

**COMPUTER AIDED SYSTEM FOR DENDRITIC CELLS DETECTION AND
COUNTING**

ANIS AZWANI BINTI MUHD SUBERI

**A thesis submitted in
fulfillment of the requirement for the award of the
Degree of Master of Electrical Engineering**

**Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia**

May, 2017

DEDICATION

For my beloved mother and father,

My supervisor,

Lecturers,

Sisters,

Best friends,

Friends,

**And everyone who involved in inspired me throughout my journey of
completing this project.**



PTTA UTHM
PERPUSTAKAAN TUNKU TUN AMINAH

ACKNOWLEDGEMENT

I would like to thank my advisor, Dr. Wan Nurshazwani binti Wan Zakaria, for all the guidance and encouragement she provided me since the very beginning of my graduate program. Her invaluable suggestions and expertise in the field have helped me immensely in attaining the goals I set out to achieve with my research. I am also very grateful to my committee member, Dr. Mohd Razali bin Md Tomari for being so supportive and giving me important feedback over the course of this thesis. I am deeply indebted to Nicolas Jaccard and Marko Usaj from University College London (UCL) and University of Ljubljana, Slovenia respectively for taking time off their busy schedules to help with my research. Their inputs on the identification of various cells in the data set have helped in shaping a lot of my research work. I would also like to thank the members of the Cancer Research Malaysia (CRM) especially Dr Lim Kue Peng and Ms. San Jiun for providing the sample images of Dendritic Cells and clear explanation on the culturing process. Finally, I would like to thank my parents and my friends for all the smiles along the way that made the many months of my research a lot more pleasant and enjoyable.

This research was supported by the Fundamental Research Grant (FRGS) under Ministry of Education Malaysia (Vot 1583).

ABSTRACT

Immunotherapy is an entirely advanced class of cancer treatment which has been highly active and exciting field in clinical therapeutics. In numerous procedures, cancer immunotherapy demands a laborious practice to recognise and count Dendritic Cells (DCs) in the harnessing of immune system. Conventionally, the laser-based technology that provides a rapid analysis such as Flow Cytometry can affect the DCs viability as the staining procedure is involved. Another highly promising method which is Phase Contrast Microscopy (PCM) involves experienced pathologists to visually examine the respective microscopy images. In fact, PCM confronts complex issues regarding imaging artifacts which can deteriorate the recognition process. As DCs counting are crucial in most cancer treatment procedures, this research proposes a pioneering system called CasDC (Computer Aided System for Dendritic Cells identification) which implements an image processing algorithm to recognise and count DCs with a label-free method. Initially, the images undergo Grayscale Normalization, H-GLAT, and Halo Removal to remove the imaging artifacts. In segmentation, morphological operators and Canny edge detector are implemented to extract the cell contours. Following that, information from the contours are characterized through the use of One-Dimensional (1D) Fourier Descriptors (FDs) and classified using Template Matching (TM). The aim of developing this system is to establish a reliable and time saving-tool as a second reader in the clinical practice. The proposed system has an enormous potential towards helping Cancer Research Institute in improving the diagnosis of cancer. Through the experiments conducted on dataset provided by the Cancer Research Institute, performance measures of 83.8%, 94.2%, 99.5% and 88.7% have been recorded for precision, recall, accuracy and F1-score respectively .

ABSTRAK

Imunoterapi adalah satu kelas rawatan kanser maju di mana menjadi bidang yang sangat aktif dan menarik dalam terapi klinikal. Dalam pelbagai prosedur, kanser imunoterapi menuntut amalan yang membebankan untuk mengenal pasti dan mengira sel-sel dendrit (DC) dalam memanfaatkan sistem imun. Secara konvensional, teknologi berasaskan laser yang mampu menyediakan analisis yang pantas seperti sitometri aliran boleh menjejaskan daya ketahanan DC disebabkan oleh penglibatan prosedur pewarnaan. Satu lagi kaedah yang mendapat perhatian iaitu mikroskop kontras fasa (PCM) melibatkan ahli patologi yang berpengalaman untuk mengkaji imej mikroskop masing-masing. Malah, PCM menghadapi isu-isu yang kompleks berkenaan artifak pengimejan yang boleh menjejaskan proses pengenalpastian. Oleh kerana pengiraan DC ini mempunyai peranan yang besar dalam kebanyakan prosedur rawatan kanser, penyelidikan ini mencadangkan satu sistem perintis dipanggil CasDC (sistem berbantuan komputer untuk pengecaman sel-sel dendrit) yang dapat melaksanakan algoritma pemrosesan imej untuk mengenal pasti dan mengira DC dengan kaedah bebas pewarnaan. Pada peringkat awal, imej menjalani normalisasi skala kelabu, H-GLAT, dan penyingkiran halo untuk membuang artifak di dalam imej. Dalam segmentasi, operator morfologi dan pengesanan *Canny* dilaksanakan untuk mendapatkan kontur sel. Berikutan itu, maklumat daripada kontur dicirikan melalui penggunaan satu dimensi (1D) deskriptor *Fourier* dan diklasifikasikan dengan menggunakan penyesuaian templat. Tujuan sistem ini dibangunkan adalah untuk menghasilkan alat yang berkebolehan dan menjimatkan masa sebagai bantuan kedua dalam amalan klinikal. Sistem yang dicadangkan ini mempunyai potensi yang besar ke arah membantu Institut Penyelidikan Kanser dalam meningkatkan diagnosis kanser. Melalui eksperimen yang berkaitan dengan set data yang disediakan oleh Institut Penyelidikan Kanser, ukuran prestasi telah direkodkan dengan masing-masing mencatat 83.8%, 94.2%, 99.5% dan 88.7% untuk kepersisan, kepekaan, kejituan dan skor-F1.

