# COLOUR TEXTURE IMAGE CLASSIFICATION USING COLOUR COMPLETED LOCAL BINARY PATTERN (CCLBP)

HUSSEIN ALI HASAN AL AIDAROS

UNIVERSITI MALAYSIA PAHANG

## UNIVERSITI MALAYSIA PAHANG

**DECLARATION OF THESIS AND COPYRIGHT**

Author's Full Name : ______________________________

Date of Birth : ______________________________

Title : ______________________________

______________________________

______________________________

Academic Session : ______________________________

I declare that this thesis is classified as:

| | | |
|---|---|---|
| ☐ | CONFIDENTIAL | (Contains confidential information under the Official Secret Act 1997)* |
| ☐ | RESTRICTED | (Contains restricted information as specified by the organization where research was done)* |
| ☑ | OPEN ACCESS | I agree that my thesis to be published as online open access (Full Text) |

I acknowledge that Universiti Malaysia Pahang reserves the following rights:

1. The Thesis is the Property of Universiti Malaysia Pahang
2. The Library of Universiti Malaysia Pahang has the right to make copies of the thesis for the purpose of research only.
3. The Library has the right to make copies of the thesis for academic exchange.

Certified by:

| | |
|---|---|
| _______________________ | _______________________ |
| (Student's Signature) | (Supervisor's Signature) |
| _______________________ | _______________________ |
| New IC/Passport Number<br>Date: | Name of Supervisor<br>Date: |

NOTE : * If the thesis is CONFIDENTIAL or RESTRICTED, please attach a thesis declaration letter.

**THESIS DECLARATION LETTER (OPTIONAL)**

Librarian,
*Perpustakaan Universiti Malaysia Pahang*,
Universiti Malaysia Pahang,
Lebuhraya Tun Razak,
26300, Gambang, Kuantan.

Dear Sir,

CLASSIFICATION OF THESIS AS RESTRICTED

Please be informed that the following thesis is classified as RESTRICTED for a period of three (3) years from the date of this letter. The reasons for this classification are as listed below.

Author's Name
Thesis Title

Reasons (i)

(ii)

(iii)

Thank you.

Yours faithfully,

________________________________
(Supervisor's Signature)

Date:

Stamp:

Note: This letter should be written by the supervisor, addressed to the Librarian, *Perpustakaan Universiti Malaysia Pahang* with its copy attached to the thesis.

## SUPERVISOR'S DECLARATION

I/We* hereby declare that I/We* have checked this thesis/project* and in my/our* opinion, this thesis/project* is adequate in terms of scope and quality for the award of the degree of *Doctor of Philosophy/ Master of Engineering/ Master of Science in …………………………..

_______________________________

(Supervisor's Signature)

Full Name :

Position :

Date :

_______________________________

(Co-supervisor's Signature)

Full Name :

Position :

Date :

# COLOUR TEXTURE IMAGE CLASSIFICATION USING COLOUR COMPLETED LOCAL BINARY PATTERN (CCLBP)

HUSSEIN ALI HASAN AL AIDAROS

Thesis submitted in fulfillment of the requirements
for the award of the degree of
Bachelor of Computer Science (Graphics & Multimedia Technology)

Faculty of Computer Systems and Software Engineering

UNIVERSITI MALAYSIA PAHANG

MAY 2019

# ACKNOWLEDGEMENTS

To begin with, I am grateful to Allah for the good health and wellbeing that were necessary to complete this project. I place on record, my sincere thank you to Prof. Dr. Kamal Zuhairi Zamli Dean of the Faculty, for the continues encouragement. I am also grateful to my supervisor Dr. Taha Hussein Rassem, I am extremely thankful and indebted to him for sharing expertise, and sincere and valuable guidance and encouragement extended to me. I take this opportunity to express gratitude to all the Department faculty members for their help and support. I also thank my parents for the unceasing encouragement, support and attention. I also place on record, my sense of gratitude to one and all, who directly or indirectly, have lent their hand in this project.

**ABSTRACT**

Local Binary Pattern (LBP) descriptor is being used successfully for the classification of textures. Also, it is been used for other tasks such as facial expression, face recognition and texture segmentation. On the other hand, these descriptors are barely used for image categorization due to their calculations which are depend on the gray image and they are invariant to monotonic light variations on the gray level. Despite the key role in distinctive the objects of these descriptors, they ignore color information. In this project, Completed Local Binary Pattern (CLBP) will be enhanced and two colour CLBP descriptors are proposed which RGB_CCLBP and HSV_CCLBP. Moreover, the datasets that have been used in this project are KTH-TIPS, KTH-TIPS 2A and Outex_TC_00013 datasets. The proposed method shows promising results despite the limitations of it.

TABLE OF CONTENT

# CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

Nowadays, texture features are spirited in many applications such as face recognition, finger detection, human detectors, object recognition and image retrieval. In addition, many of textures feature algorithms were identified by pervious literature for robust and distinctive texture features. The classification of the texture feature algorithm methods is categorised into three categories which are model-based method, statistical method and structural method.

The difference between the grey level of centre pixel of a specific local pattern and its neighbours are calculated to a histogram that is represent image texture. Then, the absolute difference was used for constructing Local Binary Pattern (LBP) descriptor. By the ability to distinguish the microstructures of an image, LBP became an interesting research topic used by many of the computer vision researchers. Also, LBP used for rotation invariant texture classification and extended for face recognition and image retrieval applications (García-Olalla, Alegre, Barreiro, Fernández-Robles, & García-Ordás, 2015).

LBP has two steps which are thresholding and encoding steps. The values of the neighbouring pixels are converted into binary values (0 or 1) by comparing value of central pixel with value of all neighbouring pixel. Then, to describe a structural pattern, encoding step converts the binary values into decimal numbers. Moreover, many LBP variants have been proposed to increase the discriminating property for the extraction process of the texture feature. There are six variants included in LBP which are Dominant LBP (DLBP), Completed Modelling of LBP (CLBP), Center-Symmetric Local Binary Pattern (CS-LBP), Local Ternary Pattern (LTP), Completed Ternary Pattern (CLTP) and Local Orientation Adaptive Descriptor (LOAD)(Zhao, Jia, Hu, & Min, 2013).

All the previous texture descriptors are used the intensity value to be extracted. They are totally ignored any colour information. All the above descriptors proposed based on the gray values only and it is difficult to use it for any color image task. Some results are used these descriptors in their system after converting the color image to the gray image(Guo, Zhang, & Zhang, 2010).

## 1.2 Problem Statement

Most of the local texture descriptors had been shown good performance for many of image processing tasks. However, most of them only focused on the intensity values of the images and totally ignored the colour information even if the image is a color image. In the color image classification using normal texture descriptors, they just converted the image from color to gray and then extract the texture descriptor. While, the color is one of the important information in the image. Considering the color information may led to improve the accuracy of the classification or recognition that lead to high and good results. Moreover, there are different color models and each model has its advantage and disadvantage. Use different color models to extract different color texture descriptor instead of gray texture descriptor may help to improve the performance of the texture descriptor.

## 1.3 Objectives

i. To study and investigate different texture local pattern features

ii. To study and apply different color local texture pattern descriptors for color texture classification

iii. To evaluate the performance of different color local texture pattern descriptors for color texture classification

## 1.4 Scope

i. This research will focus in colour texture image classification.

ii. Only three existing colour texture datasets are used. These are KTH-TIPS, KTH-TIPS 2A and Outex_TC_00013.

## 1.5 Thesis Organization

This thesis consists of five chapters and each chapter discuss different issues in the system. Below is the summary for all the chapters in the thesis:

Chapter 1 is an introduction which contains problem statement, objectives and scope of this research.

Chapter 2 is literature review which reviews three previous texture descriptors.

Chapter 3 is a methodology which explains the methodology that is implemented in the development of the system. Also, hardware and software that used in the system will be discussed.

Chapter 4 is about the implementation of the CCLBP method and discussion about the results.

