAMIAN

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**SCENE ILLUMINATION CLASSIFICATION BASED ON HISTOGRAM
QUARTERING OF CIE-Y COMPONENT**

By

MOHAMMAD HESAM HESAMIAN

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,
in Fulfilment of the Requirements for the Degree of Master of Science**

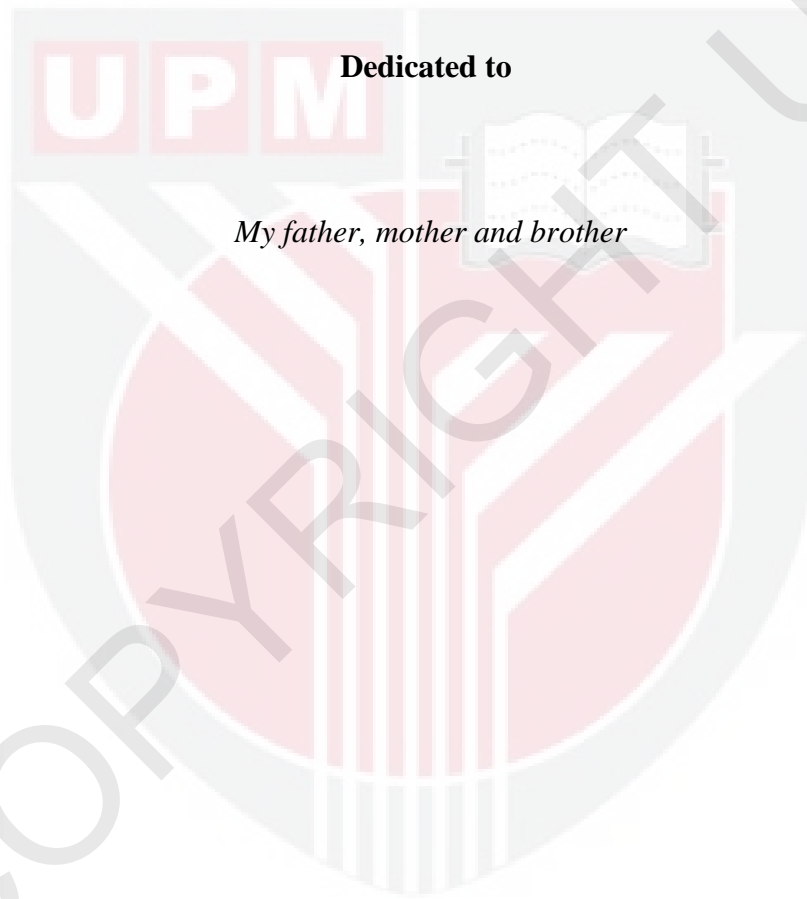
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Abstract of thesis presented to the Senate of Universiti Putra Malaysia
in fulfilment of the requirement for the Degree of Master of Science

**SCENE ILLUMINATION CLASSIFICATION BASED ON HISTOGRAM
QUARTERING OF CIE-Y COMPONENT**

By

MOHAMMAD HESAM HESAMIAN

July 2014

Chairman: Syamsiah Mashohor, PhD

Faculty: Engineering

Despite the rapidly expanding research into various aspects of illumination estimation methods, there are limited number of studies addressing illumination classification for different purposes. The increasing demand for color constancy process, wide application of it and high dependency of color constancy to illumination estimation makes this research topic challenging. Definitely, an accurate estimation of illumination in the image will provide a better platform for doing correction and finally will lead in better color constancy performance. The main purpose of any illumination estimation algorithm from any type and class is to estimate an accurate number as illumination. In scene illumination estimation dealing with large range of illumination and small variation of it is critical. Those algorithms which performed estimation carrying out lots of calculation that leads in expensive methods in terms of computing resources. There are several technical limitations in estimating an accurate number as illumination. In addition using light temperature in all previous studies leads to have complicated and computationally expensive methods. On the other hand classification is appropriate for applications like photography when most of the images have been captured in a small set of illuminants like scene illuminant. This study aims to develop a framework of image illumination classifier that is capable of classifying images under different illumination levels with an acceptable accuracy. The method will be tested on real scene images captured with illumination level is measured. This method is a combination of physic based methods and data driven (statistical) methods that categorize the images based on statistical features extracted from illumination histogram of image. The result of categorization will be validated using inherent illumination data of scene. Applying the improving algorithm for characterizing histograms (histogram quartering) handed out the advantages of high accuracy. A trained neural network which is the parameters are tuned for this specific application has taken into account in order to sort out the image into predefined groups. Finally, for performance and accuracy evaluation misclassification error percentages, Mean Square Error (MSE), regression analysis and

