HEP-2 CELL FEATURE EXTRACTION USING WAVELET AND INDEPENDENT COMPONENT ANALYSIS

by

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FINAL PROJECT REPORT

Submitted to the Department of Electrical and Electronic Engineering
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical and Electronic Engineering)

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CERTIFICATION OF APPROVAL

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13326

A project dissertation submitted to the
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Approved by,

____

Dr Ibrahima Faye
Project Supervisor

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TRONOH, PERAK

September, 2013

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, the original work is my own accept as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified source of persons.

Nur Thania Awatif Mohamad Rosdi

EXECUTIVE SUMMARY

This report consists of the author experiences and involvement gained during carrying out Final Year Project (FYP) in Universiti Teknologi Petronas (UTP). Final year project consist of two parts which is Final Year Project 1 and Final Year Project 2, conducted for 2 semesters. FYP is taken during final year and is compulsory for UTP students in completing their degree program. FYP brings the purposes to expose students to real project environment individually and to encourage on research and development.

The author’s topic is “**HEp-2 Feature Extraction using Wavelet and Independent Component Analysis”**. All the details regarding the project are compiled into this report and it is organized as follows: (i) Introduction, (ii) Literature Review, (iii) Methodology, (iv) Result and Discussion (v) Conclusion and Recommendation and lastly (vi) References and Appendices. In this report, Chapter 1 will focus on the Introduction of the project consist of Project Background, Problem Statement and Objective of the project. Additionally, it includes the details on Antinuclear Antibody (ANA) and HEp-2 Cell.

Chapter 2 discusses the reviews on previous papers which comprise of projects that have been performed using Wavelet, Independent Component Analysis and Support Vector Machine. The subsequent chapter is on methodology where the project activities, timeline, task management and software related to the project is discussed. Afterward, Chapter 4 discusses on the results including MATLAB coding, graph of feature extraction and the classification performance for both methods used.

It is then followed by conclusion and recommendation of the project. Lastly the report ends with appendices and references.

ACKNOWLEDGEMENT

Praised be to God, with His willingness I have successfully completed the Final year Project (FYP) for past 2 semesters. Upon completing the Final Year Project, I owe great thanks to many individual for their support and contribution in terms of times, efforts and advices during throughout the year.

Special gratitude I greet to my supervisor Ir. Ibrahima Faye for giving me the opportunities to do this project. He has guides and helps me in finishing my project and tasks successfully throughout the semesters. He also provides me with a lot of knowledgeable information which helps in understanding the topic. Also big thanks to my co-supervisor, Ms. Zazilah Bt. May that assist me in making the project a success. Their supervisions and supports from both of them are truly helping in the progression and smoothness of FYP.

Not to forget, FYP coordinators that have performed all the planning on project deadlines and presentations which help the students to organize the project schedule. It at the same time gives the opportunities for the students to get acknowledgment of their project from lecturers, examiners from companies and publics.

Besides, bunch of thanks to my beloved family and friends for all the supports and encouragement throughout the project duration. Last but not least, I would like to thank all parties that involved in making this Final Year Project a success.

ABSTRACT

Human antibodies work to attack any diseases or bacteria that presented inside the body. However, there is an act when human antibodies tend to attack own body cells or tissues which is called as Anti-nuclear Antibodies (ANA). ANA consist of many different types that can be recognized by its nucleus size and shape. Common method of classifying ANA is by performing Indirect Immunofluorescences (IIF) with HEp-2 cell and observed the pattern under the microscope by naked eye which said to be inaccurate, takes time and subjective. Thus, this project will study on the technique to identify and classify the pattern of ANA automatically. Algorithms are created using MATLAB software and a Graphical User Interface (GUI) is generated for the algorithm to be easily used. This work will focus more on feature extraction using **Wavelet** and **Independent Component Analysis (ICA)**. The type of Wavelet Transform that will be used is the 2D Discrete Wavelet Transform (2D DWT) and Fast ICA for Independent Component Analysis. Then Support Vector Machine (SVM) is used to perform the classifications parts using the features extracted from both methods. Different features obtained are tested in SVM and the performance of both methods is compared. From the result, it shows that by using the same classifier, Wavelet can provide better features for classification compared to ICA.

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CHAPTER 1: PROJECT BACKGROUND

1.1 BACKGROUND OF STUDY

Over the years, the applications and importance of image processing have been discussed widely. Image processing can be used to perform image de-noising, image compression, image recognition and classification of images. Common applications are medical imaging, biometrics and agriculture. In medical imaging, image processing typically being used to detect and diagnose diseases or viruses in human body, cells and tissues. In this project, image processing will be applied to classify the type of Anti-nuclear Antibodies (ANA) in human cell.

Anti-nuclear Antibodies is the act of human immune system to attack their own body cells' nucleus and tissues instead of attacking viruses and. It consists of many different types where it can be recognized by the size and shape of nucleus inside the cells [1]. Different types may lead to different diseases such as Hepatitis-C and Thyroid. Common types of ANA patterns that can be found in patients' blood cells are Homogeneous, Nucleolar, Speckled and Centromere each can be shown in Figure 1 below.

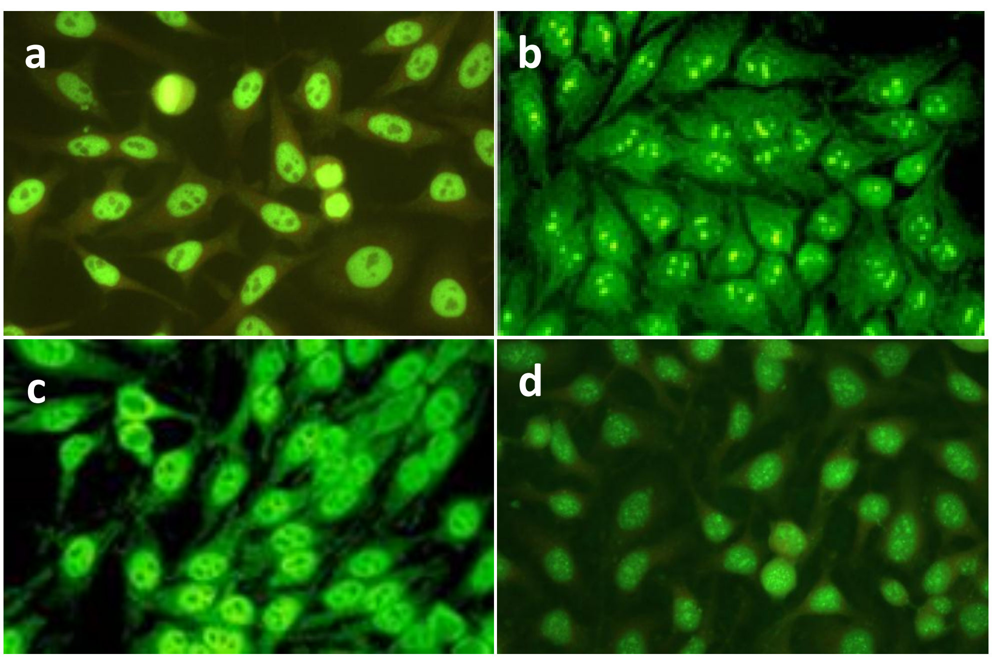


Figure 1: ANA Patterns (a) Homogeneous (b) Nucleolar (c) Speckled (d) Centromere

The technique to classify ANA patterns is known as Indirect Immunofluorescences (IIF) with HEp-2 Cell. The patient blood cells and HEp-2 cells is coated together on a microscope plate and fluorescence liquid is dropped so that patterns can be visible. HEp-2 cell will bind with the nucleus of the blood cell if ANA existed and fluorescence pattern will be visible. HEp-2 cell patterns can be recognized by numbers and size of the nucleus [2]. Currently, this pattern is analyzed directly and manually under the microscope by experts or physicians. However, this is said to be inaccurate, takes time and subjective depending on the experts' analysis. It is very impractical in this modern world to do analysis manually plus that there are lots of patients' blood cells to be analyzed in short amount of time.

Up until today, only a few researches on image processing are applied to fluorescence image and none are applied to ANA images. In this project, algorithms are generated in order to create a system that can be used to classify ANA patterns automatically. In creating the system, image processing steps applied are image pre-processing, image resizing, feature extraction and classification. Image pre-processing and resizing is used in enhancing the image so that better features can be obtained from the images. Feature extraction is used to obtain the information in the images in terms of numbers and coefficients which can be used to represent the image. In this project, two feature extraction methods are used and the performance of both methods is compared. The two different techniques chosen are Wavelet and Independent Component Analysis.

Support Vector Machine (SVM) is then used to perform the classification part by using the features extracted by Wavelet and ICA. The reasons SVM is chosen are (i) recentness and currently renowned and (ii) accurateness. In [3], SVM is used in the research and the results shows that this classifier is dependable.

All of the image processing procedures are performed using MATLAB software. The final output of the project will be the algorithm to perform features extraction and classification using Wavelet, Independent Component Analysis and Support Vector Machine. It will also decide which feature extraction gives better performance in providing the features for classification.

1.2 PROBLEM STATEMENT

Currently, the identification and classification on Anti-nuclear antibodies (ANA) is performed manually by the experts. However, manual technique is said to be inaccurate since pattern is been analyzed under microscopes by human eye. It is also very subjective depending on how the experts analyze them. This current technique correspondingly restricted to be analyzed by the experts only. At the same time, it increases the time for analyzing the image which is impractical since lots of ANA patterns need to be analyzed in a short amount of time. Automatic classification technique is needed to assist the diagnosis in order to obtain fast, objective and accurate classification results. Significant features of each pattern need to be extracted and used in classification to produce a system that can automatically identify ANA the patterns.

1.3 OBJECTIVE

The objective of the project is to perform image processing with stated techniques on fluorescence images in order to classify the type of ANA automatically. This will include:

a) To create algorithm that can help in automatic ANA Classification
b) To extract the significant features of two ANA patterns using Wavelet and Independent Component Analysis techniques
c) To apply the features extracted from both technique into the classifier which is Support Vector Machine (SVM).
d) To compare the performance of Wavelet and ICA by analyzing the accuracy classification accuracy.

1.4 SCOPE OF STUDY

The scopes of study for this project are as below:

a) Researching and understanding the theory on Antinuclear Antibodies (ANA), Indirect Immunofluorescences and Hep-2 Cell
b) Researching and understanding the theory on Wavelet, Independent Component Analysis (ICA) and Support Vector Machine (SVM)
c) Apply image pre-processing and resizing technique on ANA images
d) Apply MATLAB algorithm for feature extraction using Wavelet
e) Apply MATLAB algorithm for feature extraction using Independent Component Analysis (ICA)
f) Apply MATLAB algorithm for classification by Support Vector Machine using the features obtained from Wavelet and Independent Component Analysis
g) Compare the performance of Wavelet and Independent Component Analysis by analyzing the classification accuracy
h) Create a Graphical User Interface (GUI) using MATLAB in order for the algorithm to be easily used

1.5 THE RELEVENCY OF THE PROJECT

Classification of ANA patterns is very essential in order to identify the type of ANA exist inside patients body. By analyzing ANA type, the category of diseases the patient is experiencing can be identified. It can help in finding the suitable medications and treatments for the patient. Since the manual technique have a few defects, a better technique need to be researched and applied. This project is relevant since it applied automatic technique to replace current technique to perform ANA classification. It is very practical in this modern world to use computerized systems in performing tasks. Besides, this project at the same compares two different type of feature extraction technique, where it can be reference for others to perform ANA research later. Last but not least, it can helps in improving the health and medical field which is the key to the society's health.

1.6 THE FEASIBILITY OF THE PROJECT

The project is feasible and manageable within the two semesters given. In the first semester the theory on the topics is studied including theories on medical parts and image processing parts. While all the MATLAB coding and experiments are performed in the second semester. As an Electrical and Electronic students' point of view, this project is significant with one of EEE clusters which is Intelligent Signal and Imaging. It is achievable since EEE students already have the basic in image processing and MATLAB software itself. At the same time, it can help to improve the knowledge on the subject that could be used in the future.

2.1 FEATURE EXTRACTIONS USING WAVELET

The origin of wavelet comes from the idea of Fourier Transform which already developed years ago in 1807 by Joseph Fourier [4]. The idea of using wavelet in image processing is basically reducing the functions and signals into simple wavelet signals [5]. Wavelet transform on the other hand brings the meaning of "Representation of a function by wavelet, which represents scaled and translated copies of a finite length oscillating waveform" [6]. There are various wavelet transform existed and it can be used for different applications. Most of them are the extensions and improvement of the basic one. The basic wavelet transforms are Continuous wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). The extensions of wavelet transforms for examples are Wavelet Packets Transform, Stationary Wavelet Transform and Complex Wavelet Transform. Figure 2 below shows Discrete Wavelet Transform and Wavelet Packet Transform.