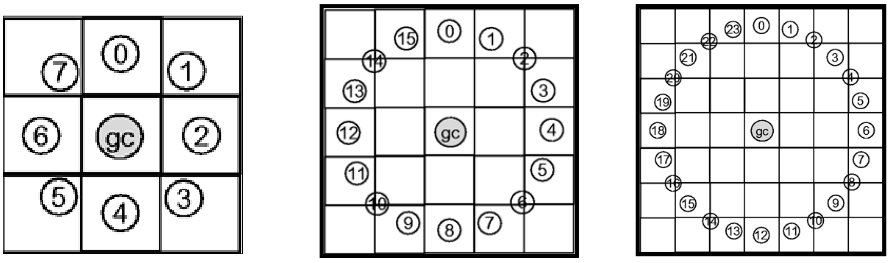
Chapter 5 is about the conclusion and overall summary of the research that has been performed.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Introduction

This chapter contains information that is related to colour images classification system. Texture classification may involve various algorithms to use in the system to make the system have a high accuracy result from the texture pattern feature descriptor chosen. Before implement the feature extraction, a radius size is assigned to carry out the feature extraction process. The radiuses size can have many sets, the most common set which is (1, 8), (2, 16) and (3, 24), all these radius sizes can come out with a set of different result as show as Figure 2.1. Moreover, there are a few of texture pattern feature descriptor that are used in texture image classification. This project finding classification techniques that have a high accuracy for texture classification among the three texture local pattern features comes into the role play of the feature extraction stage which are Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Compound Local Binary Pattern (CLBP).



(1,8) (2,16) (3,24)

Figure 2.1: Radius sizes illustration.

## 2.2 PREVIEWS ON PERVIOUS TEXTURE DESCRIPTORS

### 2.2.1 LOCAL BINARY PATTERN (LBP)

Local Binary pattern was presented by Ojala et al. in 1996. The LBP is an effective device to portray the neighborhood gray-level attributes of a surface composition. LBP surface operator has turned into a popular methodology in different applications. It can classify to deal with the generally different factual and auxiliary models of texture investigation.

The LBP has the capable to extract the uniform pattern by extract the data information of the image to be more precise in each image pixel. That makes the LBP to be efficient for arranging the neighbourhood spatial structure of a picture.

The LBP features descriptors were improved to utilize neighbourhoods of various sizes (Ojala et al., 2002). By using a roundabout neighbourhood introducing values at non-whole number pixel organizes permit any sweep and pixels in the area. Below showing the notation of P (neighbourhood) & R (radius) must be utilized for pixel neighbourhoods which imply P focus on a roundabout radius of R.

Moreover, Local Binary Pattern is a very simple texture features that use for image processing by convert the image pixel using the thresholding to the neighbourhood of each pixel and compare it with the value of the central pixel and comes out a result as binary number following by decimal number.

In this situation, p keeps running over the roundabout of the 8 neighbours of the centre pixel c. So, $i_c$ and $i_p$ are the gray scale value at c and p, the value of and s(x) which is the roundabout value of the 8 neighbours will be 1 if $u \geq 0$ and 0 generally. After that multiply the binary code with the power of 2 and add together to get the decimal code which is the LBP code.

The code of LBP is computed by utilizing equation below.

$$\mathrm{LBP}_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(i_p - i_c)2^P$$

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

This is one of the imperative perceptions since it decreases the dimensionality in the technique in view LBP histogram. Besides that, most of the facial districts comprise of uniform areas. Consequently, by utilizing LBP on them might diminish robustness.

### 2.2.2 LOCAL TERNARY PATTERN (LTP)

In a way to enhance the robustness of neighbourhood code, the Local Binary Pattern (LBP) texture descriptors are supplanted by a Local Ternary Pattern (LTP) texture features.

In LTP, the user can set the number of the threshold (Tan, X. and Triggs, B. 2010). This might make the LTP code to be more impervious to noise; however, the changes of gray -level will no more be will be no more be entirely invariant.

The pixel contrasts between the neighbouring pixels and the inside pixel has been encoded by LTP. This process can be done by compare the different of the middle pixel and P neighbours on a circle of span R. Below is the equation that computes the code of LTP.

$$\mathrm{LTP}_{\mathrm{P,R}} = \sum_{P=0}^{P-1} 2^{P} \mathrm{s}(\mathrm{i_p} - \mathrm{i_c})$$

LPT make the different state of threshold pixel three value which is to 0 or 1 or -1 by add the threshold number and subtract the threshold number to an upper and lower set pixel. While the function of the threshold is coming into the value of s(x). By put the value of threshold function to s(x) = 1 if x ≥ 0; s(x) = 0 if -t<x<t ; s(x)=-1 if x<-t. As given in mathematical statement below.

$$\mathrm{s(x)} = \begin{cases} 1, & \mathrm{x} \geq \mathrm{t}, \\ 0, & -\mathrm{t} < x < t, \\ -1, & \mathrm{x} \leq -\mathrm{t}, \end{cases}$$

A case of LTP is showing below, user specified threshold number is 5, so the central pixel wills added 5 to become an upper pattern and subtract 5 to become a lower pattern the encoding method of LTP is represented in Figure 2.5 (Rassem, T. H. and Khoo, B. E. 2014).

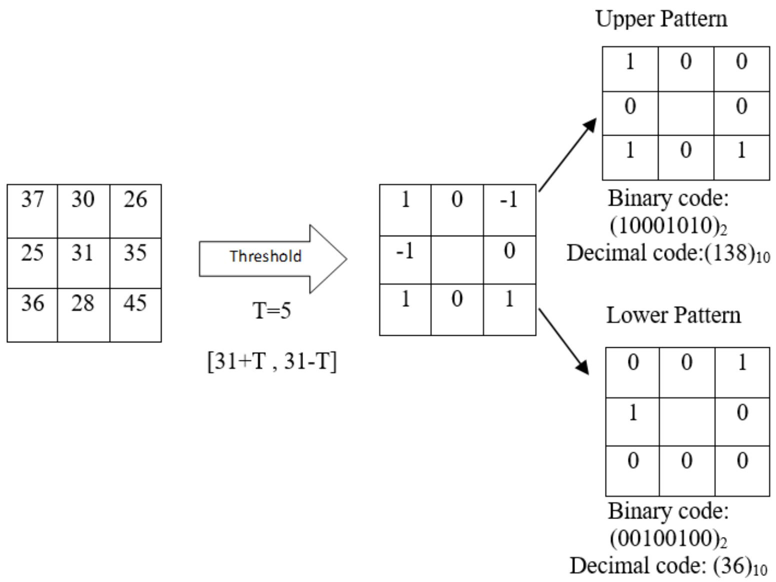



Figure 2.2: LTP encoding method.

### 2.2.3 COMPOUND LOCAL BINARY PATTERN (CLBP)

The feature extraction of algorithm Complete Local Binary Pattern (CLBP) is a summed-up form of LBP which is presented by Z. Guo et al. The CLBP also become the very successful texture pattern extraction features. CLBP has divided into three different parts which are CLBP_S, CLBP_M and CLBP_C. The part of CLBP_S is showing the different sign between the middle pixel and neighbourhood pixel in positive or negative value. While CLBP_M is showing the compare and different the magnitude of the inside pixel and neighbourhood pixel (Ahmed, F et al. 2011). Last, is the CLBP_C which demonstrates the distinction between neighbourhood pixel value and the mean of all the gray level in the image.