TABLE OF CONTENTS

DECLARATION	ii
DEDICATION	iii
ACKNOWLEDGEMENT	iv
ABSTRACT	v
ABSTRAK	vi
TABLE OF CONTENTS	vii
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF SYMBOLS AND ABBREVIATIONS	xiv
LIST OF APPENDICES	xv
LIST OF PUBLICATIONS	xvi
LIST OF AWARDS	xvii
CHAPTER 1 INTRODUCTION	1
1.1 Problem Statement	3
1.2 Aim	4
1.3 Objectives	4
1.4 Scopes and Limitations	5
1.5 Research Contributions	5
1.6 Summary	7

CHAPTER 2 LITERATURE REVIEW	8
2.1 Introduction to Immune Cell Subsets	8
2.2 The Significance of Identification of Dendritic Cells (DCs)	11
2.3 Dendritic Cells (DCs) Culture and Imaging	11
2.3.1 Commercial System for Dendritic Cells (DCs) Classifier	15
2.4 Current Technology in Cell Identification for PCM Image	17
2.4.1 Image Preprocessing and Segmentation in PCM Imaging	18
2.4.2 Feature Extraction	25
2.4.3 Classification	28
2.5 Limitation of Existing Work and Research Opportunities	29
2.6 Summary	31
CHAPTER 3 RESEARCH METHODOLOGY	32
3.1 Image Acquisition (Cell Imaging)	33
3.2 Grayscale Normalization	35
3.3 Pre-processing Stage	35
3.3.1 Local Contrast Threshold (LCT) and Halo Removal	37
3.3.2 H-GUILAT and Halo Removal	39
3.3.3 H-GLAT and Halo Removal	41
3.4 Segmentation Stage	42
3.4.1 Morphological Operators	43
3.4.2 Canny Edge Segmentation	43
3.5 Feature Extraction	44
3.5.1 Main Feature of Dendritic Cells (DCs)	44
3.5.2 One Dimensional (1D) Fourier Descriptors (FDs)	46
3.6 DCs Classification	48

3.7	Graphical User Interface (GUI)	49
3.8	Image Processing Performance Measures	51
3.8.1	Quantitative Analysis	51
3.8.2	Qualitative Analysis	53
3.9	Feasibility Study	53
3.9.1	Statistical Analysis	54
3.10	Summary	55

CHAPTER 4 RESULT AND ANALYSIS 58

4.1	Preliminary Result and Analysis	58
4.1.1	Grayscale Normalization	58
4.1.2	Pre-processing Stage	59
4.1.3	Segmentation Stage	66
4.1.4	Evaluation of Pre-processing and Segmentation Performances	66
4.1.5	Feature Extraction	68
4.1.6	DCs Classification	72
4.2	Experimental Result and Analysis	79
4.2.1	Image Pre-processing, Cells Segmentation and DCs Classification	80
4.2.2	CasDC System Performance	83
4.3	Summary	88

CHAPTER 5 CONCLUSION AND RECOMMENDATION 89

5.1	Overview	89
5.2	Achievements	89
5.3	Recommendation	91

REFERENCES 93

APPENDICES 101

VITAE 109

LIST OF TABLES

2.1	WBCs specification	9
2.2	Type of microscopy in DCs visualisation	13
2.3	Correlation of texture features	27
2.4	Previous methods applied to solve PCM imaging artifacts	30
2.5	Previous works method in feature extraction and classification	31
3.1	CasDC modules and settings	49
3.2	Manual counting in 100X magnification (Day 4)	53
3.3	Summary of group variances between two pathologists	54
3.4	One-way ANOVA analysis between two pathologists	54
3.5	Types of performance measure used to evaluate the developed method	57
4.1	Comparative performances of parametric setting in sigma, σ	61
4.2	Qualitative results of MAE on three proposed frameworks in pre-processing and segmentation stage	67
4.3	Comparison between proposed pre-processing method	68
4.4	Cell classification according to calculated parameters	69
4.5	Classification of DCs based on TM dissimilarity	72
4.6	Comparison results for the automatic detection of DCs with manual results (100X magnification)	76
4.7	Comparison results for the automatic detection of DCs with manual results (200X magnification)	77
4.8	Performance results of CasDC system	78
4.9	Performance results of DCs classification	83

LIST OF FIGURES

1.1	DCs immunotherapy procedure	1
1.2	Component of immune cells in human blood system	2
1.3	Overall research methods and contributions	6
2.1	Types of blood smear under Light Microscope	8
2.2	Differentiation of Monocytes	9
2.3	Morphology states of DCs	10
2.4	DCs cultivated through several passages	12
2.5	Process in Flow Cytometry	14
2.6	Basic cell imaging steps for systems and software	15
2.7	Cell size histogram in blood smear	16
2.8	Example of Cellometer system output	16
2.9	Current trend on PCM image processing	17
2.10	Basic stages in PCM image processing	17
2.11	Imaging artifacts in PCM image	18
2.12	Application of Histogram Equalization	19
2.13	Results in: (a) Image Reconstruction and (b) Semi-Supervised Clustering	20
2.14	Results of Gaussian Kernel Filtering method	21
2.15	Application of Active Contour method in PCM image	21
2.16	Comparison of PCM cell segmentation in overlapping condition	22
2.17	Segmentation result of K-means method	23
2.18	Threshold segmentation result using intensity profile curve	24
2.19	Result of Halo Removal method in PCM image	24
2.20	The procedure of cell features analysis	25
2.21	Canny edge and Gabor Filter in microscopy image	28
3.1	Image processing framework for DCs recognition	32

3.2	DCs counting workflow using Template Matching based on 1D Fourier Descriptors (FDs)	33
3.3	DCs imaging under PCM	34
3.4	Process of DCs culture from PBMC samples	35
3.5	Proposed pre-processing methods	36
3.6	Cell region surrounded by bright halo ring	38
3.7	Edge detection compass mask	38
3.8	Comparison between Global and Local Adaptive Threshold	40
3.9	H-GLAT and Halo Removal workflow	42
3.10	Segmentation methods to isolate cell shape	42
3.11	Proposed morphological operators	43
3.12	Sample of DCs image	45
3.13	Geometric features of each measured cell	46
3.14	a) Translation b) Scaling and c) Orientation invariances	47
3.15	General concept of Template Matching (TM) method	48
3.16	CasDC: DCs recognition and counting GUI	50
3.17	Result of batch mode	50
3.18	Evaluation measures of proposed framework	51
3.19	Correlation between two pathologists counting	55
3.20	Proposed framework in image processing part	56
4.1	Test output of grayscale normalization stage	59
4.2	Test output in profile intensity	60
4.3	MAE with standard deviation of 27.3%, 7.6% and 3.2% for $\sigma = 0.8, 1.0$ and 1.2 respectively	61
4.4	Test output in a) Halo Removal and b) Cell outline	62
4.5	Types of kernel in Halo Removal	62
4.6	Proposed pre-processing framework using a) LCT and b) Halo Removal	63
4.7	Results of H-GUILAT implementation in pre-processing stage	64
4.8	Halo Removal	64
4.9	Gaussian filtering	65
4.10	Local Adaptive Threshold applied on a) Low sigma b) High sigma and c) Logical operator AND	65
4.11	Halo Removal output	65