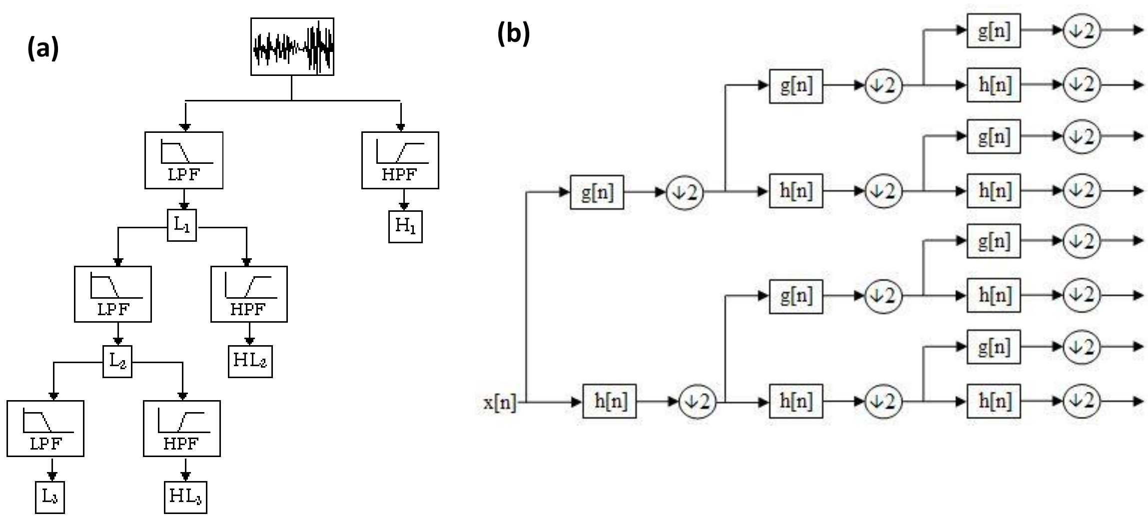


Figure 2: Wavelet transforms (a) 2D Discrete WT (b) Wavelet Packet Transform (WPT)

In Wavelet feature extraction, images will go through Wavelet Transform process where they are decomposed by using different kinds of filters to a few levels. The types of filters used are Low Pass Filter (LPF) and High Pass Filter (HPF). Few images with different signal frequencies are obtained and wavelet signals can be extracted from different directions of the images. The signals can be used as the features or coefficients to represent the images.

By using wavelet transform, types of features that can be extracted are statistical features and co-occurrences features. Wavelet Statistical features such as Mean, Variance, Max and Standard Deviation while co-occurrence features are Contrast, Energy, Entropy, Local Homogeneity and Maximum Probability [7]. Different kind of Wavelet Transforms can be used to decompose the image for example in [7], 3 levels DWT is used and about 50 features are extracted from each image. In medical applications, DWT are mostly applied in detecting diseases inside human body and organs [8]. In this paper, Parkinson disease is identified in patient's body by using DWT wavelet co-occurrences matrix.

Continuous Wavelet Transform (CWT) is also renowned in medical applications. In [9], CWT is used to extract features in the detection of biomarkers in colorectal cancer data. These biomarkers help to determine the survival time for cancer's patients while in [10] to classify Parkinson diseases. Both CWT and DWT are considered as the traditional and basic wavelet transform. Other extension of wavelet transform for example Wavelet Packet Transform (WPT), Non-separable Wavelet Transform [11] and Adaptive Wavelet Transform [12] which is introduced to complement DWT and CWT techniques.

Paper [5] shows the studies to compare WPT with Gabor Wavelet, Pyramid-Structured WT (PSWT) and Tree Structured WT (TSWT). The result shows that WPT have the best performance in feature extractions and Gabor has the least performance. However, in [13], when Gabor Wavelet is used with Adaptive Wavelet Transform, it turns out that it performs better than PSWT and TSWT. This shows that the combinations of Wavelet Transform and types of Wavelet used affect the performance in extracting the features from images.

In [12], the performances of three types of wavelet transforms which are Adaptive Wavelet Transform, Separable Wavelet Transform and Coiflet Transform are compared. Results also show that Adaptive Wavelet Transform has the best performance. This concluded that WPT and AWT are some of the wavelet transform that contribute to better performance. For this project, 2D Discrete Wavelet Transform (2D DWT) will be used since it is simple, no need of complex calculations, mostly used in science applications, high efficiency and effective in extracting the data [7, 14, 15]. Despite the fact that DWT is the basic wavelet transform, it is still widely being used and applicable. Table 1 summarizes some of the papers that discussed on 2D DWT.

Papers	[14]	[16]	[17]
Authors	S.Kakarwal, R.Deshmunk	E. Choi, J.Lee, J.Yoon	A.Subasi
Application	Extract features of face used for face recognition	Extract features for bank note classification	Extract features for EEG signal classification
Wavelet	Daubechies	Haar	Daubechies
Decomposition	5	2	3
Results	Low error when use with threshold to recognize face	Used with Euclidean minimum distance classifiers, more than 96% accuracies	Features extracted using 2 different classifiers both give result more than 93%
Advantage	- Nice features of space- frequency localization - Multiresolutional - Low complex computation	- Simplest - Fastest -Flexible frequency splitting	-Decomposed signal can construct the original signal back
Other Applications	Character recognition, Medical diagnosis, face recognition, fingerprints, automatic inspection		

Table 1: Summary of researches using 2D DWT

In 2D DWT, the LP filtered images is used as the scaling function while the HP filtered images is used as the Wavelet function. The scaling function performs decomposition of images into lower level. Wavelet function on the other hand is used as the features of the images which can be refer in Figure 2. The image will be decomposed until no more decomposition is needed. Figure 3 below shows image decomposition on 'Lena Image'. From the three levels DWT image decomposition, the upper left picture is the original images with different resolution at each level. In first level of decomposition, the other three images represent horizontal, vertical and diagonal high-frequency component respectively [18]. Images that are decomposed consist of images frequency component. With this coarse scaled features and fine scaled feature, the full structure of the object can be defined [18]. In each decomposition process of 2D DWT, features will always be extracted from the low pass filtered images, the upper left image.

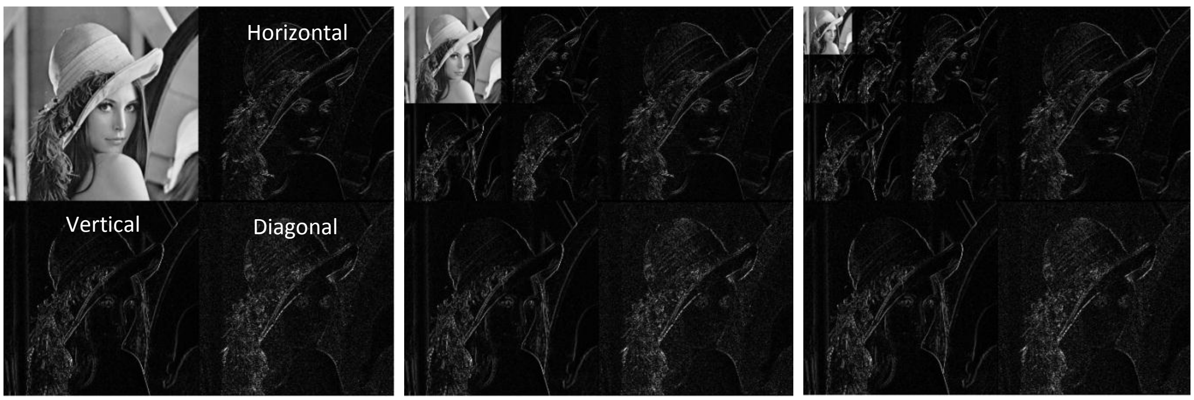


Figure 3: Decomposition of Lena Image using 2D DWT (a) First (b) Second (c) Third Level

2.2 FEATURE EXTRACTION USING INDEPENDENT COMPONENT ANALYSIS

Independent component analysis (ICA) is the method to extract independent signals from a complex signal [19]. It can be used for blind source separation where no information on the source signal and mixing method is needed [20]. Suppose if a complex signal is obtained from an image, ICA is used to break the signal into simple signal which can be used as the coefficients to represent the image. Figure 4 shows simple way to understand how ICA works.

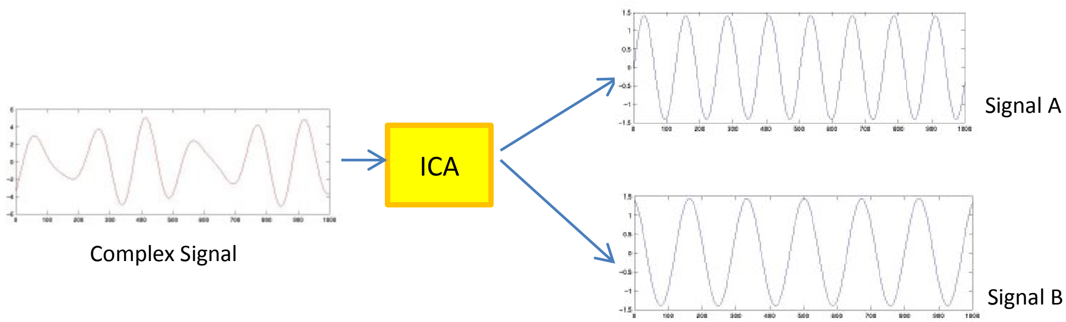


Figure 4: Independent Component Analysis

Example of ICA is to extract RGB images by color components. The components of RGB are the combinations of Red, Green and Blue component. Thus, these components can be broken into individual color components [19]. Figure 5 shows the image of hot with its image of individual color components.

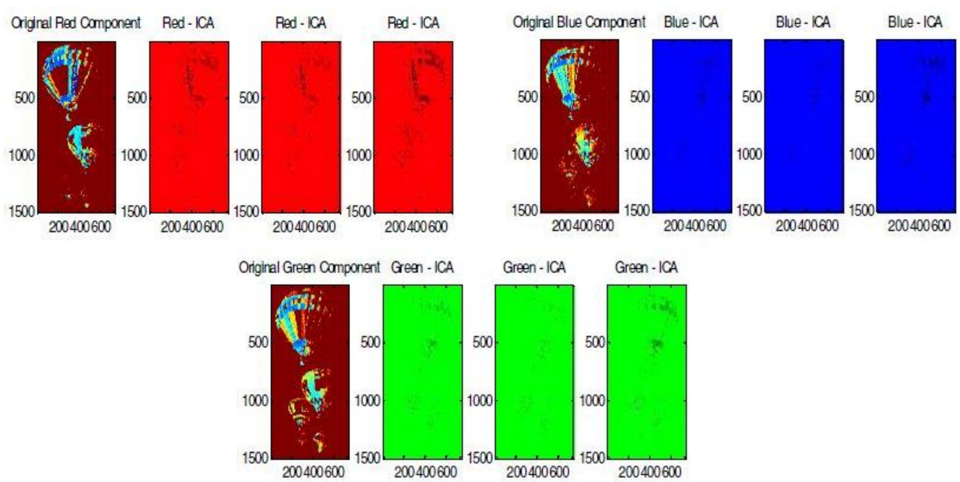


Figure 5: Independent Component Analysis of RGB Color images

Table 2 summarizes some of the research paper that have discussed and experimented on Independent Component Analysis.

Papers	[20]	[19]
Authors	T.Lan, D.Erdogmus, A.Adami, M.Pavel	Z.Ye, Y.Ye H.Mohammadian
Application	Features extraction of EEG signal for classification	Extract information from spatial moving object feature recognition
Results	Able to determine relevant low dimensional data	Able to extract features like color component, discrete entropy, relative entropy and mutual information successfully
Advantage	- Easy to implement - Low computational requirement - Select salient features	- Analyzing complex and non-linear pattern - Can be used to extract colored images
Other applications	Medical Diagnosis, Machine Vision, face recognition, biometric identification	

Table 2: Summary of researches using Independent Component Analysis

In [21], the ICA features extracted from iris is used to perform iris identification. The steps needed to perform ICA feature extraction for the iris can be concludes as below.

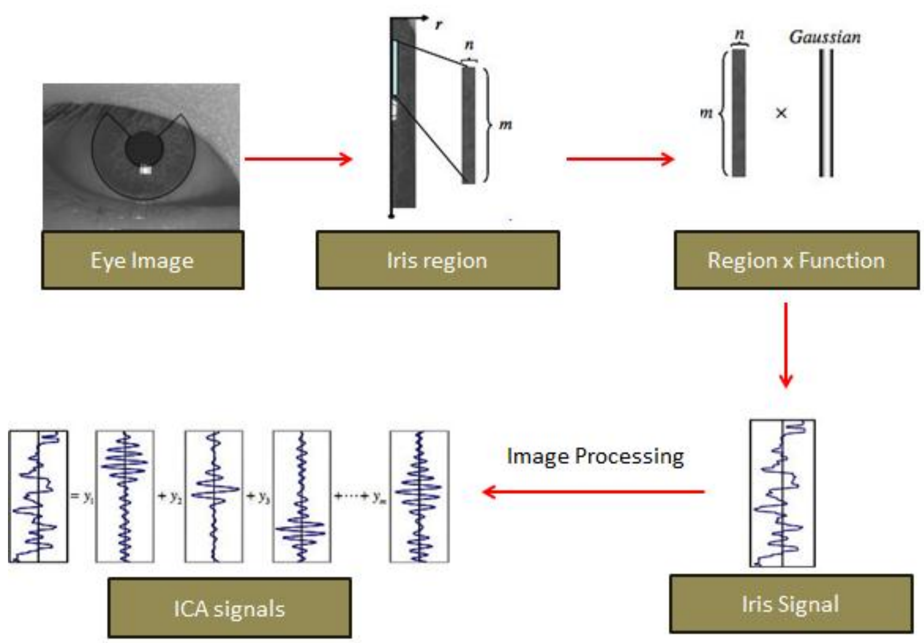


Figure 6: Iris Feature Extraction Using Independent Component Analysis

From the eye image, a large region of the iris is highlighted except for the upper iris due to some part of it is covered by the eye. Small region is chosen from the highlighted area and then it is being stretched and segmented to a certain size. The image of iris region is then multiplied by the Gaussian functions basicly to remove noises and to obtain the iris's signal. This signal is complex and can be broken into sets of simple ICA signals as shown in Figure 6. The simple signals obtained can be used to represent the image that helps to differentiate the image from other images and can be used for image classification. The steps applied to ANA images will also be the same.