The first components of CLBP_S, it is only ordinary of LBP. There is no different between CLBP_S and LBP, so they share the almost same equation showing in below.

$$\mathrm{CLBP\_S}_{P,R} = \sum_{P=0}^{P-1} 2^{P} s(i_p - i_c), \qquad s_p = \begin{cases} 1, & i_p \geq i_c \\ 0, & i_p < i_c \end{cases}$$

The following component is CLBP_M which are of proceeds with qualities rather than binary which is "1" and '0', so it cannot be specifically easily to extract as same as of CLBP_S. Therefore, the neighbourhood's pixel will change to 1 if the difference between the middle pixel and the relating neighbourhood pixel is more than the threshold mean of magnitude. Else, it will change to 0. CLBP_M is ascertained as same as CLBP_S but it manages the distinction of the magnitude.

$$\mathrm{CLBP\_M}_{P,R} = \sum_{P=0}^{P-1} 2^{P} t(m_p - c), t(m_p, c) = \begin{cases} 1, & |i_p - i_c| \geq c \\ 0, & |i_p - i_c| < c \end{cases}$$

There is $i_c$ given to a middle pixel, and P uniformly dispersed neighbours which is$i_p$, p = [0, P-1], the distinction between $i_c$ and $i_p$ can be computed by $i_p - i_c$. The c is the threshold value for determine the mean value $m_p$ from the whole image. The $s_p$ is utilized to construct the CLBP-Sign (CLBP S), though the $m_p$ is utilized to fabricate CLBP-Magnitude (CLBP M). So, here are the calculation of the sign component $s_p$ $=s(i_p - i_c)$, while magnitude component $m_p = |i_p - i_c|$ as appeared in Figure 2.6 (Ahsan et al. 2013).

| | | |
|---|---|---|
| 11 | 13 | 36 |
| 28 | 22 | 10 |
| 74 | 66 | 46 |

3*3 sample block

| | | |
|---|---|---|
| -11 | -9 | 14 |
| 6 | | -12 |
| 52 | 44 | 24 |

Local differences

| | | |
|---|---|---|
| 0 | 0 | 1 |
| 1 | | 0 |
| 1 | 1 | 1 |

Sign components

| | | |
|---|---|---|
| 11 | 9 | 14 |
| 6 | | 12 |
| 52 | 44 | 24 |

Magnitude components

| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | | 0 |
| 1 | 1 | 1 |

Final magnitude components

Figure 2.3: Sign components and magnitude components differences.

## 2.3 Comparison of different texture descriptors

**Table 2.1: Comparison of different texture descriptors.**

| | **Proposed by** | **Proposed year** | **disadvantages** | **Used for colour texture image classification** |
|---|---|---|---|---|
| **LBP** | Ojala et al. | 1994 | Small spatial area of support, noise sensitivity derives a huge variation. | No |
| **LTP** | X. Tan and B. Triggs | 2007 | Not invariant under grey-scale transform of intensity values as its encoding is based on a fixed predefined thresholding. | No |
| **CLBP** | Guo et al. | 2010 | The CLBP pattern has the same problem as of traditional LBP, sensitive to noise as the value of the centre pixel is directly used as a threshold. | No |

# CHAPTER 3

# METHODOLOGY

## 3.1 Introduction

In this chapter, methods that used for processing the colour texture images to build classification system are explained. The proposed Completed LBP (CLBP) compares both the sign and the magnitude of the pattern's central grey level value with its neighbours and combines them with all central values of the patterns. By combining sign difference, magnitude difference and threshold of central grey values of the patterns in different way three CLBP operators are constructed which are CLBP_S, CLBP_M and CLBP_C. These three operators are calculated based on two different colour spaces RGB and HSV. Then to construct the final CLBP descriptor the previous descriptors are combined. Then, Evaluate and analyse the performance of the proposed CCLBP descriptor for experimental image classification (Zhao et al., 2013).

## 3.2 Colour texture image classification system processes

To build colour texture image classification system using colour completed local binary pattern method these processes that are shown in figure 3.1 and explained in the subtopics below are needed:

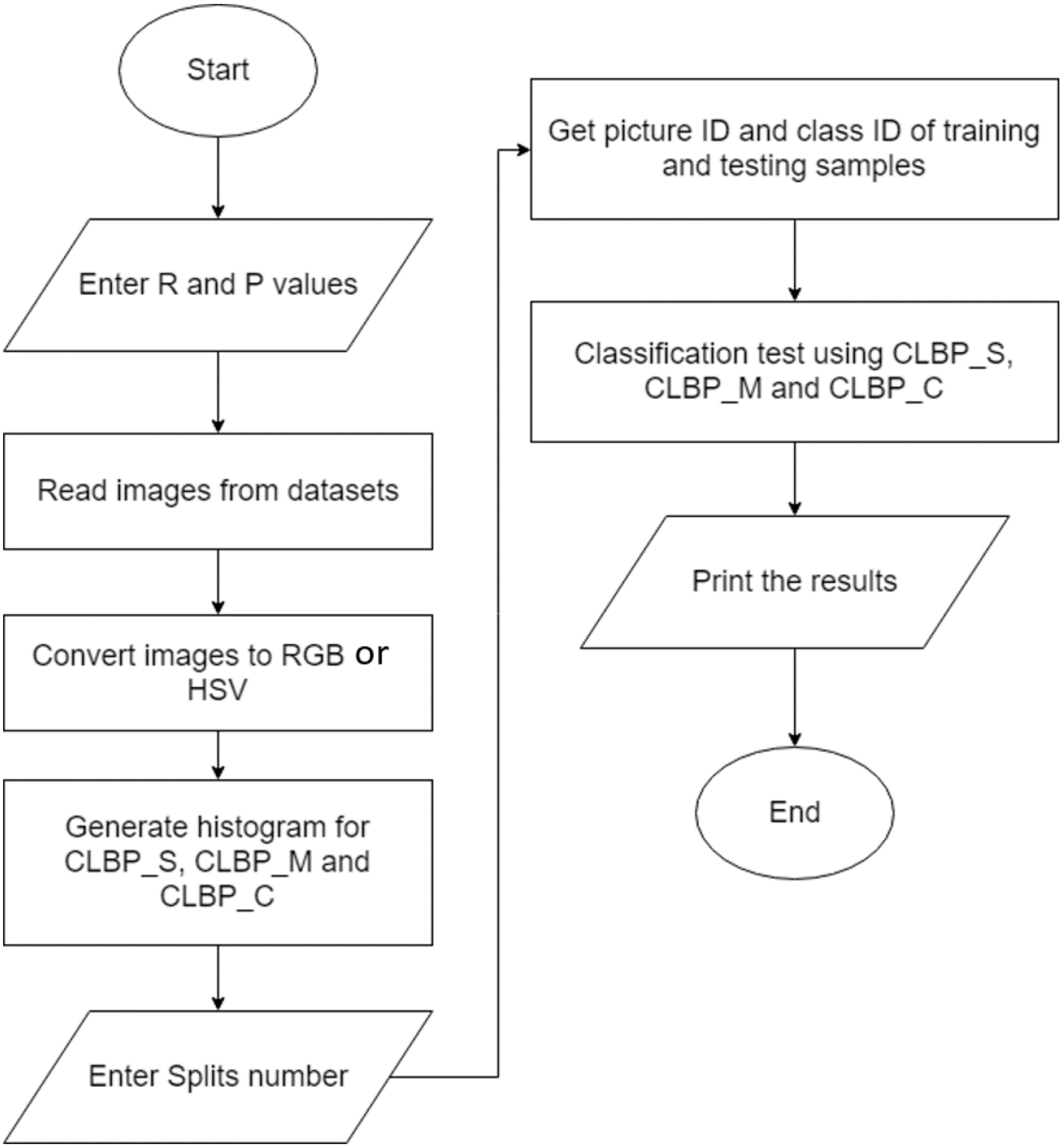



Figure 3.1: Flowchart of the colour texture image classification system.

### 3.2.1 Model Analysis for Illumination Changes and Photometric Transformations

Diagonal model and diagonal-offset model used to analyse the photometric transformations and the illumination changes of the proposed CCLBP method. Equation

3.1 expresses the diagonal model while Equation 3.2 expresses the diagonal-offset model (Rassem, Mohammed, Khoo, & Makbol, 2015).

$$\begin{pmatrix} R^c \\ G^c \\ B^c \end{pmatrix} = \begin{pmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{pmatrix} \begin{pmatrix} R^c \\ G^c \\ B^c \end{pmatrix}$$

Equation 3.1: The diagonal model.

$$\begin{pmatrix} R^c \\ G^c \\ B^c \end{pmatrix} = \begin{pmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{pmatrix} \begin{pmatrix} R^c \\ G^c \\ B^c \end{pmatrix} + \begin{pmatrix} o_1 \\ o_2 \\ o_3 \end{pmatrix}$$

Equation 3.2: The diagonal-offset model.