4.12	Test output in segmentation stage	66
4.13	Quantitative of cell segmentation error with standard deviations reading for each proposed framework	67
4.14	Scatter plot between circularity and area from T-cells, debris and DCs	69
4.15	Scatter plot between a) area/perimeter ratio and FDs b) moment invariant and FDs	70
4.16	Extraction of shape signatures in templates	71
4.17	Test output of DCs recognition	72
4.18	10 templates of DCs	73
4.19	Correlation between manual and automated counts using different types of template	74
4.20	Counting performance in function of the local window size (w) for different combination of image magnification of 100X and 200X	75
4.21	System performance for the first image data-set	79
4.22	Example of second image data set	80
4.23	Result of image processing stages	81
4.24	Result of image processing stages	82
4.25	Comparison result for CasDC and manual	84
4.26	Complex overlapping constraint in clumps cells region	85
4.27	Multiple counting occur on DCs region	86
4.28	Images with different light environments with imaging artifacts	87
4.29	Correlation between manual counts and CasDC	88

LIST OF SYMBOLS AND ABBREVIATIONS

μ	-	Mean around each pixel
σ^2	-	Variance around each pixel
M	-	Number of rows of pixel in image
N	-	Number of columns of pixel in image
Σ	-	Sigma
η	-	N by M local neighborhood of each pixel in image
ϵ	-	Epsilon
θ	-	Theta
\oplus	-	\bigoplus
A_{tc}	-	Area of T-cell
A_{db}	-	Area debris
A_{mc}	-	Area of Monocyte cell
A_{dc}	-	Area of Dendritic Cell
P_{tc}	-	Perimeter of T-cell
P_{db}	-	Perimeter of debris
P_{mc}	-	Perimeter of Monocyte cell
P_{dc}	-	Perimeter of Dendritic Cell
D_{tc}	-	Diameter of T-cell
D_{db}	-	Diameter of debris
D_{mc}	-	Diameter of Monocyte
D_{dc}	-	Diameter of Dendritic Cell

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A	Gantt chart planning for Semester 1-3	101
B	Threshold test output in Local Adaptive method	102
C1	Example of DCs classification in CasDC	103
C2	Example of DCs classification in CasDC (continued)	104
C3	Example of DCs classification in CasDC (continued)	105
D1	System performance in second image dataset	106
D2	System performance in second image dataset (continued)	107
D3	System performance in second image dataset (continued)	108



LIST OF PUBLICATIONS

1. **Anis Azwani Muhd Suberi; Wan Nurshazwani Wan Zakaria; Razali Tomari and Mei Xia Lau.** Dendritic cell recognition using template matching based on one-dimensional (1D) fourier descriptors (FD). *First International Workshop on Pattern Recognition*. Proc. SPIE. 2016. pp.100110K.
2. **Anis Azwani Muhd Suberi; Wan Nurshazwani Wan Zakaria, Razali Tomari and Kue Peng Lim.** Optimization of overlapping dendritic cell segmentation in phase contrast microscopy images. In 2016 *IEEE-EMBS Conference on Biomedical Engineering and Science*. IEEE. pp.246-250.
3. **Anis Azwani Muhd Suberi; Wan Nurshazwani Wan Zakaria, Razali Tomari.** Dendritic cell recognition in computer aided system for cancer immunotherapy. *Procedia Computer Science*. Elsevier. 105C: 177-182.
4. **Anis Azwani Muhd Suberi; Wan Nurshazwani Wan Zakaria, Razali Tomari.** Dendritic cells feature extraction using geometric features and 1D fourier descriptors. In the *9th Int. Conference on Computer and Automation Engineering (ICCAE 2017)*. Accepted
5. **Anis Azwani Muhd Suberi; Wan Nurshazwani Wan Zakaria, Razali Tomari.** An Automated Detection and Quantitative Analysis of Dendritic Cells in Phase Contrast Microscopy Images. *Journal of the International Measurement Confederation (IMEKO)*. Elsevier. Under Review.

LIST OF AWARDS

1. Best Poster Award in the 1st FKEE Postgraduate Research Conference 2016, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia.
2. Gold medal (Higher institution category) in the International Invention and Innovative Competition (INIIC-Series 2), Puteri Beach Resort, Port Dickson, Negeri Sembilan, 2016.
3. Bronze medal (Applied Research under staff category) in the Research and Innovation (R&I) Festival, Universiti Tun Hussein Onn Malaysia, 2016.
4. Silver medal in the 2017 Malaysia Technology Expo (MTE), Kuala Lumpur.
5. Gold medal in the 2017 Innovation Design Research International Symposium (IDRIS).
6. Gold medal in the 2017 Innovative Research, Invention and Application Expo (IRIA).

CHAPTER 1

INTRODUCTION

Most of the established therapies such as surgery, chemotherapy and radiotherapy are widely used to treat cancer patients. Surgery is often considered as the first therapy option to remove the tumour (Sasada *et al.*, 2015). Nevertheless, there is a tendency of removing only parts of the tumour. Following that, a combination of surgery with radiotherapy or chemotherapy is typically used in patients to kill the cancer cells (Sasada *et al.*, 2015). However, both radiotherapy and chemotherapy can introduce non-favourable outcomes towards the patient, such as serious bleeding, lack of energy and experience depression (Mellman *et al.* 2011). Recently, Dendritic Cells (DCs) immunotherapy has been widely explored and introduced as an advanced approach to boost the immune system to fight cancer (Raïch-Regué *et al.*, 2014; Sasada *et al.*, 2015). DCs immunotherapy employs and activates the body's own immune cells to fight the cancer cells as shown in Figure 1.1.

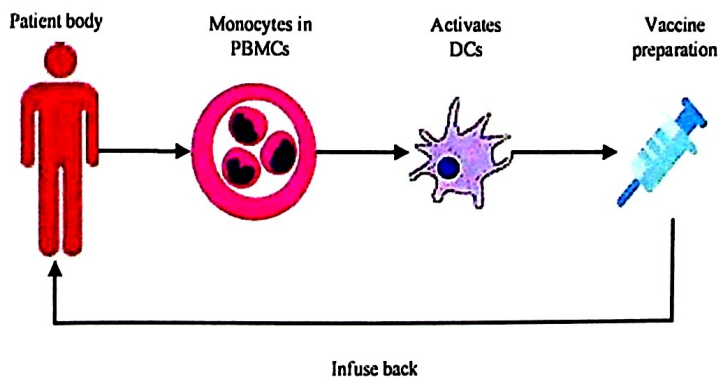


Figure 1.1: DCs immunotherapy procedure

In the cancer microenvironment, DCs have a key role for activation of T- and B-cell immunity as both represent as the Antigen-Presenting Cells (APCs) (Raïch-

Regué *et al.*, 2014; Tan *et al.*, 2010). DCs can be generated *in vitro* from Peripheral Blood Mononuclear Cells (PBMCs) (Tan *et al.*, 2010). On top of that, DCs have long and numerous tentacles as their main characteristic as shown in Figure 1.2. The identification of DCs in immunotherapy is important as the phenotype of DCs can determine the type of immune reaction in autoimmunity response. In brief, morphological cell analysis is a key issue for the preparation of cancer immunotherapy as the DCs are trained to recognise cancer antigens.