However, ICA is rarely being used for image processing. Most of the time, it is applied to separate voices and sounds. But then again, as it is uncommonly being applied to process images, an experiment should be made to test its performances on images.

2.3 CLASSIFICATION USING SUPPORT VECTOR MACHINE (SVM)

Of late, Support Vector Machine (SVM) is the most preferable method to perform classification in image processing. Support Vector Machine are first proposed by Vapnik [22].There are quite enormous researches and studies that had proven that SVM shows better classification results compared to other classifier. For example in [3], SVM and PNN are experimented upon classifying agricultural product. The result obtained showed that SVM have the classification accuracy between 70%-90% while PNN only 60%-72%. While in [22] SVM is compared with AdaBoost and Decision Tree Classifiers, both are less competitive in the accuracy for hypothyroid classification.

SVM also stated to have better performance compared to other classifiers since it have its own unique principal in classifying data [7]. Figure 7 shows the principle of classification using SVM.

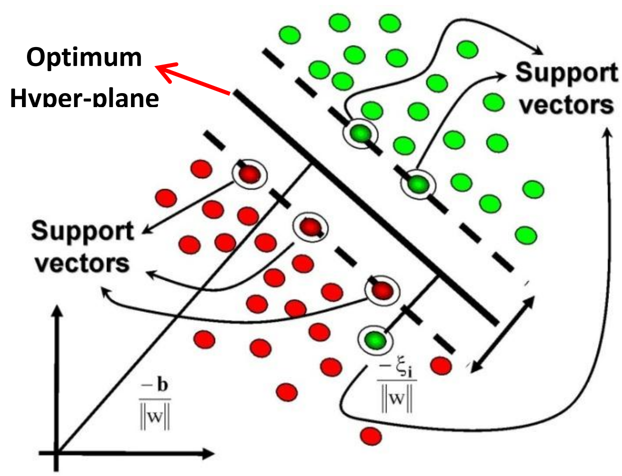


Figure 7: Classification using Support Vector Machine (SVM) Image

From the figure, we can see the features from two different groups are being separated by SVM. SVM will search and build a linear function in feature space that will act as the separator and classifier. Additionally, it will not only create function that can classify the features but it creates the one that will have the maximum margin. This linear function is known as the Optimal Hyper-Plane. It shows in the figure that the distance between Optimum Hyper-plane with either Red group and Green group are at its maximum.

The location of Optimal Hyper-plane can be decided by the support vectors [22]. Support vectors are data points from both groups that lays closest to the Optimum Hyper-plane. Suppose if the hyper-plane that the support vectors lay are L1 and L2 for each group respectively, the Optimal Hyper-plane can be plotted at the middle of these two hyper-planes where its distance from both line is equal. By creating this kind of classifiers the accuracy of classification can be improved.

In ANA pattern classification, Support Vector Machine is favorable since lots of medical classifications either on cells or organ uses SVM. Examples can be seen in [23], [9] and [24] where it is being used in diagnosis of breast cancer, detection of biomarkers for cancer data and disease selection respectively. In [23], SVM is capable to classify images for breast cancer (either benign or malignant) in ultrasonic images with high accuracy. [23], [9] and [24] also stated other advantages of SVM over other methods which are less expertise required, reduce processing time, can extract higher order statistic and dependable in classifying co-relation data.

CHAPTER 3: METHODOLOGY

3.1 RESEARCH METHODOLOGIES

This project focuses is on the image processing techniques to identify the presence of Anti-nuclear antibodies and classify the type of ANA patterns. Method of processing the fluorescence images are practically the same with all other type of images which is using basic image processing technique as below.

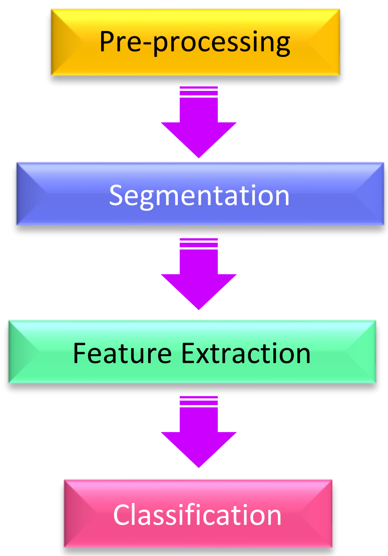


Figure 8: Flow Chart of Image Processing Step

Image pre-processing is performed generally to enhance the image quality, ensuring that next process of image processing is easier. Type of images pre-processing chosen is depending on the images conditions. Examples are Intensity Transformation (Contrast, Negative, and Log transformation), Histogram Processing, Smoothing and De-noising [25]. In this project, Image Grayscaling is used as Pre-processing method as the result in Section 4.1 IMAGE PREPROCESSING shows that the best pre-processing method for fluorescence of image is Grayscale.

Next is to perform segmentation on the image. Segmentation is basically done to portioning the image so that it can be clearly seen. For example is to apply Edge Approached which is to create cell frame making the shape of the cell clearer. For this project, image segmentation is not being performed by the author. All the images is obtained from MIVIA [26] which already being segmented by the experts. This is because the project focus is not on segmentation. However, the images obtained from

MIVIA have different dimensions and is not applicable for the method used. Thus, image resizing is performed to the images so that all images are in the same dimension which is 50x50 pixels

Next step is the feature extraction technique where two of these methods will be compared (i) Wavelet and (ii) Independent Component Analysis. From the coefficients extracted by Wavelet and ICA, Statistical features such Mean, Max and Min is obtained. Features obtained from both methods will be fed into classifier (Support Vector Machine) independently. For classification process, it involved Training Images and Testing Images [15]. For training, 70 images from each group are introduced to train the classifier. In this case, 70 images from Homogeneous and 70 from Speckled where each will performs feature extraction and all features will be fed into SVM. More than one images need to be introduced to SVM so that it can distinguish the features of each class accurately. All of the features from these images will be extracted and stored in features library.

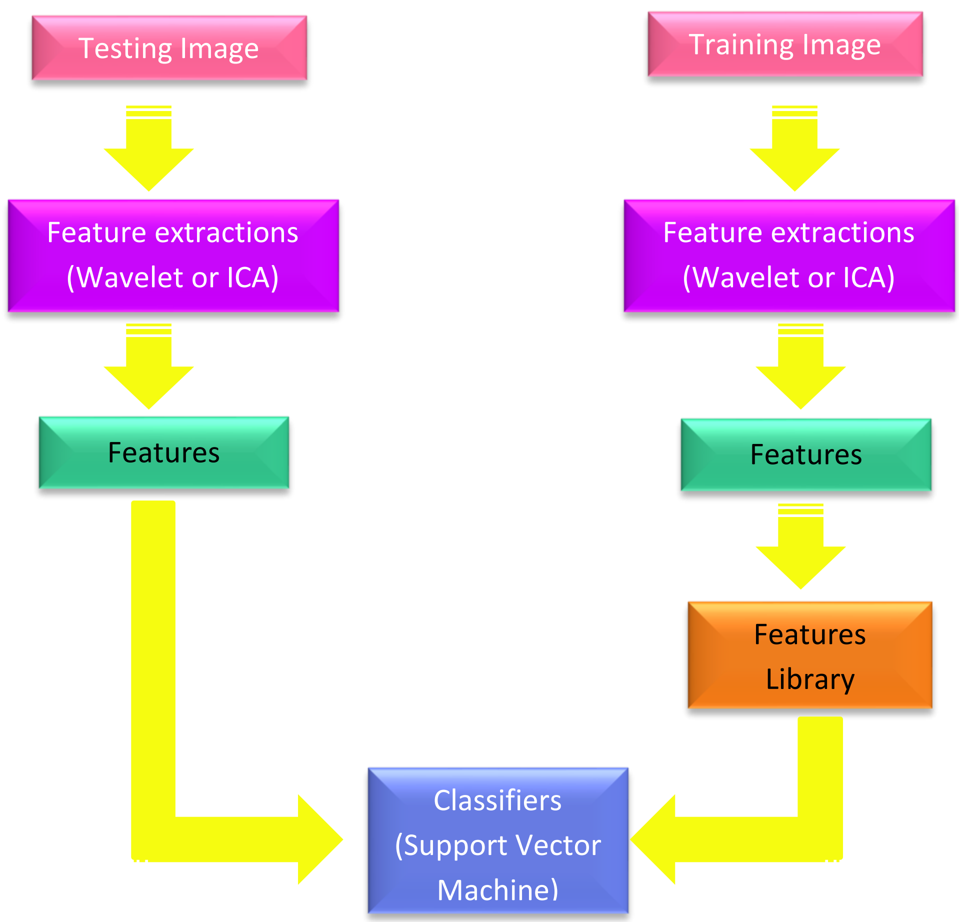


Figure 9: Flow Chart of Feature Extraction and Classification

When an image with unknown group is introduced, it needs to undergo feature extraction process to obtain the coefficients. The features of this unknown image will be then compared with features stored in the library. Then, it will be classified by SVM and decide which group this image belongs to.

3.2 PROJECT ACTIVITIES

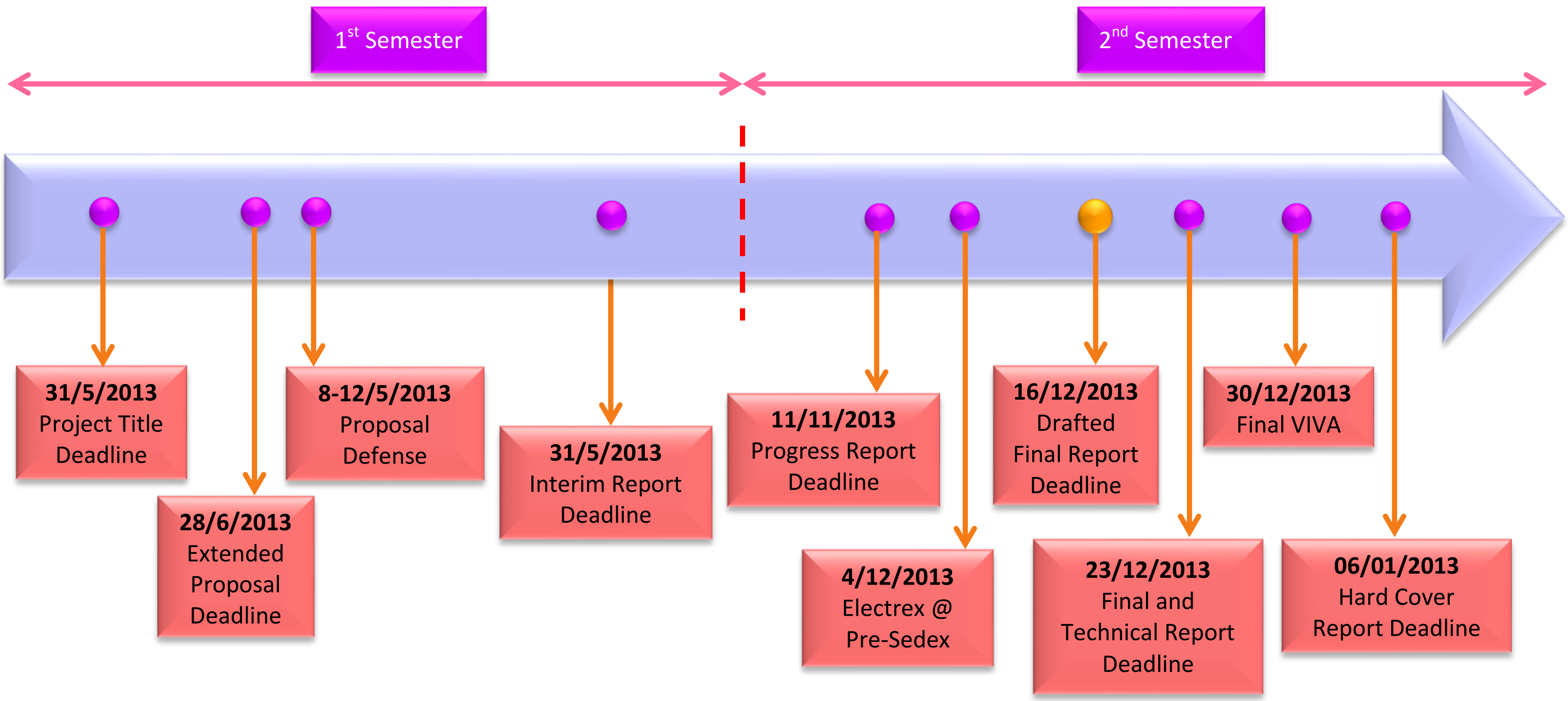
The activities accomplished along conducting this project is as below:

- FYP briefing from coordinators and talk from external personnel regarding Plagarism.
- Weekly meeting with the supervisors to update the progress of the project and discussing problems regarding FYP.
- Joining image processing classes to learn on the MATLAB coding for image processing
- Researching on theories related to the medical parts of the project
- Researching on theories related to image processing
- Performing MATLAB coding in the lab to obtain working algorithm for the project

3.3 RELEVENCY TO THE OBJECTIVE

The methodology of the research is relevant to the objective since it perform all the image processing process in achieving the final result. This project performs the pre-processing process which is needed before moving to the feature extraction process. As the objective is to compare two different types of feature extraction techniques, the methodology performs both techniques and the features from both techniques are fed into classifiers independently. The classifiers will then perform the classification and the accuracy using two feature extraction methods is compared.