When it comes to use these two models five different changes are identified to examine colour SIFT descriptors which are light intensity variations, light intensity shifts, light intensity variations and shifts, light colour variations and light colour variations and shifts. Light intensity change is expressed from Equation 3.1 and by a constant factor; i.e., a = b = c, all image values are changed. Moreover, by equal offset value (shift value) the image values are changed in the light intensity shift and the descriptor is shift invariant when the invariant is to the light intensity shifts. Furthermore, image values change by the previous two types of changes. Finally, image values in each channel are independently changed in the light colour variations and light colour variations and shifts models as Equations 3.1 expresses. While Equation 3.2 expresses the image values in each channel that are independently changed and shifted (Park et al., 2016).

#### 3.2.1.1 RGB_CCLBP

By independently computing CLBP in the all three channels of RGB's colour space and connecting the results together, the RGB_CCLBP operators are obtained. It is same with original LBP, RGB_CCLBP has no more invariant properties and it is invariant to monotonic light intensity change.

#### 3.2.1.2 HSV_CCLBP

By independently computing CLBP in the all three channels of HSV's colour space and connecting the results together, the HSV_CCLBP operators are obtained. In addition, it has been proved that in HSV colour space the (Hue) colour model has invariant property against the light intensity changes and shifts. On the other hand, HSV_CCLBP has no invariant properties because of the combination of Hue with the remaining information (Phakade, Flora, Malashree, & Rashmi, 2014). The follow equations show how to convert RGB to HSV colour space:

Changing the range of the colour space from 0to 255 to 0 to 1:

$R' = R/255$

$G' = G/255$

$B' = B/255$

$Cmax = \max(R', G', B')$

$Cmin = \min(R', G', B')$

$\Delta = \text{Cmax} - \text{Cmin}$

$$H = \begin{cases} 0^\circ \ \Delta = 0 \\ 60^\circ \times \left(\frac{G' - B'}{\Delta} mod6\right), C_{max} = R' \\ 60^\circ \times \left(\frac{B' - R'}{\Delta} + 2\right), C_{max} = G' \\ 60^\circ \times \left(\frac{R' - G'}{\Delta} + 4\right), C_{max} = B' \end{cases}$$

Equation 3.3: Calculate hue.

$$S = \begin{cases} 0, & C_{Max} = 0 \\ \frac{\Delta}{C_{Max}}, & C_{Max} \neq 0 \end{cases}$$

Equation 3.4: Calculate saturation.

### 3.2.2 Mathematical Models of CCLBP

In order to calculate CCLBP operators in each channel these formulas are used:

$$(CCLBP\_S_{P,R})^{C1} = \sum_{p=0}^{P-1} 2^p \mathrm{s}(i_p - i_c),\ s_p = \begin{cases} 1, & i_p \geq i_c, \\ 0, & i_p < i_c, \end{cases}$$

Equation 3.5: Calculate CCLBP_S for the first channel of the colour space.

$$(CCLBP\_S_{P,R})^{C2} = \sum_{p=0}^{P-1} 2^p \mathrm{s}(i_p - i_c),\ s_p = \begin{cases} 1, & i_p \geq i_c, \\ 0, & i_p < i_c, \end{cases}$$

Equation 3.6: Calculate CCLBP_S for the second channel of the colour space.

$$(CCLBP\_S_{P,R})^{C3} = \sum_{p=0}^{P-1} 2^p s(i_p - i_c),\ s_p = \begin{cases} 1, & i_p \geq i_c, \\ 0, & i_p < i_c, \end{cases}$$

Equation 3.7: Calculate CCLBP_S for the third channel of the colour space.

Where C1, C2 and C3 represent the colour space channels. Also, in order to calculate the final CCLBP_S and the CCLBP_M the following formulas are used:

$$CCLBP\_S_{P,R} = \left[(CLBP\_S_{P,R})^{C1}\ (CLBP\_S_{P,R})^{C2}\ (CLBP\_S_{P,R})^{C3}\right]$$

Equation 3.8: The formula for calculating CCLBP_S.

$$CCLBP\_M_{P,R} = \left[(CLBP\_M_{P,R})^{C1}\ (CLBP\_M_{P,R})^{C2}\ (CLBP\_M_{P,R})^{C3}\right]$$

Equation 3.9: The formula for calculating CCLBP_M.

Finally, for each colour channel, CCLBP_S, CCLBP_M and CCLBP_C are jointly or hybridized combined in order to construct the remaining operators and the concatenation of all colour channel operators gives the final CCLBP operators (Rassem et al., 2015).

## 3.3 Datasets

The datasets used for this research are described as follow:

### 3.3.1 KTH-TIPS dataset:

This dataset consists of 10 classes categorised as follow (aluminium_foil, brown_bread, corduroy, cotton, Etc) and each class has a total of 81 texture images which has the size of 200x200. The total texture images in this dataset is 810 images (Lan & Zhou, 2016).

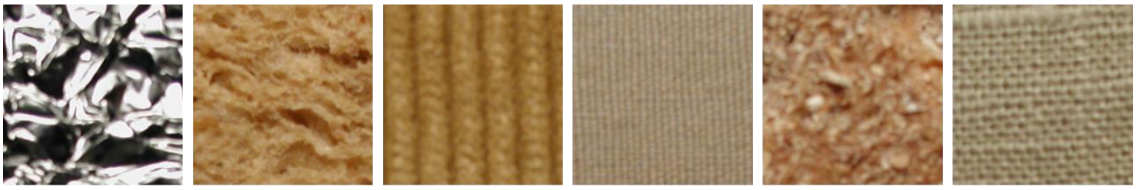


Figure 3.1: Texture image examples from KTH-TIPS dataset.

### 3.3.2 KTH-TIPS 2A dataset:

This dataset consists of 11 classes categorised as follow (linen, white_bread, wood, wool, Etc) and each class contains 432 texture images which has the size of 200x200. Also, this dataset contains a total of 4752 texture images (Liu et al., 2019).

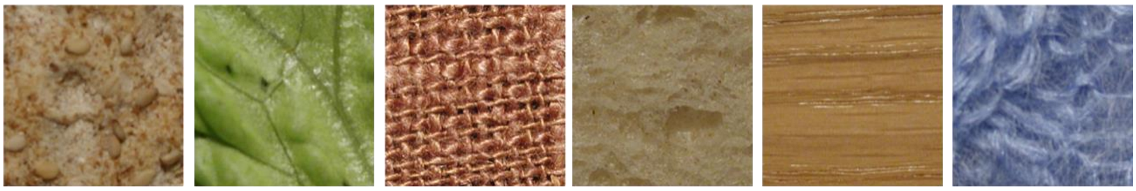


Figure 3.2: Texture image examples from KTH-TIPS 2A dataset.

### 3.3.3 Outex_TC_00013 dataset:

This dataset consists of 68 classes and each class has 20 texture images which has the size of 128x128 and the total number of images in this dataset is 1360 texture images (Kalakech, Porebski, Vandenbroucke, & Hamad, 2018).

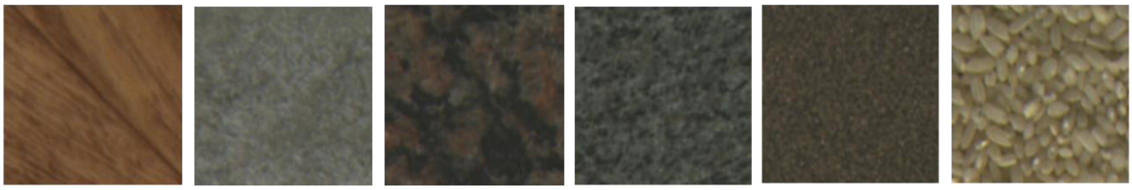


Figure 3.3: Texture image examples from Outex_TC_00013 datasets.

## 3.4 Software and Hardware requirements

### 3.4.1 Software Requirements

**Table 3.1: Software Requirements.**

| SOFTWARE | DESCRIPTION |
|---|---|
| Microsoft Word 2016 | Used for preparing documentation |
| Microsoft PowerPoint 2016 | Used for preparing presentation slides |
| Microsoft Windows 10 | A platform that runs the computer |
| Microsoft Visio | Used to create the Flowchart |
| MATLAB | Programming software used to develop the Colour texture image classification system |
| Google Chrome | Web browser used to access the internet and for searching for information that related to this research |

### 3.4.2 Hardware Requirements

**Table 3.2: Hardware Requirements.**

| HARDWARE | DESCRIPTION |
| --- | --- |
| Laptop Computer | • This hardware used for the development and implementation of the system<br>• Used for writing and preparing all the documents |
| Printer | Used for printing out the documentation |

# CHAPTER 4

# RESULTS AND DISCUSSION

## 4.1 Introduction

In this chapter, there will be a description of the implementation process of the proposed method and discussion of the results obtained by the proposed method.