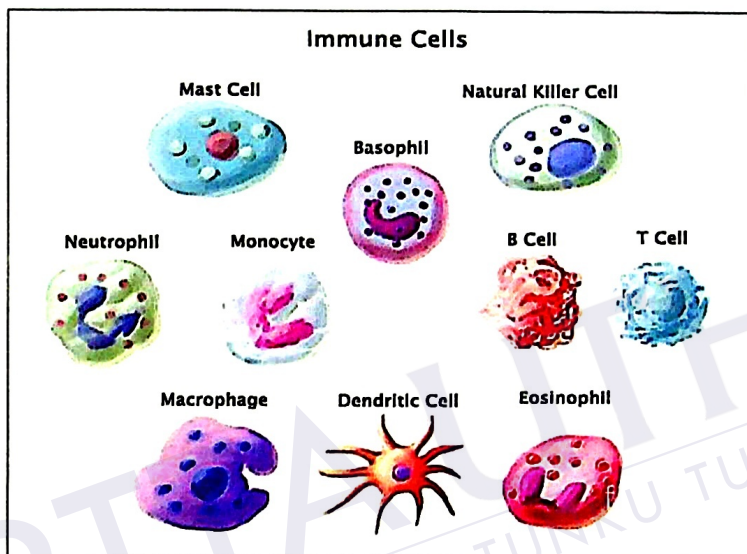


Figure 1.2: Component of immune cells in human blood system (IMDC, 2015)

During the cell culture, DCs can be characterised and recognised using Flow Cytometry (Rovati *et al.*, 2008; Tan *et al.*, 2010). However, this method involves a staining process which can affect the DC viabilities. Therefore, another promising microscopy technique called, Phase Contrast Microscopy (PCM) is used to visualise, recognise and count the amount of DCs manually before the sample is infused back into the patient body. Even though PCM is a label-free imaging modality, the identification purpose becomes challenging as the image is constituted with a variation of imaging artifacts such as halo region, low contrast and overlapping DCs (Jaccard *et al.*, 2014; Ra *et al.*, 2013; Usenik *et al.*, 2011). Such procedure is laborious, time-consuming and very dependent on the expert's skill to recognise and count DCs which can introduce human errors.

To address these circumstances, a pattern matching approach is developed to automatically recognise and count DCs in a large number of cells in PCM images. As

the initial condition, pre-processing schemes are applied to remove any imaging artifacts from the testing image. The complexity between DCs boundary and other cells can be considered distinctive to visually distinguish. Therefore, Fourier Descriptors (FDs), which are derived from One-Dimensional (1D) shape signatures is proposed in which the method has been applied in several studies particularly in shape-based image retrieval (Dalitz *et al.*, 2013; Sokic & Konjicija 2016; Yuan *et al.*, 2014). This proposed approach is capable to identify DCs with a label-free detection and low computational resources.

The overall process of DCs counting scheme of PCM image microscopy encompasses four primary stages namely, 1) Image Acquisition; 2) Pre-processing stage for both templates and testing images; 3) Computation of 1D Fourier Descriptors (FDs) to extract cell contour; and 4) DCs recognition, marking and counting process. Next, the sample images are compared to a set of template images to detect the most approximate target cell based on FDs. The cell templates have been already configured to match similar pattern of DCs to those of the templates.

During the features matching procedure, the cell shape signatures are obtained through the conversion of geometrical pixel information of shape descriptors to 1D FDs, which facilitate an efficient Template Matching (TM) to recognise, mark and count DCs in a pool of blood cells. The details on the DCs imaging classification schemes are described in Chapter 3, followed by the results and analysis in Chapter 4. Towards the end, the conclusion of the entire research with future works are discussed in Chapter 5.

1.1 Problem Statement

Identification of DCs especially in the cancer microenvironment is a unique disclosure since fighting tumor from the harnessing immune system has been a novel treatment under investigation. Besides that, pathologists figure this issue as a valuable case as the information about any diseases can be extracted from them. DCs can be defined through their key morphological feature which is tentacles (Wieder, 2003). Conventional Flow Cytometry provides an effective recognition of labelled DCs using fluorescent dyes that may cause phototoxic damage to the DCs tentacles (Tan *et al.*, 2010). Recent advances in cellular imaging have facilitated investigation of unstained living cell using PCM.

However, it involves tedious manual inspection and in certain cases, the DCs tentacles can hardly be identified due to the low image contrast and bright halo outlining the cells. The PCM turns the invisible phase shifts of the light waves emerging from the object into visible intensity by using interference with the 90° phase shifted illumination wave (Bensch & Ronneberger, 2015). Therefore, these would result in decreasing intensity which is proportional to the object thickness. This condition leads to halo region and shade-off artifacts to the image (Jaccard *et al.*, 2014; Bensch & Ronneberger, 2015). In the meantime, PCM has critical issues regarding clumping and overlapping cells which may deteriorate the recognition process (Tan *et al.*, 2010). Apart from imaging artifacts, the cell identification procedure can be very time consuming and qualitatively subjective. Such procedure is very dependent on the expert's skill to identify and count DCs. To address these circumstances, a Computer Aided System for DCs identification (CasDC) which involves pattern recognition is proposed to effectively identify and count DCs with a rapid and minimum processing time. The finding of this research would permit rapid, standardized and quantitative analysis for further cancer immunotherapy vaccine preparation.

1.2 Aim

This research aims to develop a Computer Aided System for Dendritic Cells identification (CasDC) for cancer immunotherapy vaccine preparation.

1.3 Objectives

To achieve the aim, the following objectives have been outlined:

1. To develop a pre-processing technique on the PCM images to reduce the image artifacts in preparation for segmentation of DCs.
2. To establish a feature extraction and classification algorithm for detection of DCs.
3. To develop an auxiliary Graphical User Interface (GUI) that supports efficient detection of DCs.
4. To evaluate the performance of developed system via a series of experimental programme (quantitative and qualitative analysis).