response time are used. This developed method finally will result in a high accuracy and straightforward classification system especially for illumination concept. The results of this study strongly demonstrate that light intensity with the help of a perfectly tuned neural network can be used as the light property to establish a scene illumination classification system.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Master Sains

**PENKELASAN PENCAHAYAAN Pemandangan BERDASARKAN
PEMBAHAGIAN HISTOGRAM KOMPONEN CIE-Y**

Oleh

MOHAMMAD HESAM HESAMIAN

Julai 2014

Pengerusi: Syamsiah Mashohor, PhD

Fakulti: Kejuruteraan

Di sebalik penyelidikan yang sedang berkembang pesat dari pelbagai aspek dalam kaedah penganggaran pencahayaan, kajian mengenai pengelasan pencahayaan bagi tujuan tertentu adalah terhad. Permintaan yang tinggi terhadap proses pemalaran warna ('color constancy'), aplikasinya yang luas dan kebergantungan pemalaran warna terhadap anggaran pencahayaan, menjadikan topik ini mencabar. Yang pasti, penganggaran pencahayaan yang tepat dalam sesuatu imej akan menyediakan satu platform yang lebih baik untuk sebarang penambahbaikan dan akhirnya akan menghasilkan prestasi pemalaran warna yang lebih baik. Tujuan utama bagi semua algoritma penganggaran pencahayaan dari sebarang kelas dan jenis ialah untuk menganggar satu nombor yang tepat bagi pencahayaan. Bagi scenario pemandangan, penganggaran pencahayaan berhadapan dengan lingkungan pencahayaan yang besar dan perubahan yang kecil adalah kritikal. Semua algoritma yang melaksanakan penganggaran ini melibatkan banyak pengiraan yang menjadikannya kaedah yang mahal terutamanya dari segi sumber perkomputeran. Terdapat beberapa kekangan teknikal dalam penganggaran satu nombor yang tepat bagi pencahayaan. Tambahan pula, dengan penggunaan suhu cahaya dalam kajian sebelum ini menjadikannya lebih rumit dan memerlukan pengiraan yang berkos tinggi. Di samping itu, pengelasan ini bersesuaian dengan aplikasi seperti fotografi, apabila kebanyakan imej diambil dalam set pencahayaan yang kecil seperti pencahayaan pemandangan. Kajian ini bertujuan untuk membangunkan satu rangka kerja pengelasan pencahayaan imej yang berkebolehan untuk mengklasifikasikan imej di bawah tahap-tahap pencahayaan yang berbeza dengan satu ketepatan yang boleh diterima. Kaedah ini akan diuji pada imej pemandangan yang sebenar yang diambil dengan tahap pencahayaan yang telah diukur. Teknik ini ialah gabungan kaedah berasaskan fizik dan kaedah statistik yang mengkategorikan imej berdasarkan data pencahayaan yang diekstrak daripada histogram pencahayaan imej. Keputusan yang di perolehi daripada pengelasan akan di sahkan menggunakan data

pencahayaan pemandangan. Penggunaan algoritma yang ditambah baik untuk menyifatkan histogram (*‘histogram quartering’*) dapat memberikan kelebihan ketepatan yang tinggi. Satu rangkaian neural (Neural network) terlatih yang mana parameternya telah diubahsuai untuk aplikasi tertentu telah diambil kira untuk mengatur imej kepada beberapa kumpulan yang telah ditetapkan. Akhir sekali, bagi penilaian prestasi dan ketepatan, kaedah *‘misclassification error percentages’*, dan *mean square error (MSE)* telah di gunakan. Kaedah ini akan menghasilkan sistem pengkelasan yang mudah dan mempunyai kadar ketepatan yang tinggi, terutamanya bagi konsep pencahayaan. Hasil kajian menunjukkan bahawa keamatan cahaya dengan bantuan rangkaian neural yang diperkemas secara sempurna dapat digunakan sebagai ciri-ciri cahaya dalam menghasilkan sistem pengkelasan pencahayaan pemandangan.