## 4.2 Experimental results of RGB CCLBP descriptor

### 4.2.1 Implementation

After reading all the images from the datasets, figure 4.1 shows the method of converting the images into RGB colour space. Then, histogram of CLBP_S, CLBP_M and CLBP_C will be generated. After that, Splits method in MATLAB will get the picture ID and class ID of the training and test samples as shown in figure 4.2. Finally, classification process will be done by classification test using CLBP_S, CLBP_M and CLBP_C and combining them together.

```matlab
for i=1:ClassNum;
    ims = dir(fullfile(rootpic, classes{i}, '*.png'))' ;
    ims = cellfun(@(x)fullfile(classes{i},x),{ims.name},'UniformOutput',false) ;
    for j=1:length(ims)
        filename = sprintf('%s%s',rootpic,ims{j})
            picCount = picCount+1;
            RGB = imread(filename);
            if size(RGB,3) == 1, RGB = cat(3, RGB, RGB, RGB) ; end
```

Figure 4.1: Converting the images to RGB colour space.

```matlab
col=1;
BiggestNumPicPerClass = 20;
for Auto= 1 : 8
 splits =[2 5 7 10 12 15 17 19];

TrainNumPerClass = splits(Auto);
numTrain = splits(Auto);
numTest=BiggestNumPicPerClass - numTrain ;
```

Figure 4.2: Splits method in Matlab for getting the picture ID and class ID of the training and test samples.

### 4.2.2 Results

Tables 4.1, 4.2 and 4.3 show the results of the proposed method using KTH-TIPS dataset using Splits = [30 40 50 60] and values of R = (1, 2, 3) and P = (8, 16, 24). And it shows that the highest percentage is 96.20% when Splits= 60 and values of R=1 and P=8.

**Table 4.1: Results of CCLBP descriptor using KTH-TIPS dataset based on RGB (R=1, P=8).**

| | **Splits= 30** | **Splits= 40** | **Splits= 50** | **Splits= 60** |
|---|---|---|---|---|
| **CCLBP_S** | 53.686 | 55.453 | 56.370 | 60.100 |
| **CCLBP_M** | 69.635 | 71.165 | 72.667 | 72.500 |
| **CCLBP_M/C** | 89.007 | 90.904 | 91.774 | 93.500 |
| **CCLBP_S_M/C** | 90.288 | 91.902 | 93.432 | **96.200** |
| **CLBP_S/M** | 81.474 | 84.104 | 85.758 | 88.900 |
| **CLBP_S/M/C** | 91.033 | 92.782 | 94.04 | 96.100 |

**Table 4.2: Results of CCLBP descriptor using KTH-TIPS dataset based on RGB (R=2, P=16).**

| | **Splits= 30** | **Splits= 40** | **Splits= 50** | **Splits= 60** |
|---|---|---|---|---|
| **CLBP_S** | 47.433 | 48.136 | 48.825 | 49.500 |
| **CLBP_M** | 67.049 | 69.346 | 70.903 | 72.371 |
| **CLBP_M/C** | 87.847 | 89.904 | 91.112 | 92.095 |
| **CLBP_S_M/C** | 90.452 | 92.248 | 93.325 | **93.957** |
| **CLBP_S/M** | 85.943 | 88.058 | 89.780 | 90.938 |
| **CLBP_S/M/C** | 90.449 | 91.843 | 92.993 | 93.804 |

**Table 4.3: Results of CCLBP descriptor using KTH-TIPS dataset based on RGB (R=3, P=24).**

| | **Splits= 30** | **Splits= 40** | **Splits= 50** | **Splits= 60** |
|---|---|---|---|---|
| **CLBP_S** | 40.009 | 41.214 | 41.841 | 41.704 |
| **CLBP_M** | 60.176 | 61.660 | 62.58 | 63.623 |
| **CLBP_M/C** | 84.221 | 86.382 | 88.048 | 88.690 |
| **CLBP_S_M/C** | 87.443 | 88.934 | 90.196 | 90.952 |
| **CLBP_S/M** | 81.3568 | 83.734 | 85.535 | 86.461 |
| **CLBP_S/M/C** | 88.396 | 90.0487 | 90.932 | **92.276** |

Tables 4.4, 4.5 and 4.6 show the results of the proposed method using KTH-TIPS 2A dataset using Splits = [100 180 260 340] and values of R = (1, 2, 3) and P = (8, 16, 24). And it shows that the highest percentage is 95.00% when Splits= 340 and values of R=1 and P=8.

**Table 4.4: Results of CCLBP descriptor using KTH-TIPS 2A dataset based on RGB (R=1, P=8).**

| | **Splits= 100** | **Splits= 180** | **Splits= 260** | **Splits=340** |
|---|---|---|---|---|
| **CLBP_S** | 43.587 | 44.341 | 44.767 | 44.904 |
| **CLBP_M** | 54.398 | 56.168 | 57.056 | 57.210 |
| **CLBP_M/C** | 86.295 | 89.947 | 91.659 | 92.935 |
| **CLBP_S_M/C** | 87.860 | 91.226 | 93.004 | 94.019 |
| **CLBP_S/M** | 77.581 | 81.704 | 83.726 | 85.435 |
| **CLBP_S/M/C** | 89.025 | 92.455 | 94.133 | **95.004** |

**Table 4.5: Results of CCLBP descriptor using KTH-TIPS 2A dataset based on RGB (R=2, P=16).**

| | **Splits= 100** | **Splits= 180** | **Splits= 260** | **Splits= 340** |
|---|---|---|---|---|
| **CLBP_S** | 32.199 | 32.817 | 32.812 | 32.682 |
| **CLBP_M** | 52.007 | 54.189 | 55.129 | 55.406 |
| **CLBP_M/C** | 84.279 | 87.875 | 89.933 | 91.006 |
| **CLBP_S_M/C** | 86.502 | 89.856 | 91.589 | 92.864 |
| **CLBP_S/M** | 80.811 | 85.363 | 87.811 | 89.506 |
| **CLBP_S/M/C** | 87.942 | 91.455 | 93.122 | **94.350** |

**Table 4.6: Results of CCLBP descriptor using KTH-TIPS 2A dataset based on RGB (R=3, P=24).**

| | **Splits= 100** | **Splits= 180** | **Splits= 260** | **Splits= 340** |
|---|---|---|---|---|
| **CLBP_S** | 27.780 | 28.447 | 28.823 | 28.633 |
| **CLBP_M** | 47.895 | 49.533 | 50.105 | 50.360 |
| **CLBP_M/C** | 80.999 | 84.952 | 87.206 | 88.745 |
| **CLBP_S_M/C** | 84.286 | 88.011 | 90.105 | 91.296 |
| **CLBP_S/M** | 78.387 | 82.914 | 85.243 | 87.077 |
| **CLBP_S/M/C** | 86.006 | 89.608 | 91.490 | **92.745** |

Tables 4.7, 4.8 and 4.9 show the results of the proposed method using Outex_TC_00013 dataset using Splits = [2 5 7 10 12 15 17 19] and values of R = (1, 2, 3) and P = (8, 16, 24). And it shows that the highest percentage is 79.32% when Splits= 19 and values of R=1 and P=8.