1.4 Scopes and Limitations

The restrictions and limitations during this research are:

1. This study focuses on the cell shape signatures in identifying the main characteristics of DCs for their classification.
2. MATLAB R2015a toolbox which utilizes GUI is developed to identify and count DCs.
3. The experimental studies are conducted and evaluated on selected samples of PBMCs images under PCM. All the selected samples are required to undergo culturing procedure to enhance the visibility of DCs from complex clumping region.
4. The image dataset is provided by Cancer Research Malaysia (CRM). All the ethical standards are conducted by CRM and the images are publicly available for research purposes.
5. The developed algorithm is tested on 1877×1408 and 2560×1920 size pixels of randomly selected from 135 PCM images to show the feasibility of the developed system.

1.5 Research Contributions

This research provides a framework of image processing approach in DCs classification and counting as shown in Figure 1.3. CasDC has been established in which this system offers a non-staining procedure to increase the viability of DCs and subsequently, beneficial to reduce error in DCs counting. This is the first time that Hybrid of Gaussian Kernel Filtering using low and high sigma parameter followed by Local Adaptive Threshold (H-GLAT) has been used to solve low contrast and overlapping cells in PCM images. Other than that, an automated DCs classification is provided to accelerate the clinical translation with rapid and minimum processing time through the use of Template Matching (TM) based on 1D FDs. Overall, a GUI has been developed to provide the end user with an interactive way to count DCs.

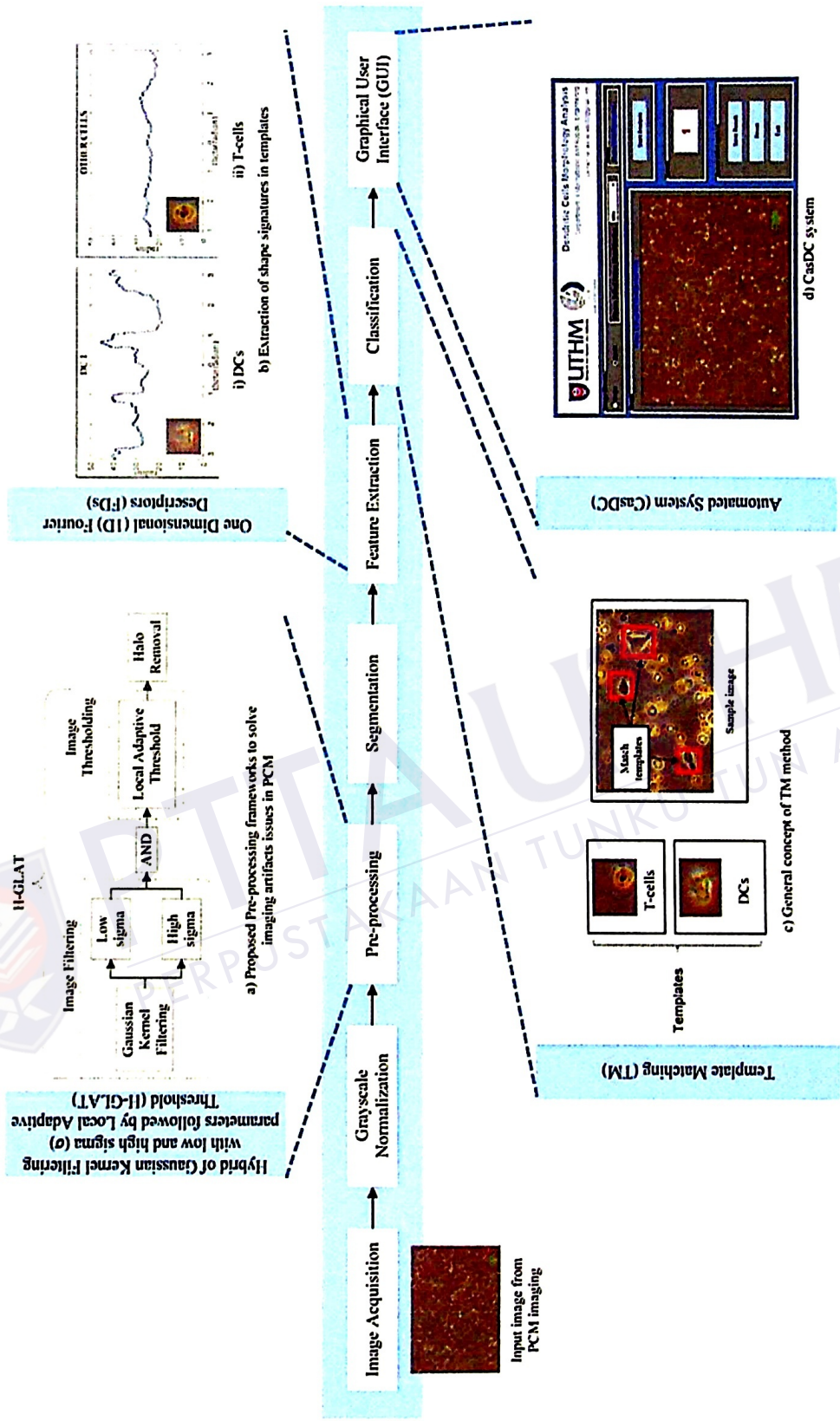


Figure 1.3: Overall research methods and contributions

1.6 Summary

This chapter briefly discusses the current issues in DCs identification for cancer immunotherapy purpose. In this procedure, DCs represent an appealing option in vaccine preparation as they have the ability to boost the immune system to fight cancer. DCs can be rapidly identified using a laser based tool called Flow Cytometry. However, this method affects the DCs viability as it acquires staining stage which might kill the tentacles. Therefore, manual counting has been practiced via a label free imaging modality which is PCM. The pathologists face a challenge to identify DCs based on the tentacles using this method due to a variation of imaging artifacts such as halo region, low contrast and clumping cells in the PCM image.

The manual counting of DCs is time consuming and highly prone to error as such procedure is laborious and depends on the expert's skill. In fact, it produces a high variance due to different levels of experience in DCs counting. Thus, this project aims to solve the problem by image processing approach to accelerate the clinical translation. Since the raw PCM images are constituted with imaging artifacts, applying image pre-processing is one of important step before classifying DCs. Towards the end, a system called CasDC is developed to provide a rapid identification of DCs in the PCM images. The next chapter describes in detail concerning DCs, PCM images and image processing techniques applied in the related studies.