3.4 KEY MILESTONE



3.5 GANTT CHARTS

Project Activities	Semestar 1														Semestar 2														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Confirmation of the project title	■	■																											
Research on Image Pre-processing						■	■																						
MATLAB Coding on Image Pre-processing								■	■																				
Research on Image Segmentation										■	■	■																	
MATLAB Coding on Image Segmentation													■	■															
Research on Feature Extraction Techniques (Wavelet and ICA)		■	■	■	■	■	■																						
MATLAB Coding on Wavelet Feature Extraction															■	■	■	■											
Research on Support Vector Machine for Classification		■	■	■	■	■	■																						
MATLAB Coding on Support Vector Machine for Classification																		■	■	■	■								
MATLAB Coding on Independent Component Analysis Feature Extraction																						■	■	■					
Extended Proposal				■	■	■																							
Proposal Defense						■	■																						
Interim Report											■	■	■																
Progress Report																						■							
Electrex																									■				
Sedex																										■			
Drafted Report																											■		
Final Report & Technical Report																												■	
VIVA																													■

3.6 SOFTWARE USED

The software used in this project is MATLAB and all coding is done fully using MATLAB software. In order for the system to be user friendly, the Graphical User Interface or GUI is developed using the MATLAB. GUI helps to display the software in more organized ways. By applying GUI, common people without expertise can also use the program easily.

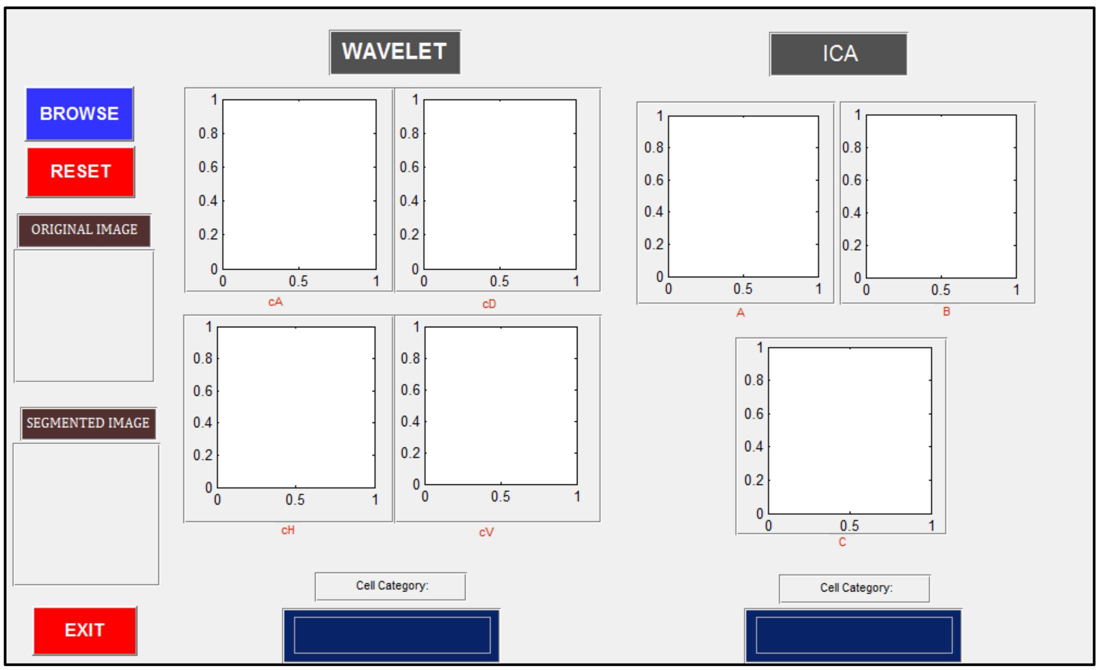


Figure 10: Graphical User Interface (GUI)

GUI, Figure 10 shows a few buttons which is BROWSE, RESET and EXIT. The BROWSE button is used to browse for images inside the computers and fed it into the software. As the images are fed, the interface will show the Original Image and Segmented Image of the cell at the left side of the GUI. Then, the features' graphs obtained using Wavelet and ICA is displayed at the middle part of GUI. At the bottom, the cell image category will be displayed.

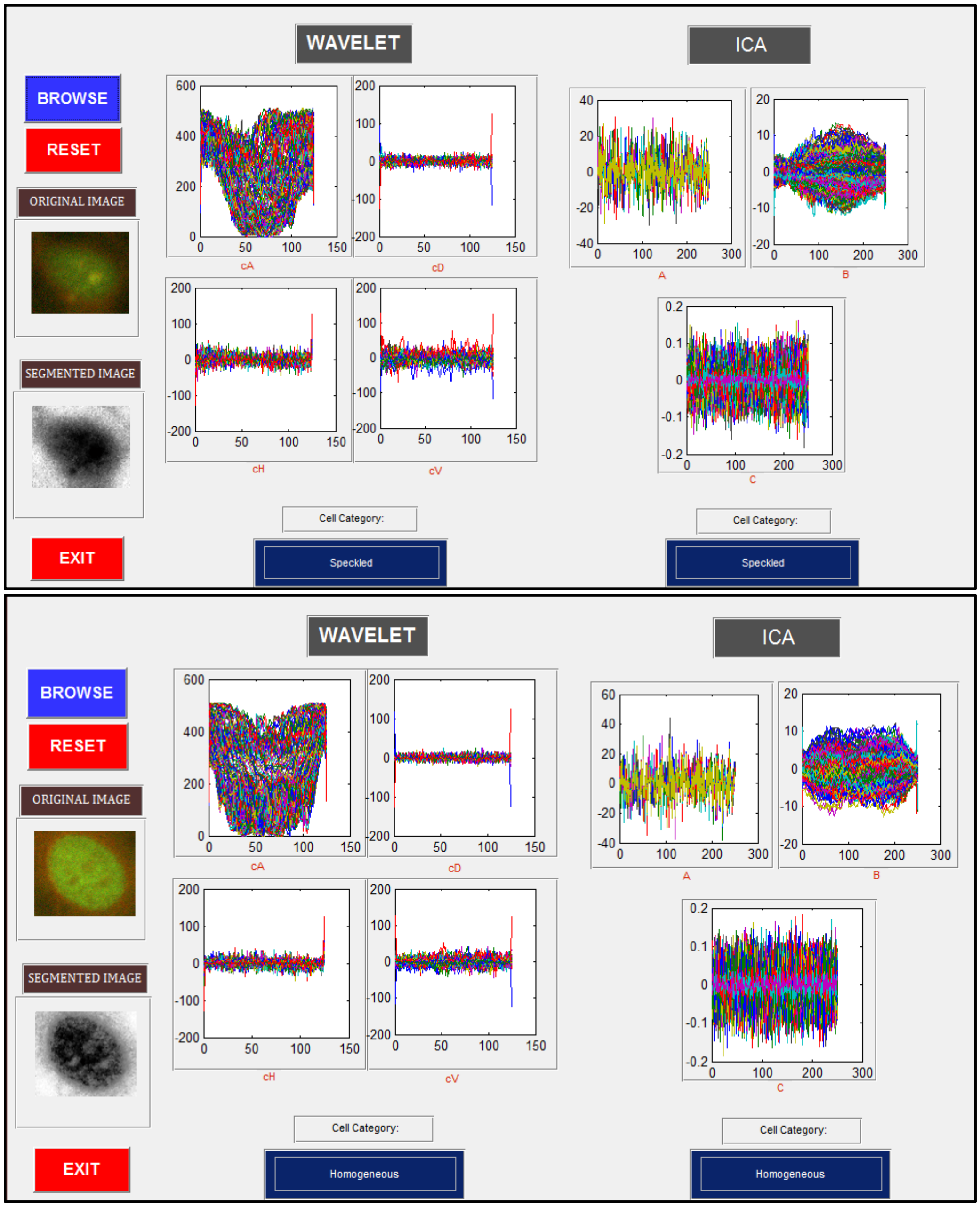


Figure 11: Graphical User Interface (GUI) when analyzing (a) Homogeneous Image (b) Speckled Image

From Figure 11 above, as the image of Homogeneous is fed into the system, the cell category is displayed. At the right is by using Wavelet and at the left is by using ICA. The RESET button is used to RESET the software before loading another images, while the exit button is used to close the GUI.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 IMAGE PREPROCESSING

Image pre-processing is needed in order to enhance the quality of the image. Figure 12a below shows the original image of Homogeneous ANA pattern which is hardly clear. In order to show the usage and the difference of pre-processed image, three different pre-processing techniques are applied to the images. Then, the best and suitable technique is chosen. The three techniques chosen are Grayscale, Negativity and Log Transformation. The coding set below had been run in the MATLAB software and the result can be seen in Figure 12b, 12c and 12d.

```
% Declare a figure to display images
figure (1);
% Read and image named homo1 with JPEG extension and put it in
a variable named 'Image'
Image = imread('homo1.tif');
% Divide the figure into two rows, two columns and choose the
first quadrant
subplot (2,2,1);
% displays the image and gives it a title
imshow(Image), title('Original image');
% converts the image to grayscale and put it in a variable
named 'ImageGray'
ImageGray = rgb2gray(Image);
% display gray image in the second quadrant
subplot (2,2,2);
imshow(ImageGray), title('Gray image');
% Compute Image negative
NegativeImage = 255-ImageGray;
% display negative image in the third quadrant
subplot (2,2,3);
imshow(NegativeImage,title('Negative image');
% Compute log image
LogImage = log(1+double(ImageGray));
% display negative image in the fourth quadrent
subplot (2,2,4);
imshow(LogImage), title('Log image');
```

Table 3: MATLAB Coding on Image Pre-processing

Figures 12b, 12c and 12d show the images of the ANA's Homogeneous pattern after pre-processed using Grayscale, Negativity and Log Transformation respectively.

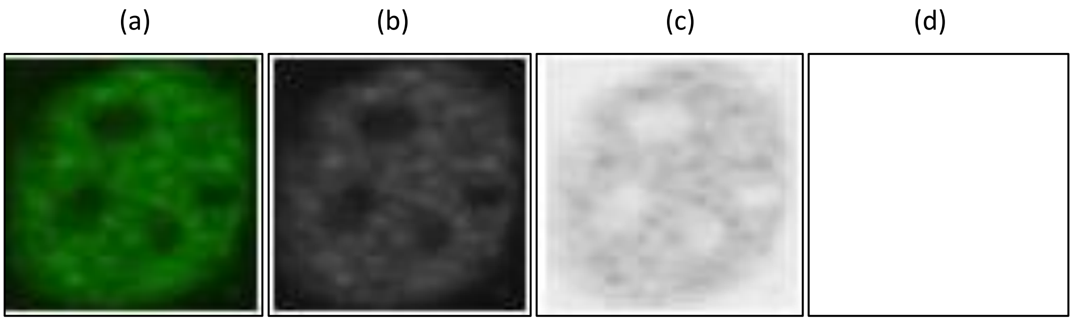


Figure 12: Images pre-processing (a) Original (b) Greyscale (c) Negative (d) Log Transformed

From all the three images, image (d) which undergoes Log Transformation produced an unclear image while image (b) which was pre-processed using Grayscale produced the clearest cells shape. As a result, this experiment shows that image pre-processing helps in enhancing the image but then the suitable method is depending on the type of image. Thus in this project, the pre-processing method chosen is the Grayscale.

4.2 IMAGE RESIZING

Wavelet and ICA both extract the features in array of data. The numbers of features extracted are totally dependent to the size of the image. Thus, it is very important for all images to be in the same size so that the numbers of features extracted are the same for all images. Besides, when performing classification method using SVM, it is mandatory to have the same length of data array.

```
Resize=imresize (Image,[50 50]);
%Resize the image by 50x50 pixels
```

Table 4: MATLAB Coding on Image Resizing

The image is cropped and resize with the size of 50x50 pixels.

4.3 WAVELET FEATURE EXTRACTION

```
[cA1,cH1,cV1,cD1] = dwt2(ImageGray1,'db1');
%Apply 2D Discrete Wavelet Transform to Grayscale Image
%Use 'db1' (Doubechies) as the wavelet
%Image Decomposition with level 1
m1 = min(cA1);
%Choose minimum value of approximation coefficient as the features
```

Table 5: MATLAB Coding on 2D Discrete Wavelet Transform

For Wavelet Transform, 2D Discrete Wavelet Transform with Level 1 is used. As this image only can only be decompose up until Level 1, the decomposition stopped at the first level only. More decomposition will results in zero values for cH and cD. The Wavelet type used is Daubechies since it is simple and mostly used in many applications. By applying 2D DWT, four vectors can be obtained which are cA, cH, cV and cD. cA is the approximation coefficient of the image while cH, cV and cA contrariwise are the details coefficient of horizontal, vertical and diagonal direction respectively. Figure 13 below shows the four coefficients obtained after performing 2D DWT to Homogeneous Image. For speckled image on the other hand can be seen in Figure 14.