**Table 4.7: Results of CCLBP descriptor using Outex_TC_00013 dataset based on RGB (R=1, P=8).**

| | **Splits = 2** | **Splits = 5** | **Splits = 7** | **Splits = 10** | **Splits = 12** | **Splits = 15** | **Splits = 17** | **Splits = 19** |
|---|---|---|---|---|---|---|---|---|
| **CLBP_S** | 14.264 | 17.042 | 17.624 | 18.752 | 19.003 | 19.644 | 20.177 | 20.165 |
| **CLBP_M** | 23.591 | 27.026 | 28.064 | 30.320 | 30.896 | 31.991 | 32.543 | 32.985 |
| **CLBP_M/C** | 60.568 | 65.600 | 68.505 | 70.944 | 72.366 | 73.129 | 72.984 | 73.838 |
| **CLBP_S_M/C** | 64.347 | 66.480 | 70.452 | 72.195 | 73.913 | 74.373 | 74.561 | 74.632 |
| **CLBP_S/M** | 52.943 | 58.263 | 62.911 | 64.847 | 67.052 | 67.902 | 69.875 | 70.000 |
| **CLBP_S/M/C** | 65.638 | 67.514 | 72.095 | 73.264 | 74.355 | 74.941 | 78.526 | **79.321** |

**Table 4.8: Results of CCLBP descriptor using Outex_TC_00013 dataset based on RGB (R=2, P=16).**

| | **Splits = 2** | **Splits = 5** | **Splits = 7** | **Splits = 10** | **Splits = 12** | **Splits = 15** | **Splits = 17** | **Splits = 19** |
|---|---|---|---|---|---|---|---|---|
| **CLBP_S** | 14.625 | 18.357 | 17.513 | 18.827 | 18.991 | 19.783 | 20.652 | 21.579 |
| **CLBP_M** | 20.557 | 27.238 | 27.953 | 30.468 | 30.997 | 30.880 | 33.467 | 33.306 |
| **CLBP_M/C** | 61.018 | 66.366 | 67.494 | 71.290 | 71.259 | 72.018 | 72.504 | 72.566 |
| **CLBP_S_M/C** | 62.907 | 67.159 | 69.341 | 73.361 | 72.802 | 73.268 | 73.450 | 73.450 |
| **CLBP_S/M** | 51.443 | 57.058 | 60.400 | 63.736 | 66.941 | 66.891 | 68.764 | 79.499 |
| **CLBP_S/M/C** | 61.582 | 69.351 | 71.865 | 74.031 | 75.174 | 76.062 | 76.621 | **77.460** |

**Table 4.9: Results of CCLBP descriptor using Outex_TC_00013 dataset based on RGB (R=3, P=24).**

| | **Splits = 2** | **Splits = 5** | **Splits = 7** | **Splits = 10** | **Splits = 12** | **Splits = 15** | **Splits = 17** | **Splits = 19** |
|---|---|---|---|---|---|---|---|---|
| **CLBP_S** | 13.763 | 17.825 | 16.687 | 17.999 | 18.068 | 20.168 | 20.544 | 20.751 |
| **CLBP_M** | 18.828 | 25.357 | 26.681 | 29.862 | 30.596 | 29.473 | 32.811 | 33.772 |
| **CLBP_M/C** | 60.900 | 65.982 | 66.682 | 70.746 | 70.679 | 71.876 | 71.997 | 71.896 |
| **CLBP_S_M/C** | 60.836 | 66.645 | 68.156 | 72.952 | 71.862 | 72.877 | 72.439 | 73.009 |
| **CLBP_S/M** | 50.262 | 55.830 | 59.573 | 62.822 | 65.637 | 65.919 | 67.354 | 70.355 |
| **CLBP_S/M/C** | 60.980 | 68.333 | 70.915 | 72.840 | 73.823 | 74.714 | 75.424 | **75.630** |

## 4.3 Experimental results of HSV CCLBP descriptor

### 4.3.1 Implementation

After reading all the images from the datasets, figure 4.3 shows the method of converting the images into HSV colour space by converting the images from RGB to HSV. Then, histogram of CLBP_S, CLBP_M and CLBP_C will be generated. After that, Splits method in MATLAB will get the picture ID and class ID of the training and test samples as same step in 4.2.1. Finally, classification process will be done by classification test using CLBP_S, CLBP_M and CLBP_C and combining them together.

```
for i=1:ClassNum;
    ims = dir(fullfile(rootpic, classes{i}, '*.png'))' ;
    ims = cellfun(@(x)fullfile(classes{i},x),{ims.name},'UniformOutput',false) ;
    for j=1:length(ims)
        filename = sprintf('%s%s',rootpic,ims{j})
            picCount = picCount+1;
            RGB = imread(filename);
            if size(RGB,3) == 1, RGB = cat(3, RGB, RGB, RGB) ; end

            HSV = rgb2hsv(RGB);
```

Figure 4.3: Converting the images to HSV colour space.

### 4.3.2 Results

Tables 4.10, 4.11 and 4.12 shows the results of the proposed method using KTH-TIPS dataset using Splits = [30 40 50 60] and values of R = (1, 2, 3) and P = (8, 16, 24). And it shows that the highest percentage is 97.95% when Splits= 60 and values of R=2 and P=16.

**Table 4.10: Results of CCLBP descriptor using KTH-TIPS dataset based on HSV (R=1, P=8).**

| | **Splits= 30** | **Splits= 40** | **Splits= 50** | **Splits= 60** |
|---|---|---|---|---|
| **CCLBP_S** | 54.074 | 54.870 | 55.016 | 55.828 |
| **CCLBP_M** | 56.727 | 57.892 | 58.932 | 59.247 |
| **CCLBP_M/C** | 93.615 | 94.719 | 95.783 | 96.276 |
| **CCLBP_S_M/C** | 93.694 | 94.841 | 95.461 | 96.061 |
| **CLBP_S/M** | 88.233 | 90.090 | 91.432 | 92.295 |
| **CLBP_S/M/C** | 94.456 | 95.560 | 96.364 | **96.790** |

**Table 4.11: Results of CCLBP descriptor using KTH-TIPS dataset based on HSV (R=2, P=16).**

| | Splits= 30 | Splits= 40 | Splits= 50 | Splits= 60 |
|---|---|---|---|---|
| **CCLBP_S** | 36.794 | 37.217 | 37.332 | 37.004 |
| **CCLBP_M** | 48.480 | 50.239 | 51.293 | 52.204 |
| **CCLBP_M/C** | 94.013 | 95.192 | 95.667 | 96.152 |
| **CCLBP_S_M/C** | 94.221 | 95.439 | 96.454 | 96.728 |
| **CLBP_S/M** | 91.001 | 92.831 | 94.170 | 94.876 |
| **CLBP_S/M/C** | 95.717 | 96.743 | 97.541 | **97.947** |

**Table 4.12: Results of CCLBP descriptor using KTH-TIPS dataset based on HSV (R=3, P=24).**

| | Splits= 30 | Splits= 40 | Splits= 50 | Splits= 60 |
|---|---|---|---|---|
| **CCLBP_S** | 34.258 | 34.363 | 34.196 | 34.214 |
| **CCLBP_M** | 47.709 | 49.063 | 50.619 | 51.204 |
| **CCLBP_M/C** | 92.211 | 93.695 | 94.603 | 95.123 |
| **CCLBP_S_M/C** | 92.741 | 94.497 | 95.087 | 95.909 |
| **CLBP_S/M** | 88.252 | 89.563 | 91.048 | 91.528 |
| **CLBP_S/M/C** | 93.968 | 95.192 | 96.070 | **96.576** |

Tables 4.13, 4.14 and 4.15 shows the results of the proposed method using KTH-TIPS 2A dataset using Splits = [100 180 260 340] and values of R = (1, 2, 3) and P = (8, 16, 24). And it shows that the highest percentage is 97.37% when Splits= 340 and values of R=3 and P=24.