CHAPTER 2

LITERATURE REVIEW

Many studies have discussed the motivation of carrying an in depth study on Dendritic Cells (DCs) in cancer immunotherapy by the clinical practitioners. In brief, this review focuses on four areas: 1) Introduction to Immune Cell Subsets; 2) Significance of Identifying DCs; 3) DCs Culture and Imaging; and 4) Current Technology in Identification for PCM Image.

2.1 Introduction to Immune Cell Subsets

White Blood Cells (WBCs) or known as Leukocytes involve in maintaining immune system by protecting the body against any diseases and sensing foreign organism. Besides that, they are essential in the diagnosis of cancer as the information about any diseases can be extracted from them (O'Neill *et al.*, 2015; Ma *et al.*, 2013). The production of WBCs is derived from multipotent cell in the bone marrow. There are five types of WBCs which are Monocyte, Lymphocyte, Neutrophil, Basophil, and Eosinophil as shown in Figure 2.1.

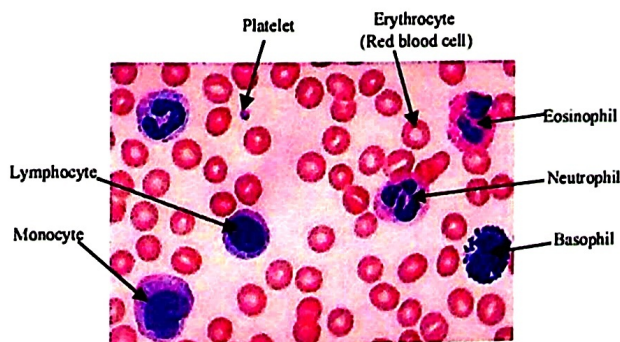


Figure 2.1: Types of blood smear under Light Microscope (Sarrafzadeh *et al.*, 2014)

REFERENCES

- Ali, J., Ahmad, A.R., George, L.E., Der, C.S. and Aziz, S. Red blood cell recognition using geometrical features. *IJCSI Int. Journal of Computer Science Issues*. 2013. 10(1): 90-94.
- Al-Kubati, A.A.M., Saif, J.A. and Taher, M.A. Evaluation of Canny and Otsu image segmentation. *Int. Conference on Emerging Trends in Computer and Electronics Engineering*. PSRC. 2012. pp. 23-25.
- Aljoscha-Perez, M., Willaert, R. and Sahli, H. A segmentation framework for phase contrast and fluorescence microscopy images. *Int. Journal of Pattern Recognition and Artificial Intelligence*. 2014. 28(7): 1460013.
- Aljarrah, I.A., Ghorab, A.S. and Khater, I.M. Object recognition system using template matching based on signature and principal component analysis. *Int. Journal of Digital Information and Wireless Communications (IJDIWC)*. 2012. 2(2): 156-163.
- Ambriz-Colin, F., Torres-Cisneros, M. and Debeir, O. Detection of biological cells in phase-contrast microscopy images. *Fifth Mexican Int. Conference on Artificial Intelligence*. IEEE. 2006. pp. 68-77.
- Avci, E. A new blood cell recognition algorithm based on directed vector method. *Journal of Applied Biological Sciences*. 2015. 9(3): 18-20.
- Bensch, R. and Ronneberger, O. Cell segmentation and tracking in phase contrast images using graph cut with asymmetric boundary costs. *12th Int. Symposium on Biomedical Imaging (ISBI)*. IEEE. 2015. pp. 1220-1223.
- Bhonsle, S. and Klinzmann, A., Park, F. *Centroid Distance Function and the Fourier Descriptor with Applications to Cancer Cell Clustering*. Undergraduate Report. University of California; 2011.
- Bradbury, L. and Wan, J.W. A spectral k-means approach to bright-field cell image segmentation. *Annual Int. Conference of the IEEE Engineering in Medicine and Biology*. IEEE. 2010. pp. 4748-4751.

- Braiki, M., Benzinou, A., Nasreddine, K., Labidi, S. and Hymery N. Segmentation of dendritic cells from microscopic images using mathematical morphology. *Second Int. Conference on Advanced Technologies for Signal and Image Processing*. IEEE. 2016. pp. 282-287.
- Chen, S., Zhao, M., Wu, G., Yao, C. and Zhang, J. Recent advances in morphological cell image analysis. *Computational and Mathematical Methods in Medicine, 2012*. 2012: 101536.
- Chen, C., Wang, W., Ozolek, J.A. and Rohde, G.K. A flexible and robust approach for segmenting cell nuclei from 2D microscopy images using supervised learning and template matching. *Cytometry Part A*. 2013. 83(5): 495-507.
- Curry MD, Choladda Vejabhuti. (2015). *Differential Blood Count: Reference Range, Interpretation, Collection and Panels* [online]. Retrieved on October 20, 2015, from <http://emedicine.medscape.com/article/2085133-overview>
- Dalitz, C., Brandt, C., Goebels, S. and Kolanus, D. Fourier descriptors for broken shapes. *EURASIP Journal on Advances in Signal Processing*. 2013. 2013(1): 1-11.
- Davies, E.R. *Machine Vision: Theory, Algorithms, Practicalities*. Elsevier. 2004.
- Fellers, T.J. and Davidson M.W. (2012). *Introduction to Confocal Microscopy* [online]. Retrieved on March 3, 2016, from <http://www.olympusmicro.com/primer/techniques/confocal/confocalintro.html>
- Ferenbach, D. and Hughes, J. Macrophages and dendritic cells: what is the difference? *Kidney International*. 2008. 74(1): 5-7.
- Feudjio, C.K., Tiedeu, A., Noubeg, M.L., Gordan, M., Vlaicu, A. and Domngang, S. Extracting and smoothing contours in mammograms using fourier descriptors. *Journal of Biomedical Science and Engineering*. 2014. 7(3):119-129.
- Frejlichowski, D. An experimental comparison of seven shape descriptors in the general shape analysis problem. *Int. Conference Image Analysis and Recognition*. Springer Berlin Heidelberg. 2010. pp. 294-305.
- Ghosh, M., Das, D., Mandal, S., Chakraborty, C., Pala, M., Maity, A.K., Pal, S.K. and Ray, A.K. Statistical pattern analysis of white blood cell nuclei morphometry. *Students' Technology Symposium (TechSym)*, IEEE. 2010. pp. 59-66.
- Habibzadeh, M., Krzyżak, A. and Fevens, T. Comparative study of shape, intensity and texture features and support vector machine for white blood cell