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This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science.

The members of the Supervisory Committee were as follows:

Syamsiah binti Mahohor, PhD

Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Mohd Iqbal bin Saripan, PhD

Professor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

Wan Azizun binti Wan Adnan, PhD

Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

BUJANG BIN KIM HUAT, PhD

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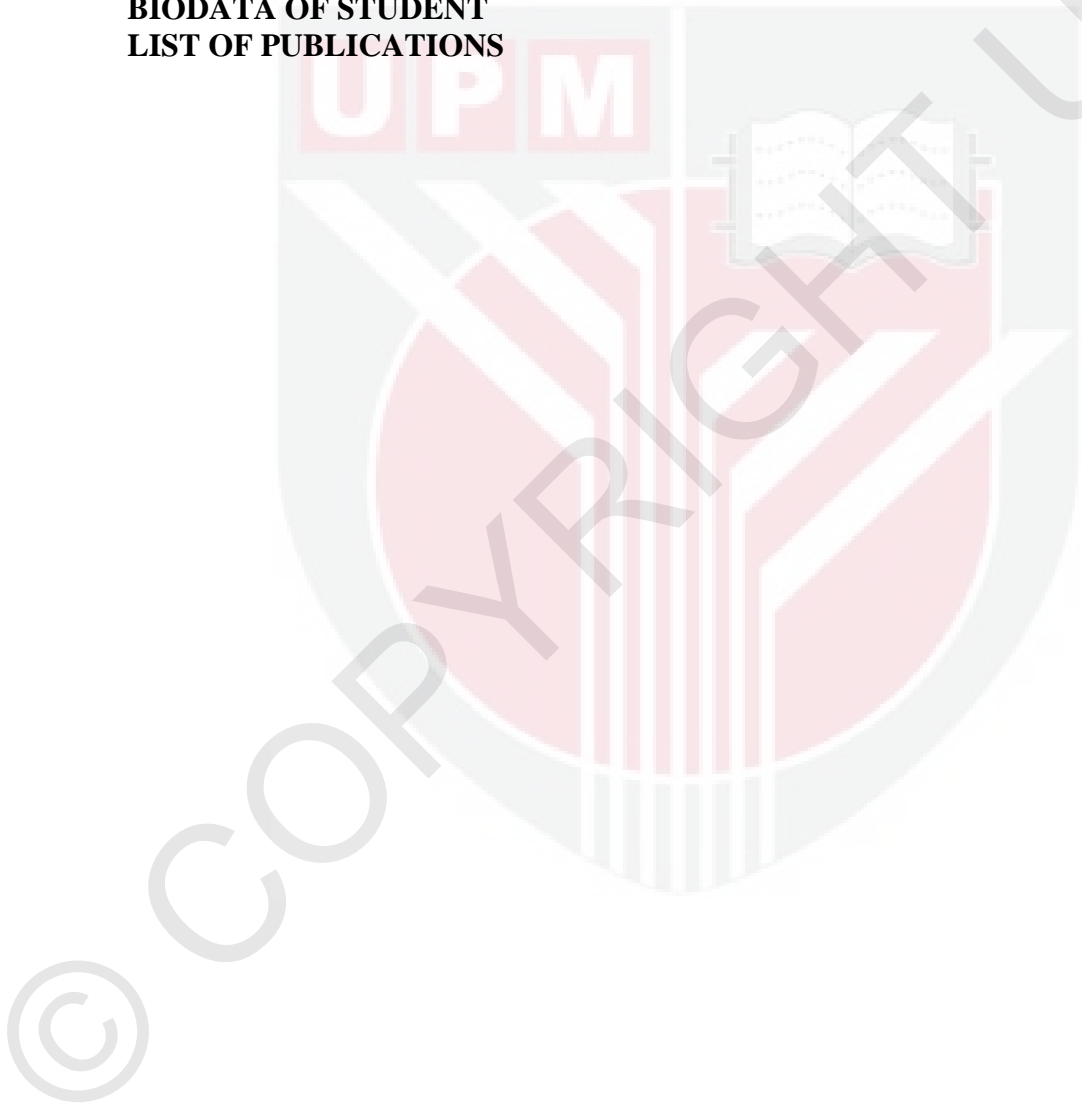
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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BP	Back Propagation
CBIR	Content based image retrieval
CIE XYZ	Color model
CPU	Central Processing Unit
E(x)	Estimation of surrounding illumination
GHz	Giga Hertz
HVS	Human Visual System
ISO DATA	Iterative Self Organizing Data Analysis
Klux	Kilo Lux
LR	Learning Rate
MC	Momentum Constant
MSE	Mean Square Error
MU	Weight Update Rate
NN	Neural Network
Q1	First Quarter