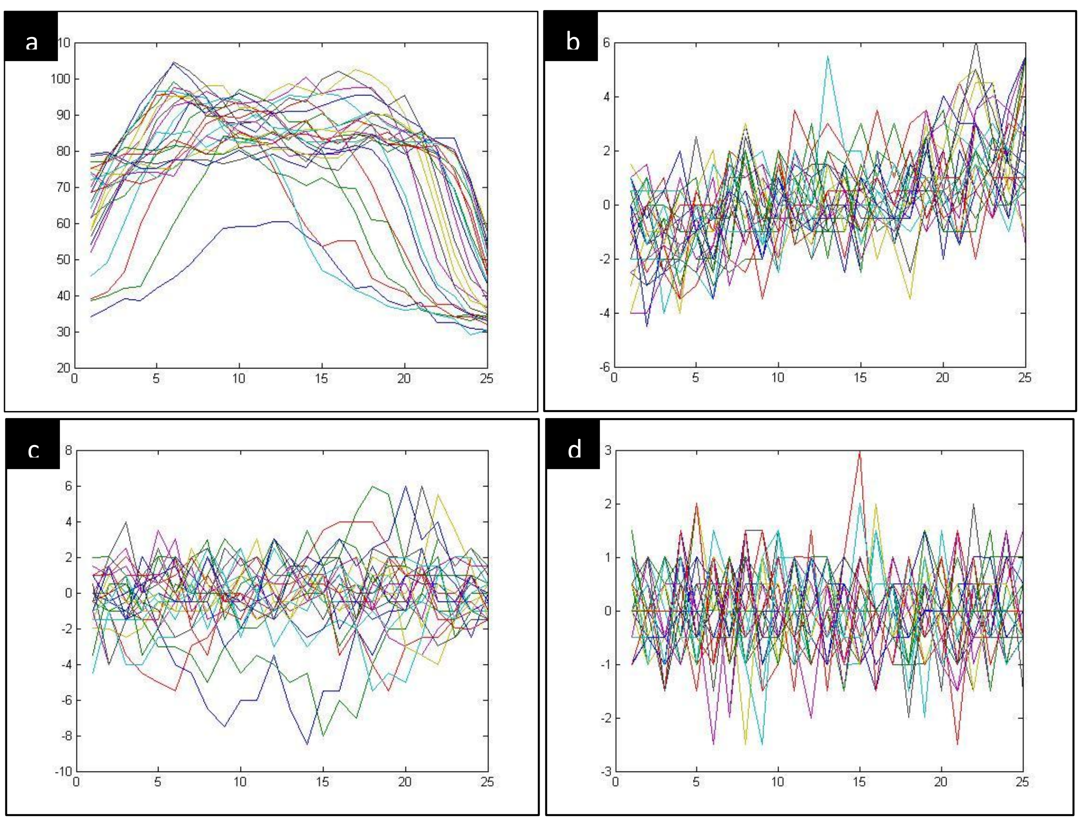


Figure 13: 2D DWT on Homogeneous Image (a) cA (b) cH (c) cV (d) cD

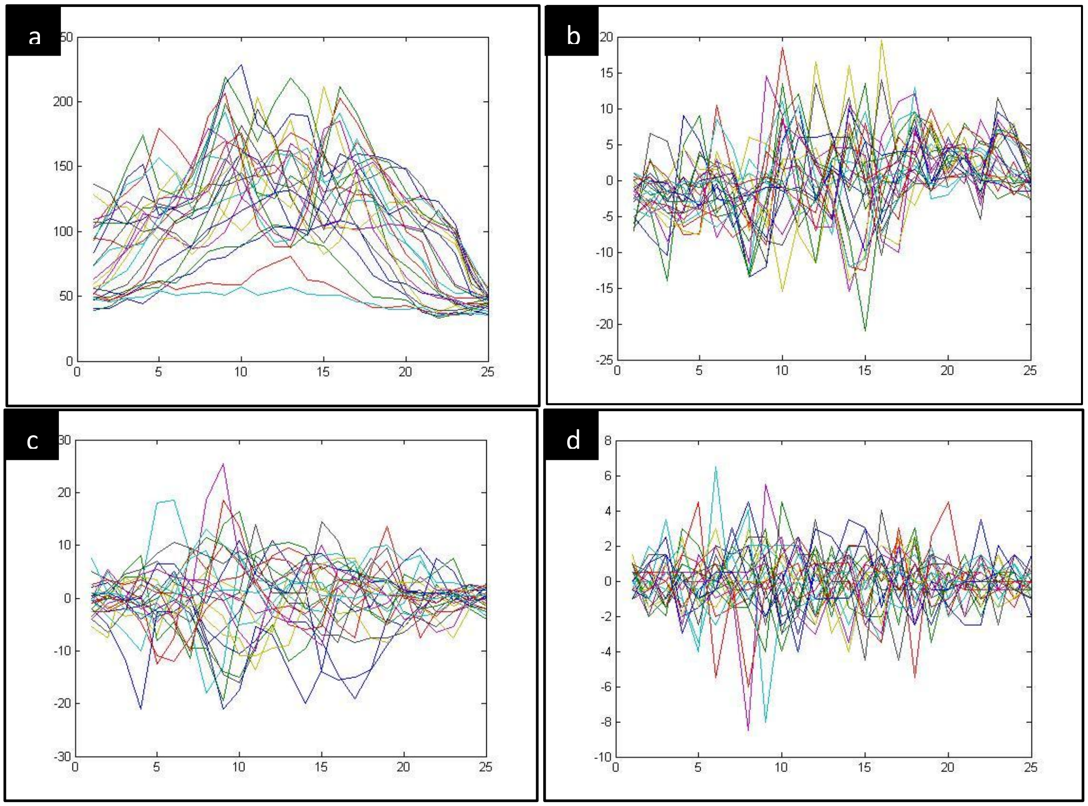


Figure 14: 2D DWT on Speckled Image (a) cA (b) cH (c) cV (d) cD

From the images, graph of cA shows quite a distinct pattern between Homogeneous and Speckled. The range of cA values for Speckled is also twice larger than Homogeneous which is about 40 to 250 and 30 to 110 respectively. For cH, the difference in graph pattern is not too clear, however the range difference in very large. Homogeneous only ranges from -6 to 6 while speckled, -25 to 20. The same goes to cV and cD, where the shape of the graph is about the same for both ANA pattern, but dissimilar in the range of values. Speckled image shows bigger ranges and higher values compared to Homogeneous in all type of features. From the graph, we can also say that Wavelet features shows quite diverse values for different ANA type which will be helpful to the classifier.

From a 50x50 pixel image, cA, cH, cV and cD obtained are 25x25 matrix where each row corresponds to an observation and each column corresponds to a feature or variable. From this, the statistical features are computed for instance mean, maximum (max) and minimum (min). The Max values from 25x25 matrices will create matrices of 1x25 and the same goes to Min and Mean. First, cA, cH, cV and cD is compared using Mean (either one between Mean, Max and Min). From the four features, the best is picked and is tested using Min and Max. Thus, two comparisons will be made (i) cA, cH, cV and cD, (ii) Mean, Max and Min. The result can be seen in Table 10 to Table 13.

Figure 15 shows the graph of mean, max and min values of Approximation Coefficient (cA) for Homogeneous and Speckled Image. Note that 'cyan' represent the max, 'magenta' for the mean and min is represented by 'yellow' color.

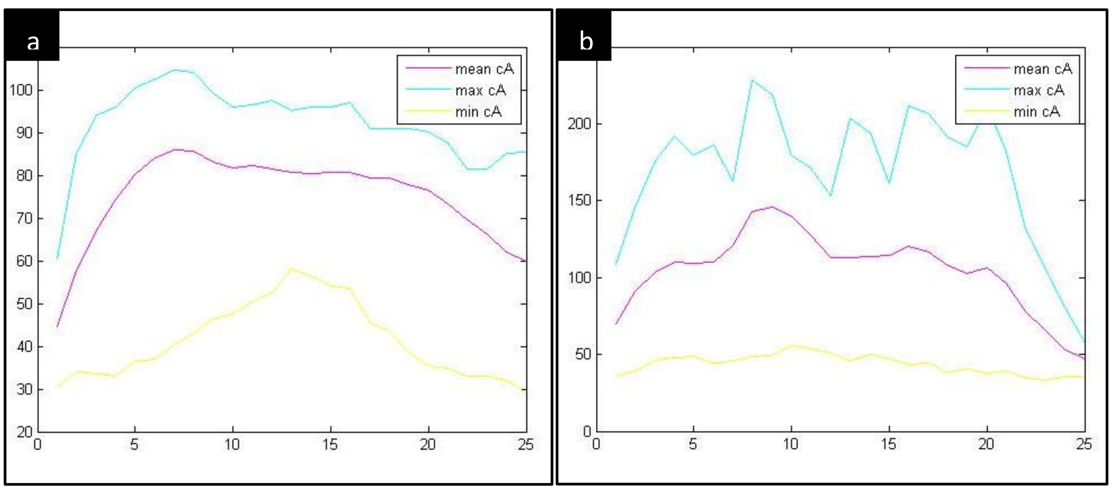


Figure 15: mean, max and min values of cA (a) Homogeneous (b) Speckled

The graph shows that Max values for Homogeneous is small (ranges from 60 to 105) compared to Speckled (ranges from 50 to 230). As for Mean values, 30 to 60 and 50 to 150 for Homogeneous and Speckled respectively. Next, Min for Homogeneous is -40 to 85 whereas Speckled is 25 to 55.

Figure 16, 17, 18 shows the graph of mean, max and min values of Horizontal Coefficient (cH), Vertical Coefficient (cV) and Diagonal Coefficient (cD) for both ANA patterns.

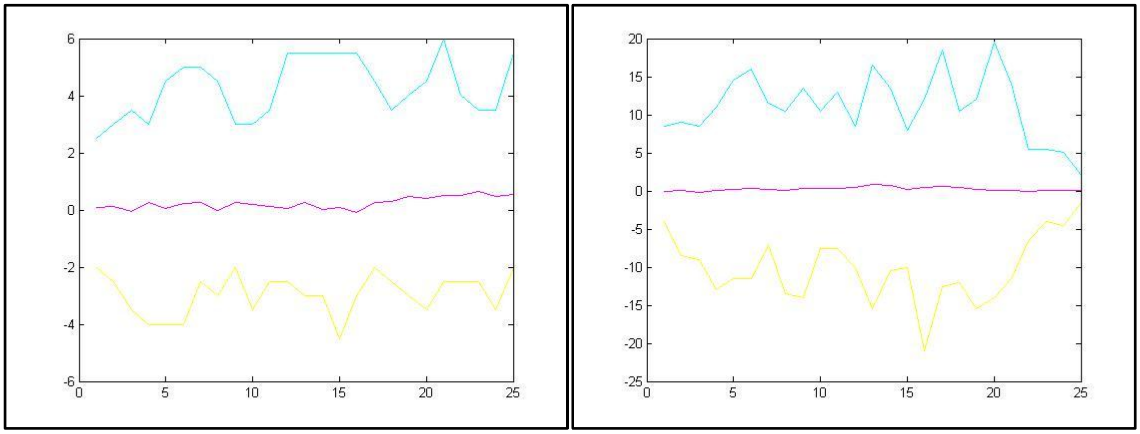


Figure 16: mean, max and min values of cH (a) Homogeneous (b) Speckled

The mean of cH for Homogeneous and Speckled images is practically the same which is at 0. As for Max, Homogeneous is located between 2 to 6 only while Speckled is larger which is 5 to 20. Then for Min, -2 to -6 for Homogeneous and -5 to -25 for speckled. Thus, for cH, we can conclude from cH graph, Max and Min of both patterns shows large alteration but Mean are practically indistinguishable.

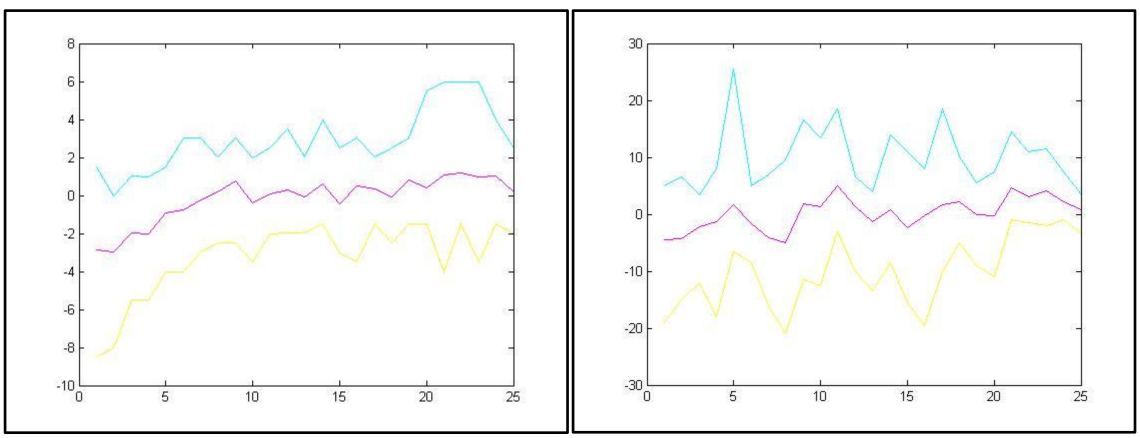


Figure 17: mean, max and min values of cV (a) Homogeneous (b) Speckled

Next is the Max of cV graph where Homogeneous shows values between 0 to 8. Speckled then again shows larger range starting from 0 to 30. Followed by Mean for Homogeneous is -3 to 2 and -5 to 5 for Speckled. Lastly Min ranges from -1 to -9 for Homogeneous and -20 to 0 for Speckled.