- classification. *Journal of Theoretical and Applied Computer Science*. 2013. 7(1): 20-35.
- Hasskamp, J.H., Zapas, J.L. and Elias, E.G. Dendritic cell counts in the peripheral blood of healthy adults. *American Journal of Hematology*, 2005. 78(4): 314-315.
- He, K., Sun, J. and Tang, X. Guided image filtering. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2013. 35(6): 1397-1409.
- Heiberger, R.M. and Neuwirth, E. One-way anova. In: *R through Excel*. Springer New York. pp. 165-179; 2009.
- Heine, G.H., Ortiz, A., Massy, Z.A., Lindholm, B., Wiecek, A., Martínez-Castelao, A., Covic, A., Goldsmith, D., Süleymanlar, G., London, G.M. and Parati, G. Monocyte subpopulations and cardiovascular risk in chronic kidney disease. *Nature reviews Nephrology*. 2012. 8(6): 362-369.
- Hiremath, P.S., Bannigidad, P. and Geeta, S. Automated identification and classification of white blood cells (leukocytes) in digital microscopic images. *IJCA Special Issue on "Recent Trends in Image Processing and Pattern Recognition" RTIPPR*. 2010. (2): 59-63.
- Huang, Y. and Liu, Z. Segmentation and tracking of lymphocytes based on modified active contour models in phase contrast microscopy images. *Computational and Mathematical Methods in Medicine*. 2015. 2015:1-9
- IMDC, Innovate Malaysia Design Competition. (2015). *Cancer Research Malaysia Design Challenge* [online]. Retrieved on September 16, 2015, from http://innovate.dreamcatcher.asia/page_01.html
- Jaccard, N., Griffin, L.D., Keser, A., Macown, R.J., Super, A., Veraitch, F.S. and Szita, N. Automated method for the rapid and precise estimation of adherent cell culture characteristics from phase contrast microscopy images. *Biotechnology and Bioengineering*. 2014. 111(3): 504-517.
- Jafari, A.A., Mardani-Fard, H.A. and Sadooghi-Alvandi, S.M. One-way ANOVA with unequal variances. *Communications in Statistics-Theory and Methods*. 2012. 41(22): 4200-4221.
- Jahan-Tigh, R.R., Ryan, C., Obermoser, G. and Schwarzenberger, K. Flow cytometry. *Journal of Investigative Dermatology*. 2012. 132(10): e1.
- Juneau, P.M. *New Algorithms for the Analysis of Live-Cell Images Acquired in Phase Contrast Microscopy*. Ph.D. Thesis. Université Laval; 2015

- Kang, M.S., Lee, J.E., Kim, H.R. and Kim, M.H. Classification of tumor cells in phase-contrast microscopy image using fourier descriptor. *Journal of Biomedical Engineering Research*. 2012 33(4): 169-176.
- Kang, M.S., Song, S.M., Lee, H. and Kim, M.H. Cell morphology classification in phase contrast microscopy image reducing halo artifact. In *SPIE BiOS*. International Society for Optics and Photonics. 2012. pp. 822711-822711.
- Kaur, H. and Kaur, L. Performance comparison of different feature detection methods with gabor filter. *Int. Journal of Science and Research (IJSR)*. 2014. 3(5): 1879-1886
- Kurita, H. and Masuda, R. Application of the gabor filters and k-means method for characterization of geometrical properties of parenchyma cell walls. *Journal of Texture Studies*. 2012. 43(5): 339-349.
- Landolt, N.T.K., Lakhonphon, S. and Ananworanich, J. Contraception in HIV-Positive Female Adolescents. *AIDS Research and Therapy*. 2011. 8(1): 1.
- Le Douce, V., Herbein, G., Rohr, O. and Schwartz, C. Molecular mechanisms of HIV-1 persistence in the monocyte-macrophage lineage. *Journal of Retrovirology*. 2010. 7(32):1-16.
- Li, F., Zhou, X., Zhao, H. and Wong, S.T. Cell segmentation using front vector flow guided active contours. *Int. Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer Berlin Heidelberg. 2009. pp. 609-616.
- LLC, Nexcelom Bioscience (2003). *Cell Size Assay and Cell Counting Based on Cell Size Range* [online]. Retrieved on October 23, 2015, from <http://www.nexcelom.com/Applications/cell-size-assay.php>
- Ma, Y., Shurin, G.V., Peiyuan, Z. and Shurin, M.R. Dendritic cells in the cancer microenvironment. *Journal of Cancer*. 2013. 4(1): 36-44.
- Majurski, M., Zheng, C., Chalfoun, J., Dima, A. and Brady, M. Comparison of shape signature sub-sampling methods for cell tracking. *Bioimage Informatics Conference*. NIST. 2015. pp. 3-7.
- Mellman, I., Coukos, G. and Dranoff, G. Cancer immunotherapy comes of age. *Nature*. 2011. 480(7378): 480-489.
- Miyahira, A. (2012). *Types of Immune Cells Present in Human PBMC - Sanguine Bio Researcher Blog* [online]. Retrieved on October 19, 2015, from <http://technical.sanguinebio.com/types-of-immune-cells-present-in-human-pbmc/#>

- Mohammadi, A., Mehrzad, J., Mahmoudi, M., Schneider, M. and Haghparast, A. Effect of culture and maturation on human monocyte-derived dendritic Cell surface markers, necrosis and antigen binding. *Biotechnic & Histochemistry*. 2015. 90(6): 445-452.
- Morse, B.S. *Lecture13: Edge Detection*. Brigham Young University; 2003.
- O'Neill, D.W., Adams, S. and Bhardwaj, N. Manipulating dendritic cell biology for the active immunotherapy of cancer. *Blood*. 2015. 104(8): 2235-2246.
- Phukpattaranont, P., Kayasut, K., Boonyaphiphat, P. and Limsiroratana, S. Computer aided system for nuclear stained breast cancer cell counting. *Breast Cancer-Recent Advances in Biology, Imaging and Therapeutics*. INTECH Open Access Publisher. 2011. pp. 329.
- Ra, H.K., Kim, H., Yoon, H.J., Son, S.H., Park, T. and Moon, S. A robust cell Counting approach based on a normalized 2D cross-correlation scheme for in-line holographic images. *Lab on a Chip*. 2013. 13(17): 3398-3409.
- Raïch-Regué, D., Glancy, M. and Thomson, A.W. Regulatory dendritic cell therapy: from rodents to clinical application. *Immunology Letters*. 2014. 161(2): 216-221.
- Rovati, B., Mariucci, S., Manzoni, M., Bencardino, K. and Danova, M. Flow cytometric detection of circulating dendritic cells in healthy subjects. *European Journal of Histochemistry: EJH*. 2008. 52(1): 45.
- Sarrafzadeh, O., Rabbani, H., Talebi, A. and Banaem, H.U. Selection of the best features for leukocytes classification in blood smear microscopic images. *SPIE Medical Imaging*. International Society for Optics and Photonics. 2014. pp. 90410P-90410P.
- Sasada, A., Takagi, M., Tabata, S., Abe, M. and Abe, H. A patient with stage IV gastric cancer who acquired complete remission after undergoing multi-peptide dendritic cell immunotherapy in combination with standard therapies. *Personalized Medicine Universe*. 2015. 4: 70-72.
- Seroussi, I., Veikherman, D., Ofer, N., Yehudi-Resheff, S. and Keren, K. Segmentation and tracking of live cells in phase-contrast images using directional gradient vector flow for snakes. *Journal of Microscopy*. 2012. 247(2): 137-146.
- Sharma, M. and Chouhan, V. Objective Evaluation parameters of image segmentation algorithms. *Int. Journal of Engineering and Advanced Technology*. 2012. 2: 84-87.