Q2	Second quarter
Q3	Third Quarter
Q4	Fourth Quarter
R	Regression Coefficient
$R(\lambda)$	Camera sensor response
RGB	Red, Green and Blue color model
$S(\lambda)$	Surface reflectance
SIV	Surrounding Illumination Value
Y	Illumination component

CHAPTER ONE

INTRODUCTION

1.1 Introduction

Image as a way of collecting data is used widely in many aspects of knowledge. A wide range of applications and systems are applying images as their input material and analysis performed on them[1]. This range cover form home fun applications to medical, military and astronomy applications[2]. But in all of the image applications dealing with illumination is a challenge. From home application in which poor lighting will result in low quality images, to pattern recognition systems which the illumination can affect the result of classification system.

Generally, light sources have a huge effect on the perception of colors. Practically, no color will be exist in the absence of light source. Varying amount of light from a light source makes changes in the perceived colors. For example a dark red surface will appear as a light orange under a high illumination yellow light source. Since human eye has ability of perceiving a constant color of an object under varying illumination, similar color constancy is indispensable for many computer vision and image processing tasks. It can be applied in many fields like object recognition, data base retrieval, color balance, material detection, machine vision and scene classification.

The color constancy process can be defined as transforming source images being taken under different colored light source to a target image captured under a white light source. In other word, color constancy tries to eliminate the effect of light source color and its intensity on the objects color[1].

Any color constancy process or algorithm consists of two critical primary stages: illumination estimation and illumination correction. Highly dependency of color constancy process to illumination estimation proves the importance of illumination estimation.

Definitely, an accurate estimation of illumination in the image will provide a better platform for doing correction and finally will lead in better color constancy performance. On the other hand it is impossible to expect significant results from a color constancy process which is established on not accurate estimation.

Scene classification systems also like other image based systems have been affected widely by illumination variation. Scene classification as one of the subsets of CBIR (content based image retrieval) has many usages in scene recognition, event classification, enquiry and retrieval. Hence, performing a good illumination estimation will increase the efficiency in all above mentioned applications.

1.2 Background

Previously many illumination estimation systems have been proposed in order to estimate the illumination value of the environment in which image captured from. All of them have some common limitation for example using strict assumptions[3], space dependent[4], being limited to some certain illumination condition[5], having complicated calculation or being costly. On account of all short coming of illumination estimation and better performance of illumination classification in case of scene illumination issue, scene illumination classification become a hot research topic in color constancy process. Moreover, illumination classification has been addressed by fewer studies and until now, there is no study focused on light intensity property.

1.3 Problem Statement

Despite the rapidly expanding research into various aspects of illumination estimation methods, still there is an increasing demand for illumination estimation process in order to achieve better results in color constancy[6]. The limited number of studies addressing illumination classification for different purposes highlights the necessity of this study. Hence this study seeks to investigate this area by proposing a new method which aims to classify scene illumination by focusing on light source intensity that is not explored by any study before.