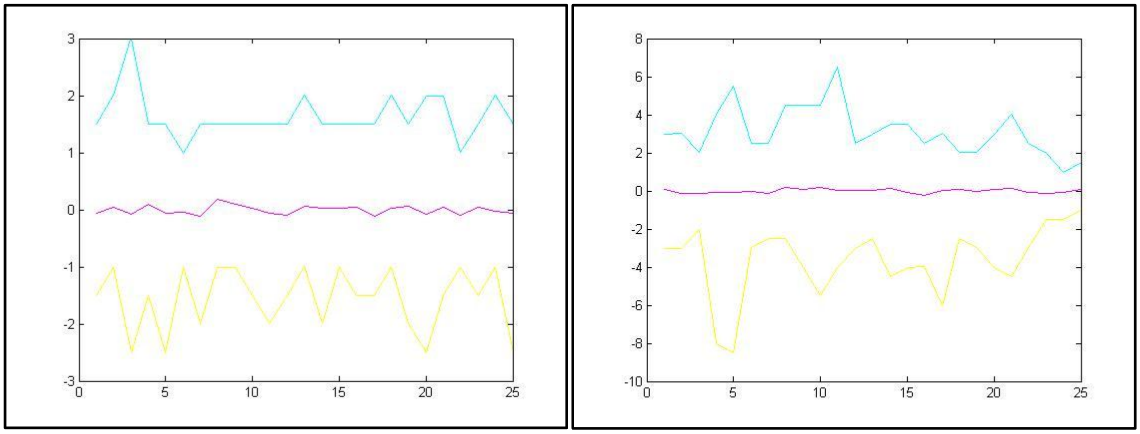


Figure 18: mean, max and min values of cD (a) Homogeneous (b) Speckled

cD graph shows the same Mean for both which is at 0. Homogeneous have Max of 1 to 3 and Speckled's Max is 1 to 7. Whereas for Min is -1 to -3 and -2 to -10 for Homogeneous and Speckled respectively.

4.4 INDEPENDENT COMPONENT ANALYSIS FEATURE EXTRACTION

```
[A,B,C] = fastica(ImageGray);
%Apply fast ICA for Grayscale Image
%3 Independent Component is obtained
m = mean(A);
%Choose mean value of approximation coefficient as the features
```

Table 6: MATLAB Coding on Independent Component Analysis

Fast Independent Component Analysis [27] is chosen to extract independent features from the grayscale image. Three components is obtained by using Fast ICA which are A, B and C. As ICA mainly used to separate the complex signal to individual signal, two of the features that can be considered as independent are the approximation of mixing signals and approximation of separating signal which is B and C. Also, an independent signal is retrieves using FastICA which is matrix A.

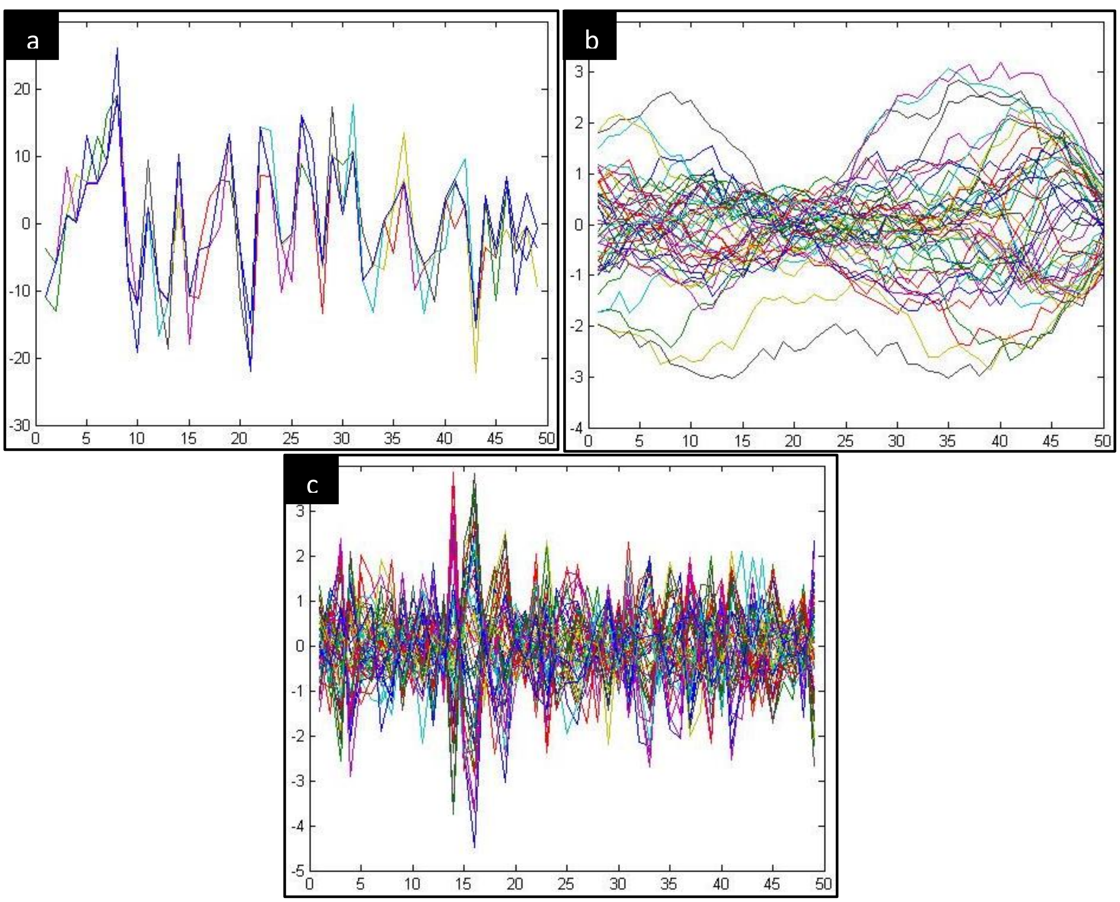


Figure 19: Fast ICA on Homogeneous Image (a) A (b) B (c) C

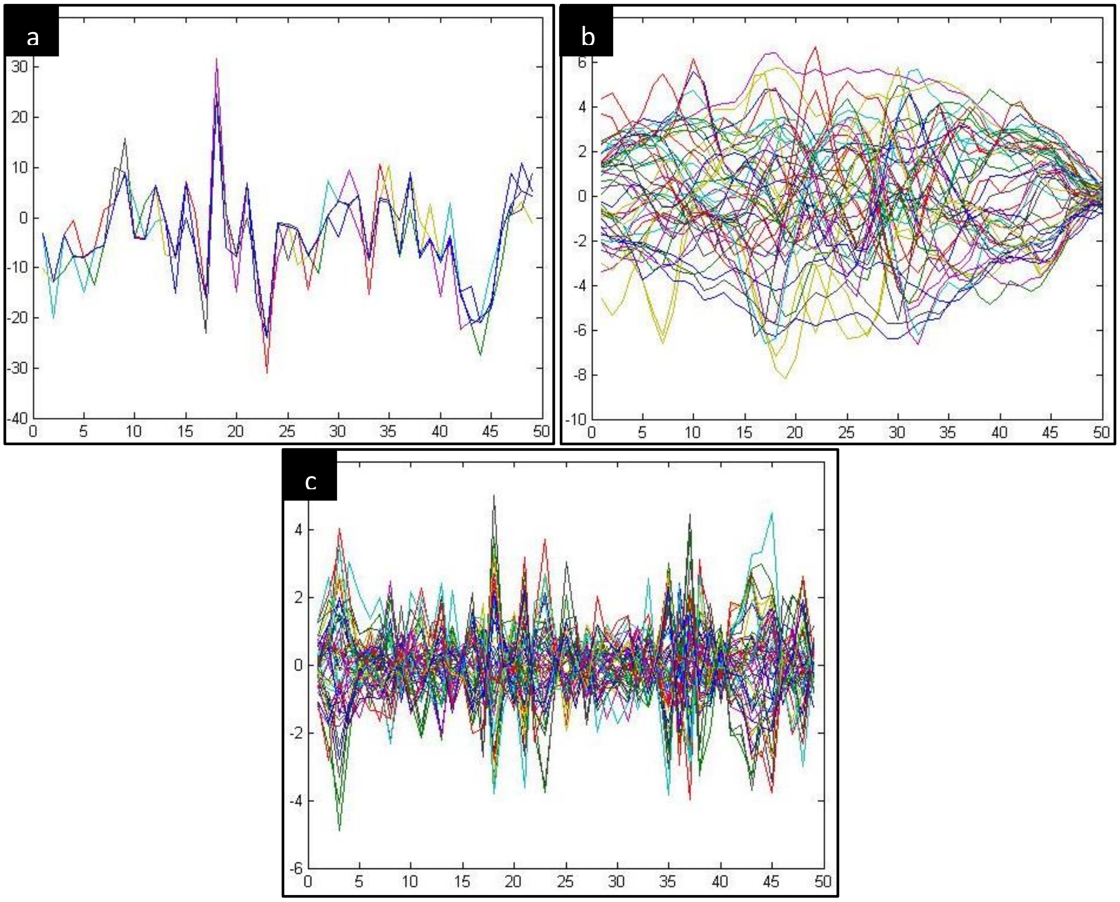


Figure 20: Fast ICA on Speckled Image (a) A (b) B (c) C

Figure 19 above shows the three coefficients obtained after performing FastICA to Homogeneous Image. For speckled image on the other hand can be seen in Figure 20. Features A and C for both pattern are somewhat the same. However, we can see that feature B, which is Approximation of Mixing Signal, shows some difference in the shape of the graph. The range values of A and C also does not show much difference. For Homogeneous, the range of B is -4 to 4, while for Speckled is -10 to 8. Still, using ICA, features obtained from Speckled has higher values and ranges compared to features obtained from Homogeneous.

Using ICA, from 50x50 pixel image, A, B, and C obtained are 49x50, 50x49 and 49x50 respectively. Each row corresponds to an observation and each column corresponds to a feature or variable. From this, the statistical features is computed for instance of Mean, Max and Min. The Max values from 49x50 matrices will create matrices of 1x50 and from 50x49 features will create 1x49 matrices. The same is applied to Min and Mean.

All the comparisons on result will be performed same as Wavelet. The result can be seen in Table 14 and Table 17. Figure 21 shows the graph of mean, max and min values of ICA Independent Signal (A) for Homogeneous and Speckled Image. Note that 'cyan' represent the max, 'magenta' for the mean and min is represented by 'yellow' color.

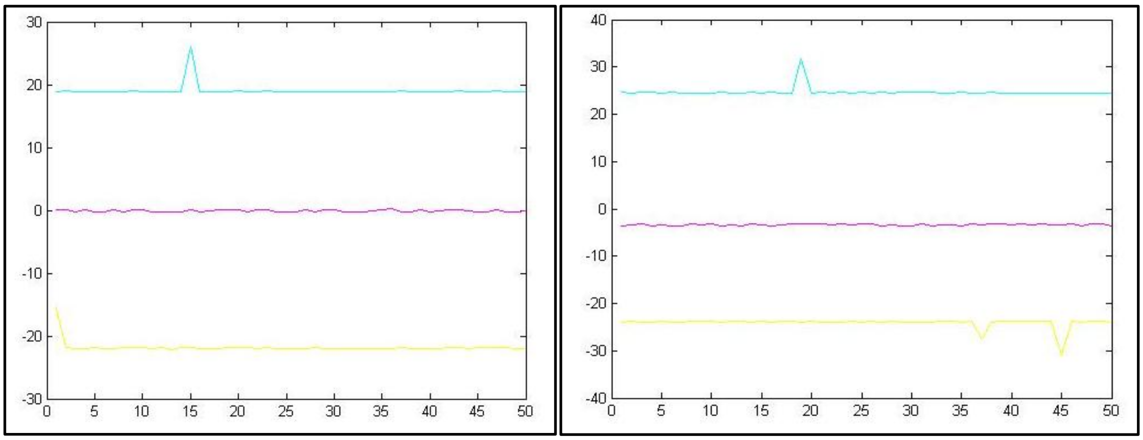


Figure 21: mean, max and min values of A (a) Homogeneous (b) Speckled

Using Mean as the features, Homogeneous shows values in range of 0 and for Speckled, about -5 to 0. While for the Max, majority of the values are just below 20 for Homogeneous while for Speckled, about 25. Conversely, Min for Speckled is lower compared to Homogeneous which is -24 and -21 respectively. Thus, features obtained from using FastICA can be said to be closer with each other.

Figure 22 and 23 shows the graph of mean, max and min values of B and C for Homogeneous and Speckled Image.

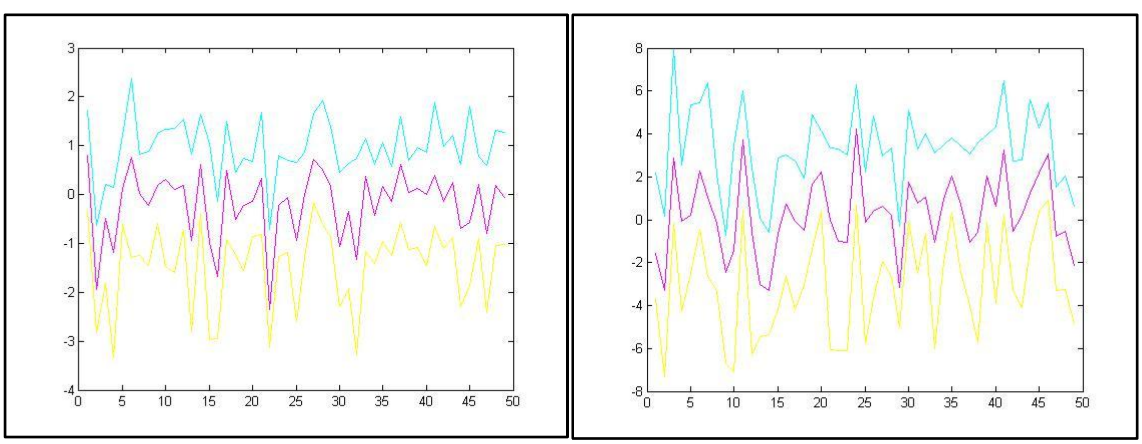


Figure 22: mean, max and min values of B (a) Homogeneous (b) Speckled

For B, the range for Min, Mean and Max are intercepting with each other. Min for Homogeneous ranges from -3 to 0 and for Speckled is -8 to 1. Next is Max values, -0.5 to 2.5 and 0 to 8 for Homogeneous and Speckled respectively. Lastly for Mean, Homogeneous ranges from -2 to 1 and Speckled -4 to 4.