**Table 4.13: Results of CCLBP descriptor using KTH-TIPS 2A dataset based on HSV (R=1, P=8).**

| | Splits= 100 | Splits= 180 | Splits= 260 | Splits= 340 |
|---|---|---|---|---|
| **CCLBP_S** | 53.309 | 53.905 | 54.450 | 55.159 |
| **CCLBP_M** | 55.063 | 56.098 | 58.076 | 58.579 |
| **CCLBP_M/C** | 92.948 | 93.069 | 95.207 | 95.609 |
| **CCLBP_S_M/C** | 92.928 | 93.095 | 94.906 | 95.394 |
| **CLBP_S/M** | 87.787 | 89.407 | 90.876 | 91.608 |
| **CLBP_S/M/C** | 93.620 | 95.383 | 95.851 | **96.074** |

**Table 4.14: Results of CCLBP descriptor using KTH-TIPS 2A dataset based on HSV (R=2, P=16).**

| | Splits= 100 | Splits= 180 | Splits= 260 | Splits= 340 |
|---|---|---|---|---|
| **CCLBP_S** | 53.642 | 54.268 | 54.783 | 55.390 |
| **CCLBP_M** | 55.396 | 56.500 | 58.409 | 58.912 |
| **CCLBP_M/C** | 93.282 | 93.402 | 95.560 | 95.942 |
| **CCLBP_S_M/C** | 93.261 | 93.428 | 95.239 | 95.727 |
| **CLBP_S/M** | 88.199 | 89.740 | 91.209 | 91.941 |
| **CLBP_S/M/C** | 93.411 | 95.788 | 97.144 | **97.302** |

**Table 4.15: Results of CCLBP descriptor using KTH-TIPS 2A dataset based on HSV (R=3, P=24).**

| | Splits= 100 | Splits= 180 | Splits= 260 | Splits= 340 |
|---|---|---|---|---|
| **CCLBP_S** | 53.420 | 53.035 | 54.450 | 55.053 |
| **CCLBP_M** | 55.174 | 55.000 | 58.136 | 58.531 |
| **CCLBP_M/C** | 93.060 | 93.000 | 95.203 | 95.601 |
| **CCLBP_S_M/C** | 93.030 | 93.005 | 94.106 | 95.314 |
| **CLBP_S/M** | 87.077 | 89.500 | 90.436 | 91.602 |
| **CLBP_S/M/C** | 92.934 | 96.210 | 96.954 | **97.368** |

Tables 4.16, 4.17 and 4.18 shows the results of the proposed method using Outex_TC_00013 dataset using Splits = [2 5 7 10 12 15 17 19] and values of R = (1, 2, 3) and P = (8, 16, 24). And it shows that the highest percentage is 78.91% when Splits= 19 and values of R=3 and P=24.

**Table 4.16: Results of CCLBP descriptor using Outex_TC_00013 dataset based on HSV (R=1, P=8).**

| | **Splits = 2** | **Splits = 5** | **Splits = 7** | **Splits = 10** | **Splits = 12** | **Splits = 15** | **Splits = 17** | **Splits = 19** |
|---|---|---|---|---|---|---|---|---|
| **CLBP_S** | 15.698 | 18.365 | 18.466 | 19.147 | 20.951 | 20.153 | 21.488 | 21.904 |
| **CLBP_M** | 24.983 | 28.364 | 29.990 | 31.333 | 31.369 | 32.157 | 33.366 | 35.311 |
| **CLBP_M/C** | 60.963 | 66.324 | 69.347 | 71.982 | 73.852 | 74.953 | 73.458 | 74.189 |
| **CLBP_S_M/C** | 61.983 | 67.638 | 71.955 | 73.697 | 74.741 | 75.513 | 75.698 | 75.325 |
| **CLBP_S/M** | 50.862 | 59.225 | 70.344 | 65.669 | 68.963 | 68.624 | 70.551 | 71.934 |
| **CLBP_S/M/C** | 58.744 | 69.200 | 72.701 | 75.480 | 76.865 | 77.752 | 78.844 | **78.790** |

**Table 4.17: Results of CCLBP descriptor using Outex_TC_00013 dataset based on HSV (R=2, P=16).**

| | **Splits = 2** | **Splits = 5** | **Splits = 7** | **Splits = 10** | **Splits = 12** | **Splits = 15** | **Splits = 17** | **Splits = 19** |
|---|---|---|---|---|---|---|---|---|
| **CLBP_S** | 14.888 | 17.090 | 17.753 | 18.547 | 18.805 | 18.679 | 18.950 | 18.602 |
| **CLBP_M** | 17.544 | 20.873 | 22.042 | 23.182 | 23.737 | 24.600 | 24.941 | 24.926 |
| **CLBP_M/C** | 59.087 | 69.087 | 71.950 | 74.485 | 75.772 | 76.935 | 77.156 | 77.764 |
| **CLBP_S_M/C** | 59.638 | 70.154 | 73.049 | 75.680 | 76.485 | 77.814 | 77.789 | **78.897** |
| **CLBP_S/M** | 51.517 | 63.083 | 67.022 | 70.310 | 72.130 | 73.876 | 74.750 | 75.926 |
| **CLBP_S/M/C** | 58.017 | 69.283 | 72.354 | 74.845 | 76.279 | 77.382 | 77.514 | 78.529 |

**Table 4.18: Results of CCLBP descriptor using Outex_TC_00013 dataset based on HSV (R=3, P=24).**

| | **Splits = 2** | **Splits = 5** | **Splits = 7** | **Splits = 10** | **Splits = 12** | **Splits = 15** | **Splits = 17** | **Splits = 19** |
|---|---|---|---|---|---|---|---|---|
| **CLBP_S** | 11.112 | 12.442 | 12.714 | 12.923 | 13.064 | 13.097 | 13.318 | 13.029 |
| **CLBP_M** | 18.598 | 22.298 | 23.736 | 25.135 | 25.770 | 27.108 | 27.343 | 28.323 |
| **CLBP_M/C** | 60.133 | 69.676 | 72.414 | 74.670 | 76.128 | 76.820 | 77.421 | 77.411 |
| **CLBP_S_M/C** | 60.702 | 70.527 | 73.522 | 75.519 | 76.584 | 77.441 | 78.112 | 78.455 |
| **CLBP_S/M** | 52.357 | 64.082 | 67.995 | 71.554 | 72.810 | 74.917 | 76.387 | 76.897 |
| **CLBP_S/M/C** | 59.649 | 69.656 | 72.760 | 75.383 | 76.477 | 77.858 | 78.519 | **78.911** |

## 4.4 Summary

To sum up, the proposed method in this research (CCLBP) has shown good results for KTH-TIPS and KTH-TIPS 2A datasets while for Outex_TC_00013 dataset the results was not satisfying. Furthermore, HSV colour space has better results than RGB colour space. So, it can be said that the proposed method is good in term of colour texture images classification, but in term of some datasets it needs to be improved. Table 4.19 shows summary of the highest classification, (for all values of R and P, for all datasets used and for all colour spaces that have been used), for all descriptors.

**Table 4.19: Summary of the highest classification, (for all values of R and P, for all datasets used and for all colour spaces that have been used), for all descriptors.**

| | RGB Colour Space | | | | | | | | | HSV Colour Space | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | KTH-TIPS | | | KTH-TIPS2A | | | Outex_TC00013 | | | KTH-TIPS | | | KTH-TIPS2A | | | Outex_TC00013 | | |
| | R1, P8 | R2, P16 | R3, P24 | R1, P8 | R2, P16 | R3, P24 | R1, P8 | R2, P16 | R3, P24 | R1, P8 | R2, P16 | R3, P24 | R1, P8 | R2, P16 | R3, P24 | R1, P8 | R2, P16 | R3, P24 |
| CCLBP_S | 60.1 | 49.5 | 41.7 | 44.9 | 32.8 | 28.6 | 20.2 | 19.1 | 17.8 | 55.8 | 37.0 | 34.2 | 44.5 | 38.2 | 31.9 | 15.3 | 18.6 | 13.0 |
| CCLBP_M | 72.5 | 72.4 | 63.6 | 57.2 | 55.4 | 50.4 | 33.0 | 31.4 | 29.4 | 59.2 | 52.2 | 51.2 | 54.9 | 50.0 | 52.4 | 27.9 | 24.9 | 28.3 |
| CCLBP_M/C | 93.5 | 92.1 | 88.7 | 92.9 | 91.0 | 88.7 | 73.8 | 71.2 | 69.6 | 96.3 | 96.2 | 95.1 | 95.9 | 95.4 | 93.2 | 76.7 | 77.8 | 77.4 |
| CCLBP_S_M/C | **96.2** | 94.0 | 91.0 | 94.0 | 92.9 | 91.3 | 74.6 | 72.8 | 70.0 | 96.1 | 96.7 | 95.9 | 95.6 | 96.1 | 95.0 | 78.6 | 78.9 | 78.5 |
| CCLBP_S/M | 88.9 | 90.9 | 86.5 | 85.4 | 89.5 | 87.1 | 70.0 | 68.5 | 66.3 | 92.3 | 94.9 | 92.2 | 91.7 | 95.6 | 90.7 | 76.7 | 75.9 | 76.9 |
| CCLBP_S/M/C | 96.1 | 93.8 | 92.3 | **95.0** | 94.4 | 92.7 | **79.3** | 77.0 | 75.1 | 96.8 | **97.9** | 96.6 | 91.1 | 97.3 | **97.4** | 78.8 | 78.5 | **78.9** |

# CHAPTER 5

# CONCLUSION

## 5.1 Introduction

This chapter is about the summary of overall system research which is about Colour Texture Image Classification system using Colour Completed Local Binary Pattern (CCLBP) method.