The first step of color constancy process is the illumination estimation[7]. Illumination estimation aims to estimate an accurate number for the illuminant which has huge direct effect on next steps of color constancy process. Finally, illumination estimation performance will affect the results of color constancy and color correction process. Therefore a high performance and effective illumination estimation will provide a high performance color constancy.

Those algorithms which perform illumination estimation by analyzing light source color temperature, carrying out lots of calculation that leads in expensive methods in terms of computing resources and unstable methods[7]. Most of the applications that using the output of illumination estimation systems do not necessarily need an exact illumination number for their further processing. As far as scene images are usually can be divided into some general groups, illumination classification is a better option to replace illumination estimation in order to categorize the illumination data in some classes[8].

Focusing too much on the extracted data from color temperature of light in image and ignoring the intensity property of light can be interpreted as one of the barriers to achieve better performance. Covering this gap by using some data extracted from the intensity of light is proposed as a potential solution.

There are several technical limitations in estimating an accurate number as illumination[9]. For example changing the angle between camera and light source will change the amount of received light. Although no change happens in the surrounding illuminant but we will get a different illumination value. On the other hand, classification is appropriate for applications like photography when most of the images have been captured in a small set of illuminants like scene illuminant.

The point of developing an illumination classification system is to prepare a better platform for color constancy process and decrease the need for illumination estimation and many relevant expensive computations to the minimal level possible[10]. Developing a high accuracy classification method the on image illumination will increase the accuracy color constancy methods.

1.4 Research Aim and Objectives

This study aims to develop a framework of image illumination classifier that is capable of classifying images under different illumination levels with an acceptable accuracy. This developed method finally will result in a high accuracy classification system especially for illumination concept.

The followings are the main objectives of this research:

- I. To use light intensity represented by CIE-Y component for image illumination classification instead of light temperature.
- II. To design the neural network architecture for image illumination classification using statistical and physic based features.
- III. To apply an improving algorithm of histogram quartering which can increase the system performance by offering better histogram matching.
- IV. To tune the neural network parameters to increase the accuracy and finding the best parameter set.

1.5 Scope of Study

This study mainly focused on classifying the scene images based on their illumination. The data which have been used are real scene images captured by a Canon D5 camera in various illumination conditions. More than 800 RGB images in the format of JPEG have collected from Serdang and Putrajaya in Malaysia for this study. Implementation and testing was done on a Core2Duo Intel processor with the power of 2.4 GHz. All the coding and programs were written using Matlab 7.11.0584 (R2010B).

1.6 Contribution of Thesis

In this research an illumination classification system designed and developed. This method performed the classification based on analyzing the light intensity and its related effects in image which previously has not been addressed in other study. It proves that in scene illumination classification light intensity is capable enough to perform high accuracy rate.

In this study benefiting from two main types of classification algorithms results in having less computational load and the high accuracy of classification. On the other hand proposed method does not based on strict assumptions.

There are many well-known illumination estimation algorithms like Gray worlds and Gamut mapping which based on many strict assumptions, computationally expensive and moreover some of them need many detail side information of illumination.

The proposed method in this thesis is carrying out not much huge mathematical computation compare to Gamut mapping approach which reduces the system load and caused in faster response. This method has low complexity and flexible; that with applying very little changes it can be modified for many other applications.

The main contribution of this study lies in the fact that illumination information extracted from the CIE-Y component can be used for illumination classification. The proposed method without requiring any extra information like using specific object in the scene, can classify the image illumination.

1.7 Outline of Thesis

The remaining chapters of this thesis are organized as follow:

Chapter 2 is a critical literature review which will provide the reader with necessary information about image illumination classification methods and neural network based classification, their strengths and weak points.

Chapter 3 is dealing with the applied methodology. It discusses about idea, relevant theory, development of method and improving steps of proposed method. The steps are involved with data collection, preprocessing of image, neural network architecture design, feature extraction, improvement of proposed algorithm and illumination classification.

Chapter 4 is related to analyzing and discussing about the achieved results of classification system. It draws a comparison with the other algorithms introduced in literature in order to highlights the performance of proposed method.

Chapter 5 summarizes the obtained results and makes a conclusion. In the second part it suggest some further ideas for future studies to cover the weak points based on analyzed results.

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