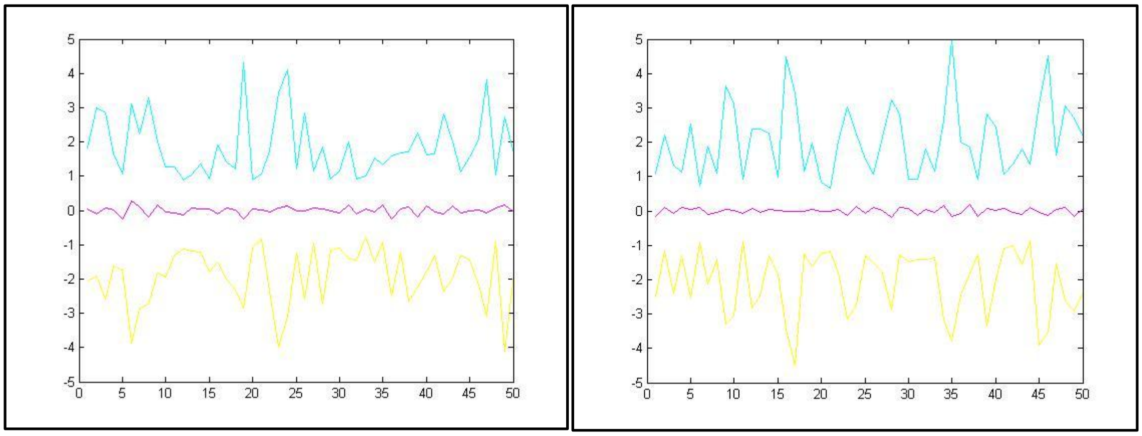


Figure 23: mean, max and min values of C (a) Homogeneous (b) Speckled

Next is for C graph, the Mean ranges at 0 for both types. Same goes to Max and Min where they range at 1 to 5 and -1 to -5 for both ANA types.

4.5 SUPPORT VECTOR MACHINE

Feature extraction coding in Table 7 is performed to 70 Homogeneous images and 70 Speckled images. The features obtained are to be set as the training images.

```
      %----------------------TRAINING IMAGES-------------------%
Training = cat(1,m1,m2,m3,m4,m5,m6,...m139,m140);
Group = 0;0;0;0;0;0;0;.....;1;1;1;1;1;1;1]
ImageTrain = svmtrain(Training,Group);
```

Table 7: MATLAB Coding on Training Images

From the coding, line "`Training = cat(1,m1,m2,m3,m4....`" shows list of features obtained from 140 training images. "`cat`" is used to arrange the array of data in rows thus make training to have 140x25 matrices. The line "`Group = [0;0;0;0;`" shows that the group is mapped to the training by arranged it by column thus making the Group image a matrices of 140x1. In theory, the training images are being arranged as follows.

Image	Array of Features	Group
1	0,10,23,12….	1
2	27,27,50,11…	1
. .	. .	. .
139	4,32,23,10….	0
140	4,32,23,10….	0

The testing images also need to undergo the same feature extraction method as the testing images.

```
%---------------------TESTING IMAGES-------------------%
disp ('Please key in image name. Example : Sample1.tif')
prompt = 'Image Name: ';
Image0 = input (prompt, 's');

ImageT = imread(Image0);
ResizeT=imresize (ImageT, [50 50]);
ImageGrayT = rgb2gray(ResizeT);
[cAT,cHT,cVT,cDT] = dwt2(ImageGrayT,'db1');
mT = min(cAT);
```

Table 8: MATLAB Coding on Feature Extraction of Testing Image

The paragraph "`disp ('Please...`" is to call the image in the file so that it can be tested. The next paragraph is to perform feature extraction to testing image.

The next step is to perform the classifications of the testing image. The features obtained from testing image will be compared with the training images using the function ‘svmclassify’. Suppose of the features is closer to Homogeneous features, SVM will classify the testing image as Homogeneous and vice versa. 60 images, 30 of each group are used as the testing image. The accuracy of the Wavelet and Independent Component Analysis is tested which gives the results as the Table 10 until Table 17.

```
%----------------------CLASSIFY IMAGES-------------------%
Class = svmclassify(ImageTrain,mT);

if Class==0;
disp ('This Cell is categorized as Homogeneous');
else
disp ('This Cell is categorized as speckled');
end
```

Table 9: MATLAB Coding on Image Classification

4.5.1 Wavelet

cA, cH, cV and cD is compared using Mean as features. Table 10 is for Homogeneous while Table 11 is for Speckled.

Homogeneous	Mean cA	Mean cH	Mean cV	Mean cD
Test Image 1	Correct	Correct	Correct	Correct
Test Image 2	Correct	Correct	Correct	Correct
Test Image 3	Correct	Correct	Correct	Correct
Test Image 4	Correct	Correct	Correct	Correct
Test Image 5	Correct	Correct	Correct	Correct
Test Image 6	Incorrect	Incorrect	Incorrect	Incorrect
Test Image 7	Incorrect	Incorrect	Incorrect	Incorrect
Test Image 8	Correct	Correct	Correct	Correct
Test Image 9	Correct	Correct	Correct	Correct
Test Image 10	Correct	Correct	Correct	Correct
Test Image 11	Correct	Correct	Correct	Correct
Test Image 12	Correct	Correct	Correct	Correct
Test Image 13	Correct	Correct	Correct	Correct
Test Image 14	Correct	Correct	Correct	Correct
Test Image 15	Correct	Correct	Correct	Correct
Test Image 16	Correct	Correct	Correct	Correct
Test Image 17	Correct	Correct	Correct	Correct
Test Image 18	Correct	Correct	Correct	Correct
Test Image 19	Correct	Correct	Correct	Correct
Test Image 20	Correct	Correct	Correct	Correct
Test Image 21	Correct	Correct	Correct	Correct
Test Image 22	Correct	Correct	Correct	Correct
Test Image 23	Correct	Correct	Correct	Correct
Test Image 24	Correct	Correct	Correct	Correct
Test Image 25	Correct	Correct	Correct	Correct
Test Image 26	Correct	Correct	Correct	Correct
Test Image 27	Correct	Correct	Correct	Correct
Test Image 28	Correct	Correct	Correct	Correct
Test Image 29	Correct	Correct	Correct	Correct
Test Image 30	Correct	Correct	Correct	Correct
Accuracy	93.33%	93.33%	93.33%	93.33%

Table 10: Classification using Mean cA, cH, cV and cD for Homogeneous Image

Speckled	Mean cA	Mean cH	Mean cV	Mean cD
Test Image 1	Correct	Correct	Correct	Correct
Test Image 2	Incorrect	Incorrect	Incorrect	Incorrect
Test Image 3	Correct	Correct	Correct	Correct
Test Image 4	Correct	Correct	Correct	Correct
Test Image 5	Correct	Correct	Correct	Correct
Test Image 6	Correct	Correct	Correct	Correct
Test Image 7	Correct	Correct	Correct	Correct
Test Image 8	Correct	Incorrect	Correct	Correct
Test Image 9	Correct	Correct	Correct	Correct
Test Image 10	Correct	Correct	Correct	Correct
Test Image 11	Correct	Correct	Correct	Correct
Test Image 12	Correct	Correct	Correct	Correct
Test Image 13	Correct	Correct	Correct	Correct
Test Image 14	Correct	Correct	Correct	Correct
Test Image 15	Correct	Correct	Correct	Correct
Test Image 16	Correct	Incorrect	Correct	Correct
Test Image 17	Correct	Correct	Correct	Correct
Test Image 18	Incorrect	Incorrect	Incorrect	Incorrect
Test Image 19	Correct	Correct	Correct	Correct
Test Image 20	Incorrect	Incorrect	Incorrect	Incorrect
Test Image 21	Incorrect	Incorrect	Incorrect	Incorrect
Test Image 22	Correct	Correct	Correct	Correct
Test Image 23	Correct	Correct	Correct	Correct
Test Image 24	Incorrect	Incorrect	Incorrect	Incorrect
Test Image 25	Correct	Correct	Correct	Correct
Test Image 26	Correct	Correct	Correct	Correct
Test Image 27	Correct	Correct	Correct	Correct
Test Image 28	Correct	Correct	Correct	Correct
Test Image 29	Correct	Correct	Correct	Correct
Test Image 30	Correct	Correct	Correct	Correct
Accuracy	83.33%	76.67%	83.33%	83.33%

Table 11: Classification using Mean cA, cH, cV and cD for Speckled Image

Thus, from the result the total accuracy of using Mean of cA, cH, cV and cD is calculated:

- Mean of cA = (93.33 + 83.33) / 2 = 88.33%

- Mean of cH = (93.33 + 76.67) / 2 = 85.00%
- Mean of cV = (93.33 + 83.33) / 2 = 88.33%
- Mean of cD = (93.33 + 83.33) / 2 = 88.33%

From Table 10 and 11, it shows that the highest accuracy of the system obtained is 88.33%. This accuracy obtained by using Mean cA, cV and cD as the features. Mean cH on the other hand shows slightly different values with the accuracy of 85% which is 3.3% lesser. However, it can be concluded that using different Wavelet features does not bring much differences in classification accuracy.

From the result, we can also see that with four different features used, most of them classified the same images wrongly. Some of the images are being wrongly classified four times such as Test Image 6 and 7 for Homogeneous and Test Image 2, 18, 20, 21 and 24 for Speckled. This shows that some images have higher possibility to be misclassified due to reasons like unclear image or non-uniform contrast of the image.

As cA, cV and cD gives the highest accuracy, one of them is then being used to test other statistical features which are Max and Min. The results are shown in Table 12 and 13 where cA is being used.

cA is used to test two other Statistical features which are Max and Min. The results are summarized in Table 12 and 13.

Homogeneous	Mean cA	Max cA	Min cA
Test Image 1	Correct	Incorrect	Correct
Test Image 2	Correct	Correct	Incorrect
Test Image 3	Correct	Incorrect	Correct
Test Image 4	Correct	Correct	Incorrect
Test Image 5	Correct	Incorrect	Correct
Test Image 6	Incorrect	Correct	Incorrect
Test Image 7	Incorrect	Correct	Incorrect
Test Image 8	Correct	Correct	Correct
Test Image 9	Correct	Incorrect	Correct
Test Image 10	Correct	Correct	Correct
Test Image 11	Correct	Correct	Correct
Test Image 12	Correct	Incorrect	Correct
Test Image 13	Correct	Correct	Correct
Test Image 14	Correct	Correct	Correct
Test Image 15	Correct	Incorrect	Correct
Test Image 16	Correct	Correct	Correct
Test Image 17	Correct	Correct	Correct
Test Image 18	Correct	Correct	Correct
Test Image 19	Correct	Correct	Correct
Test Image 20	Correct	Correct	Correct
Test Image 21	Correct	Correct	Correct
Test Image 22	Correct	Correct	Correct
Test Image 23	Correct	Correct	Correct
Test Image 24	Correct	Correct	Correct
Test Image 25	Correct	Correct	Correct
Test Image 26	Correct	Correct	Correct
Test Image 27	Correct	Correct	Correct
Test Image 28	Correct	Correct	Correct
Test Image 29	Correct	Correct	Correct
Test Image 30	Correct	Correct	Correct
Accuracy	93.33%	80.00%	86.67%

Table 12: Classification using Mean, Max and Min for Homogeneous Image

Speckled	Mean cA	Max cA	Min cA
Test Image 1	Correct	Correct	Correct
Test Image 2	Incorrect	Correct	Correct
Test Image 3	Correct	Correct	Correct
Test Image 4	Correct	Correct	Correct
Test Image 5	Correct	Correct	Correct
Test Image 6	Correct	Correct	Correct
Test Image 7	Correct	Correct	Correct
Test Image 8	Correct	Correct	Correct
Test Image 9	Correct	Correct	Correct
Test Image 10	Correct	Correct	Correct
Test Image 11	Correct	Correct	Correct
Test Image 12	Correct	Correct	Correct
Test Image 13	Correct	Correct	Correct
Test Image 14	Correct	Correct	Correct
Test Image 15	Correct	Correct	Correct
Test Image 16	Correct	Correct	Correct
Test Image 17	Correct	Correct	Correct
Test Image 18	Incorrect	Incorrect	Correct
Test Image 19	Correct	Correct	Correct
Test Image 20	Incorrect	Correct	Incorrect
Test Image 21	Incorrect	Correct	Correct
Test Image 22	Correct	Correct	Incorrect
Test Image 23	Correct	Correct	Incorrect
Test Image 24	Incorrect	Incorrect	Correct
Test Image 25	Correct	Correct	Correct
Test Image 26	Correct	Correct	Correct
Test Image 27	Correct	Correct	Correct
Test Image 28	Correct	Correct	Correct
Test Image 29	Correct	Correct	Correct
Test Image 30	Correct	Correct	Correct
Accuracy	83.33%	93.33%	90.00%

Table 13: Classification using Mean, Max and Min for Speckled Image

Thus, from the result the total accuracy of using Mean, Max and Min for cA can be calculated:

- Mean of cA = (93.33 + 83.33) / 2 = 88.33%
- Max of cA = (80.00 + 93.33) / 2 = 86.67%
- Min of cA = (86.67 + 90.00) / 2 = 88.33%

Referring to the data, it shows that by using Mean and Min as the coefficient, the accuracy is the same which is 88.33% while using Max, the accuracy is a bit lower which is 86.67%. However, the difference is less than 2% which is still acceptable.