- Silveira, G.F., Wowk, P.F., Machado, A.M.B., Dos Santos, C.N.D. and Bordignon, J. Immature dendritic cells generated from cryopreserved human monocytes show impaired ability to respond to LPS and to induce allogeneic lymphocyte proliferation. *PLoS one*. 2013. 8(7): e71291.
- Singh, T.R., Roy, S., Singh, O.I., Sinam, T. and Singh, K. A new local adaptive thresholding technique in binarization. *International Journal of Computer Science Issues*. 2012. 8(6): 271–277.
- Sokic, E. and Konjicija, S. Phase preserving fourier descriptor for shape-based image retrieval. In *Signal Processing: Image Communication*. 2016. 40: 82-96.
- Stehman, S.V. Selecting and interpreting measures of thematic classification accuracy. *Remote Sensing of Environment*. 1997. 62(1): 77-89.
- Stoklasa, R., Bálek, L., Krejčí, P. and Matula, P. Automated cell segmentation in phase-contrast images based on classification and region growing. *12th Int. Symposium on Biomedical Imaging (ISBI)*. IEEE. 2015. pp. 1447-1451.
- Su, H., Yin, Z., Huh, S. and Kanade, T. Cell segmentation in phase contrast microscopy images via semi-supervised classification over optics-related features. *Medical Image Analysis*. 2013. 17(7): 746-765.
- Suzuki, T., Fujikura, K., Higashiyama, T. and Takata, K. DNA staining for fluorescence and laser confocal microscopy. *Journal of Histochemistry & Cytochemistry*. 1997. 45(1): 49-53.
- Taherisadr, M., Nasirzonouzi, M., Baradaran, B. and Mehdizade, A. New approach to red blood cell classification using morphological image processing. *Shiraz E-Medical Journal*. 2013. 14(1): 44-53.
- Tan, Y.F., Leong, C.F. and Cheong, S.K. Observation of dendritic cell morphology under light, phase-contrast or confocal laser scanning microscopy. *The Malaysian Journal of Pathology*. 2010. 32(2): 97-102.
- Tian, D.P. A review on image feature extraction and representation techniques. *International Journal of Multimedia and Ubiquitous Engineering*. 2013. 8(4): 385-396.
- Tomari, R., Zakaria, W.N.W., Jamil, M.M.A., Nor, F.M. and Fuad, N.F.N. Computer aided system for red blood cell classification in blood smear image. *Procedia Computer Science*. 2014. 42: 206-213.
- Tyler, K. *Fourier descriptors: Properties and utility in leaf classification*. ECE 533

Fall; 2006.

- Usaj, M., Torkar, D., Kanduser, M. and Miklavcic, D., 2011. Cell counting tool parameters optimization approach for electroporation efficiency determination of attached cells in phase contrast images. *Journal of Microscopy*. 2011. 241(3): 303-314.
- Usenik, P., Vrtovec, T., Pernuš, F. and Likar, B. Automated tracking and analysis of phospholipid vesicle contours in phase contrast microscopy images. *Medical & Biological Engineering & Computing*. 2011. 49(8): 957-966.
- Vale, A.M.P.G., Guerreiro, A.M.G., Dória Neto, A.D., Cavalvanti Junior, G.B., Leitão, V.C.L.T.D. and Martins, A.M. Automatic segmentation and classification of blood components in microscopic images using a fuzzy approach. *Revista Brasileira de Engenharia Biomédica*. 2014. 30(4): 341-354.
- Wieder, E. Dendritic Cells: A Basic Review. *International Society for Cellular Therapy*. 2003. Retrieved September 23, 2015, from http://c.ymcdn.com/sites/www.celltherapysociety.org/resource/resmgr/files/PDF/Resources/OnLine_Dendritic_Education_Brochure.pdf
- Xiong, W., Chia, S.C., Lim, J.H., Shvetha, S. and Ahmed, S. Detection of unstained living neurospheres from phase contrast images with very large illumination variations. *Annual Int. Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. 2011. pp. 6154-6157.
- Xu, H., Dawson, R., Forrester, J.V. and Liversidge, J. Identification of novel dendritic cell populations in normal mouse retina. *Investigative Ophthalmology & Visual Science*. 2007. 48(4): 1701-1710.
- Yen Ruen, L., En Sheng, L., Hai Seng, O. and Mat Isa, N.A. Dendritic cell classification imaging system. 2016 Innovate Malaysia Design Conference. 2016. IMDCOn. pp.145-160.
- Yin, J., Li, H., Du, J. and He, P. Low illumination image retinex enhancement algorithm based on guided filtering. *3rd Int. Conference on Cloud Computing and Intelligence Systems*. IEEE. 2014. pp. 639-644.
- Yin, Z., Kanade, T. and Chen, M. Understanding the phase contrast optics to restore artifact-free microscopy images for segmentation. *Medical Image Analysis*. 2012. 16(5):1047-1062.
- Yuan, Z., Li, F., Zhang, P. and Chen, B. Description of shape characteristics through

fourier and wavelet analysis. *Chinese Journal of Aeronautics*. 2014. 27(1): 160-168.

Zhang, C., Huber, F., Knop, M. and Hamprecht, F.A. Yeast cell detection and segmentation in bright field microscopy. *11th Int. Symposium on Biomedical Imaging (ISBI)*. IEEE. 2014. pp. 1267-1270.