## 5.2 Overall System Research Summarization

Texture features are spirited in many applications such as face recognition, finger detection, human detectors, object recognition and image retrieval. In addition, many of textures feature algorithms were identified by pervious literature for robust and distinctive texture features. The classification of the texture feature algorithm methods is categorised into three categories which are model-based method, statistical method and structural method.

This project is a research-based project that used three different datasets to obtain the images which are KTH-TIPS, KTH-TIPS 2A and Outex_TC_00013 datasets. From each dataset images are taken for training process and testing process.

The Colour Texture Image Classification system uses Colour Completed Local Binary Pattern (CCLBP) method based on two colour space which are RGB colour space and HSV colour space for the classification process. Histogram is been generated for CLBP_S, CLBP_M and CLBP_C. Then, classification process is done by using these operators and combining them together.

The implementation has been done by using MATLAB software. The performance has been tested correctly and the objective is accepted.

## 5.3 Research Constraints/Limitations

During the research phase, there are some constraints/limitations occurred, which are:

- Image quality limitation: image quality affects the result of the classification. For example, texture features extraction process is difficult when it comes to use unclear images.

- Time limitation: it requires a lot of times to get perfect research. For people who are doing researches the limitation of time is one of the worst problems. Because, the work needed to be done as it stated in the timeline.

- Ideas limitation: lack of ideas is treated as a difficulty in completing this research, it is a major problem. But, for researchers who need to do researches in the right timeframe this research may help. Extra studies are needed to enhance the system for future work.

## 5.4 Future Work

Future work of this project can be done by using different types of colour spaces. Moreover, it can be done by using different method for the classification instead of CLBP method.

## 5.5 Summary

Even with the limitations occurred the Colour Texture Image Classification Using Colour Completed Local Binary Pattern (CCLBP) method is successfully completed. More studies are needed to be explored for better results.

# REFERENCES

García-Olalla, O., Alegre, E., Barreiro, J., Fernández-Robles, L., & García-Ordás, M. T. (2015). Tool Wear Classification Using LBP-based Descriptors Combined with LOSIB-based Enhancers. *Procedia Engineering*, *132*, 950–957. https://doi.org/10.1016/j.proeng.2015.12.582

Guo, Z., Zhang, L., & Zhang, D. (2010). A Completed Modeling of Local Binary Pattern. *IEEE Transaction on Image Processing*, *19*(6), 1657–1663. https://doi.org/10.1109/TIP.2010.2044957

Kalakech, M., Porebski, A., Vandenbroucke, N., & Hamad, D. (2018). Unsupervised Local Binary Pattern Histogram Selection Scores for Color Texture Classification. *Journal of Imaging*, *4*(10), 112. https://doi.org/10.3390/jimaging4100112

Kalluri, H. K., & Prasad, M. V. N. K. (2016). Palmprint Identification Using Gabor and Wide Principal Line Features. *Procedia Computer Science*, *93*(September), 706–712. https://doi.org/10.1016/j.procs.2016.07.272

Lan, R., & Zhou, Y. (2016). Quaternion-Michelson Descriptor for Color Image Classification. *IEEE Transactions on Image Processing*, *25*(11), 5281–5292. https://doi.org/10.1109/TIP.2016.2605922

Liu, L., Chen, J., Fieguth, P., Zhao, G., Chellappa, R., & Pietikäinen, M. (2019). From BoW to CNN: Two Decades of Texture Representation for Texture Classification. *International Journal of Computer Vision*, *127*(1), 74–109. https://doi.org/10.1007/s11263-018-1125-z

Park, W., Pak, S., Shim, H., Le, H. A. N., Im, M., Chang, S., & Yu, J. (2016). Photometric transformation from RGB Bayer filter system to Johnson–Cousins BVR filter system. *Advances in Space Research*, *57*(1), 509–518. https://doi.org/10.1016/j.asr.2015.08.004

Phakade, S. V, Flora, D., Malashree, H., & Rashmi, J. (2014). *Automatic Fruit Defect Detection Using HSV and RGB Color Space Model*. (3), 67–73.

Rassem, T. H., Mohammed, M. F., Khoo, B. E., & Makbol, N. M. (2015). Performance evaluation of Completed Local Ternary Patterns (CLTP) for medical, scene and event image categorisation. *2015 4th International Conference on Software Engineering and Computer Systems, ICSECS 2015: Virtuous Software Solutions for Big Data*, 33–38. https://doi.org/10.1109/ICSECS.2015.7333119

Zhao, Y., Jia, W., Hu, R. X., & Min, H. (2013). Completed robust local binary pattern for texture classification. *Neurocomputing*, *106*, 68–76. https://doi.org/10.1016/j.neucom.2012.10.017

Ojala, T., Pietikäinen, M., & Harwood, D. (1996). A comparative study of texture measures with classification based on featured distributions. *Pattern recognition*, *29*(1), 51-59.

Tan, X., & Triggs, B. (2010). Enhanced local texture feature sets for face recognition under difficult lighting conditions. *Image Processing, IEEE Transactions on*, *19*(6), 1635-1650.

Guo, Z., Zhang, L., & Zhang, D. (2010). A completed modelling of local binary pattern operator for texture classification. *Image Processing*, *IEEE Transactions on*, *19*(6), 1657-1663.

Ahsan, Tanveer, Rifat Shahriar, and Uipil Chong. (2013). Application of Completed Local Binary Pattern for Facial Expression Recognition on Gabor Filtered Facial Images. *International Journal of Digital Content Technology and its Applications* 7.12.2013: 88.

Rassem, T. H., Mohammed, M. F., Khoo, B. E., & Makbol, N. M. (2015, August). Performance evaluation of Completed Local Ternary Patterns (CLTP) for medical, scene and event image categorisation. In *Software Engineering and Computer Systems (ICSECS), 2015 4th International Conference on* (pp. 33-38), 2015.

Rassem, T. H., & Khoo, B. E. (2014). Completed local ternary pattern for rotation invariant texture classification. *The Scientific World Journal*, *2014*.

Li, L., Fieguth, P. W., & Kuang, G. (2011). Generalized Local Binary Patterns for Texture Classification. In *BMVC* (pp. 1-11).

Raja, G. M., & Sadasivam, V. (2013). Optimized local ternary patterns: A new texture model with set of optimal patterns for texture analysis. *Journal of Computer Science*, *9*(1), 1.

Shrivastava, N., & Tyagi, V. (2014). An effective scheme for image texture classification based on binary local structure pattern. *The Visual Computer*,*30*(11), 1223-1232.

Reddy, K. S., Kumar, V. V., & Reddy, B. E. (2015). Face Recognition Based on Texture Features using Local Ternary Patterns. *International Journal of Image, Graphics and Signal Processing (IJIGSP)*, *7*(10), 37.

Ojala, T., Pietikäinen, M., & Mäenpää, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, *24*(7), 971-987.

Ahmed, F., Hossain, E., Bari, A. S. M. H., & Shihavuddin, A. S. M. (2011, November). Compound local binary pattern (CLBP) for robust facial expression recognition.

In *Computational Intelligence and Informatics (CINTI), 2011 IEEE 12th International Symposium on* (pp. 391-395). IEEE.

Faudzi, S. A. A. M., & Yahya, N. (2014, June). Evaluation of LBP-based face recognition techniques. In *Intelligent and Advanced Systems (ICIAS), 2014 5th International Conference on* (pp. 1-6). IEEE.