It is also observed that none of the Test Images is being wrongly classified three times. However, Test Image 6 and 7 for Homogeneous and Test Image 18, 20 and 24 for Speckled are wrongly classified 2 times. This prove that any of these image are either unclear or unbalance in their contract, which cause the Wavelet to extract wrong features.

From the results obtained in Table 10 until Table 13, it can be said that for wavelet, using different features (e.g. cA, cV, cH and cD) gives accuracy which is practically the same. cA, cV and cD gives the same accuracy of 88.33%. cV gives accuracy of 80% which is only 3.33% difference. The images that are being misclassified are also the same. The same goes to using different Statistical features (e.g. Mean, Max and Min) gives different percentage but not too distant from each other. Mean and Min give the same percentage which is 88.33% while Max gives about 2% differences. Thus for Wavelet, it can be concluded that all features will give the same range of classification accuracy.

4.5.2 Independent Component Analysis

A, B, and C is compared using Min as features. Table 14 is for Homogeneous while Table 15 is for Speckled.

Homogeneous	Min A	Min B	Min C
Test Image 1	Correct	Incorrect	Correct
Test Image 2	Correct	Correct	Incorrect
Test Image 3	Correct	Incorrect	Incorrect
Test Image 4	Correct	Correct	Correct
Test Image 5	Correct	Correct	Incorrect
Test Image 6	Correct	Incorrect	Incorrect
Test Image 7	Correct	Incorrect	Incorrect
Test Image 8	Correct	Incorrect	Incorrect
Test Image 9	Correct	Correct	Correct
Test Image 10	Correct	Incorrect	Correct
Test Image 11	Correct	Incorrect	Incorrect
Test Image 12	Correct	Correct	Incorrect
Test Image 13	Correct	Correct	Correct
Test Image 14	Correct	Incorrect	Incorrect
Test Image 15	Correct	Correct	Correct
Test Image 16	Correct	Correct	Correct
Test Image 17	Correct	Correct	Incorrect
Test Image 18	Correct	Correct	Correct
Test Image 19	Correct	Correct	Correct
Test Image 20	Correct	Correct	Correct
Test Image 21	Correct	Correct	Incorrect
Test Image 22	Correct	Correct	Correct
Test Image 23	Correct	Correct	Incorrect
Test Image 24	Correct	Correct	Incorrect
Test Image 25	Correct	Correct	Correct
Test Image 26	Correct	Correct	Correct
Test Image 27	Correct	Correct	Incorrect
Test Image 28	Correct	Correct	Correct
Test Image 29	Correct	Correct	Incorrect
Test Image 30	Correct	Correct	Correct
Accuracy	100.00%	73.33%	50.00%

Table 14: Classification using Min A, B and C for Homogeneous Image

Speckled	Min A	Min B	Min C
Test Image 1	Incorrect	Correct	Correct
Test Image 2	Incorrect	Correct	Correct
Test Image 3	Incorrect	Correct	Correct
Test Image 4	Incorrect	Incorrect	Correct
Test Image 5	Incorrect	Correct	Incorrect
Test Image 6	Incorrect	Correct	Correct
Test Image 7	Incorrect	Correct	Correct
Test Image 8	Incorrect	Incorrect	Incorrect
Test Image 9	Incorrect	Correct	Correct
Test Image 10	Incorrect	Incorrect	Incorrect
Test Image 11	Incorrect	Correct	Correct
Test Image 12	Incorrect	Correct	Incorrect
Test Image 13	Incorrect	Correct	Incorrect
Test Image 14	Incorrect	Correct	Correct
Test Image 15	Incorrect	Correct	Correct
Test Image 16	Incorrect	Correct	Correct
Test Image 17	Incorrect	Correct	Incorrect
Test Image 18	Incorrect	Incorrect	Correct
Test Image 19	Incorrect	Correct	Correct
Test Image 20	Incorrect	Incorrect	Correct
Test Image 21	Incorrect	Correct	Correct
Test Image 22	Incorrect	Correct	Correct
Test Image 23	Incorrect	Incorrect	Correct
Test Image 24	Incorrect	Correct	Correct
Test Image 25	Incorrect	Correct	Correct
Test Image 26	Incorrect	Correct	Correct
Test Image 27	Incorrect	Correct	Correct
Test Image 28	Incorrect	Incorrect	Correct
Test Image 29	Incorrect	Incorrect	Correct
Test Image 30	Incorrect	Incorrect	Correct
Accuracy	00.00%	70.00%	80.00%

Table 15: Classification using Min A, B and C for Speckled Image

Hence, from the result the total accuracy of using Min of A, B, and C is calculated:

- Min of A = (100.00 + 00.00) / 2 = 50.00%
- Min of B = (73.33 + 70.00) / 2 = 71.66%
- Min of C = (50.00 + 80.00) / 2 =65.00 %

From Table 14 and 15, it shows that the highest accuracy of the system obtained is 71.66%. This accuracy is obtained by using Min of B as the features. Referring back to the features graph in previous section, B has the most distinct graph between the two types. The accuracies obtained from A and C is quite far to B which is 50% and 65% respectively. Thus, it can be concluded that using different ICA features the difference in accuracy is practically high. The highest and lowest value differences are more than 20%.

Apart from that, Min A classified every image as Homogeneous. Thus the accuracy obtained is 50%. When we refer back to the features graph obtained for Min B, the values are intercepting each other. Thus, we can say that this is the main reasons SVM cannot classified the image correctly.

As B gives the highest accuracy, it is then being used to test other statistical features which are Max and Min. The results are shown in Table 12 and 13.

Table 16 and 17 summarize the result obtained by using Mean, Max and Min B.

Homogeneous	Mean B	Max B	Min B
Test Image 1	Correct	Correct	Incorrect
Test Image 2	Correct	Correct	Correct
Test Image 3	Incorrect	Incorrect	Incorrect
Test Image 4	Correct	Correct	Correct
Test Image 5	Incorrect	Incorrect	Correct
Test Image 6	Incorrect	Incorrect	Incorrect
Test Image 7	Incorrect	Incorrect	Incorrect
Test Image 8	Correct	Incorrect	Incorrect
Test Image 9	Incorrect	Correct	Correct
Test Image 10	Incorrect	Incorrect	Incorrect
Test Image 11	Correct	Correct	Incorrect
Test Image 12	Correct	Correct	Correct
Test Image 13	Correct	Correct	Correct
Test Image 14	Incorrect	Incorrect	Incorrect
Test Image 15	Correct	Correct	Correct
Test Image 16	Correct	Correct	Correct
Test Image 17	Correct	Correct	Correct
Test Image 18	Incorrect	Correct	Correct
Test Image 19	Correct	Correct	Correct
Test Image 20	Correct	Correct	Correct
Test Image 21	Correct	Correct	Correct
Test Image 22	Correct	Correct	Correct
Test Image 23	Incorrect	Incorrect	Correct
Test Image 24	Correct	Correct	Correct
Test Image 25	Correct	Correct	Correct
Test Image 26	Correct	Correct	Correct
Test Image 27	Correct	Correct	Correct
Test Image 28	Correct	Correct	Correct
Test Image 29	Correct	Correct	Correct
Test Image 30	Correct	Correct	Correct
Accuracy	70.00%	73.33%	73.33%

Table 16: Classification using Mean, Max and Min for Homogeneous Image

Speckled	Mean B	Max B	Min B
Test Image 1	Incorrect	Correct	Correct
Test Image 2	Correct	Correct	Correct
Test Image 3	Incorrect	Correct	Correct
Test Image 4	Incorrect	Incorrect	Incorrect
Test Image 5	Correct	Correct	Correct
Test Image 6	Correct	Correct	Correct
Test Image 7	Correct	Correct	Correct
Test Image 8	Incorrect	Incorrect	Incorrect
Test Image 9	Incorrect	Correct	Correct
Test Image 10	Incorrect	Incorrect	Incorrect
Test Image 11	Correct	Correct	Correct
Test Image 12	Correct	Correct	Correct
Test Image 13	Incorrect	Incorrect	Correct
Test Image 14	Incorrect	Correct	Correct
Test Image 15	Incorrect	Correct	Correct
Test Image 16	Incorrect	Correct	Correct
Test Image 17	Incorrect	Incorrect	Correct
Test Image 18	Incorrect	Incorrect	Incorrect
Test Image 19	Correct	Correct	Correct
Test Image 20	Correct	Incorrect	Incorrect
Test Image 21	Incorrect	Correct	Correct
Test Image 22	Incorrect	Incorrect	Correct
Test Image 23	Incorrect	Incorrect	Incorrect
Test Image 24	Incorrect	Incorrect	Correct
Test Image 25	Incorrect	Correct	Correct
Test Image 26	Incorrect	Correct	Correct
Test Image 27	Correct	Correct	Correct
Test Image 28	Correct	Correct	Incorrect
Test Image 29	Correct	Correct	Incorrect
Test Image 30	Incorrect	Incorrect	Incorrect
Accuracy	36.67%	63.33%	70.00%

Table 17: Classification using Mean, Max and Min for Speckled Image

Thus, from the result the total accuracy of using Mean, Max and Min of B can be calculated:

- Mean of B = (70.00 + 36.67) / 2 = 53.33%
- Max of B = (73.33 + 63.33) / 2 = 68.33%
- Min of B = (73.33 + 70.00) / 2 = 71.66%

Referring to the data, it shows that by using Max and Min as the coefficient, the accuracy is about the same which is 68.33% and 71.66% respectively. Whereas using Mean, the accuracy is the lowest which is 53.33% only. Overall, we can say that using different statistical features (Mean, Max and Min) for ICA effect on the accuracy difference.

It is also observed that most of the same images are being misclassified. Generally, from the results obtained in Table 14 until Table 17, it can be said that for ICA, using different features (e.g. A, B, and C) gives large difference in accuracy. The highest is by using Approximation of Mixing signal. Thus for ICA, it can be concluded that all features will give different range of classification accuracy.

CHAPTER 5: CONCLUSION AND RECOMENDATION

5.1 RECOMMENDATION

From the result of the project, it is shown that most of the features from Wavelet give accuracy more than 80% which is acceptable and quite reliable range. However, ICA gives the accuracy of 50% to 72% only. Nevertheless, the accuracy of the program can be further improved up to more than 95% in order for the system to be fully dependable. In order to get a good result, the initial enhancement to the images plays an important role. Thus, one of the recommended ways to increase the accuracy of the system is by improving the pre-processing and segmentation steps. The most accurate pre-processing steps and better segmentation step can be applied to get clearer images before extracting the features from them. For instance, by using Equalize Histogram to balance the contrast of the images since the image contrast also affect image's coefficients. Others are for instance image sharpening and image de-noising.

Moreover, as training and testing image comes in large numbers (140 training images, 60 testing image), images shuffling can be performed. Images between training and testing are shuffled for a few times and the average accuracy is taken. As the image is shuffled, the highest accuracy images proved that some of the image sets can be used to be the training image sets.

Next, is by changing the type of Wavelet transform and Wavelet type itself. Example is by changing 2D Discrete Wavelet Transform into another type of Wavelet Transform such as Stationary Wavelet Transform or Adaptive Wavelet Transform. The type of Wavelet can also be changed into Haar, Coiflet and Symlet. For ICA, this project used FastICA. Thus for further research, other types of ICA can be used for example independent component by color component.

5.2 CONCLUSION

Referring back to the main objective, the performance of Wavelet and ICA is to be compared at the end of the project. As a result of, it can be concluded that Wavelet gives better accuracy compared to ICA. Wavelet accuracy ranges from 85% to 88.33% while ICA from 50% to 71.66%. The accuracy for Wavelet is quite dependable and acceptable. But then for ICA, it can be said that this technique is not too suitable to be applied to fluorescence images. The next objective to performed classification of ANA automatically also have been achieved. The system (mainly using Wavelet) can be used to classify two ANA patterns, Homogeneous and Speckled with acceptable accuracy.

From the system, it also can be conclude that using different Features for Wavelet does not affect much on accuracy difference. However, ICA gives a large difference in accuracy when using different features. Same goes to using different Statistical features, Wavelet shows insignificant difference while ICA shows huge variance in accuracy.

Apart from that, we observed that the accuracy is sometimes affected by the low quality of images. For instance, Test Image 6 and 7 from Homogeneous and Test Image 18, 20 and 24 from Speckled are wrongly classified most of the times. This proved that this image either have low contrast or ununiformed contrast which cause them to be misclassified for most of the time.

Hence as a whole, it can be concluded that Wavelet give better performance compared to ICA when extracting features from ANA images.

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APPENDICES

a. MATLAB CODING FOR WAVELET

```
%----------------------TRAINING IMAGE FEATURE EXTRACTION------------------%
clc; clear all;close all;

Image = imread('C:\Users\thania\Documents\MATLAB\PICS\Trial 2\h1\1.png');
Resize=imresize (Image, [50 50]);
ImageGray = rgb2gray(Resize);
[cA,cH,cV,cD] = dwt2(ImageGray,'db1');
f = min(cA);

%----------------------------TRAINING IMAGE FEATURES --------------------%
f1=[-2.93719038623652,3.81923624976847,3.03076330372642,...]
f2=[6.50361403430190,-4.86194339580985,3.16984194753601,...]
f3= [2.84389717603174,4.88846923531903,2.00389873283500,...]
.
.
f138=[-4.13852288976711,-3.94270229576542,-3.80392810860021,...]
f139=[1.06308350556614,-4.66862294415928,-3.68781534335114,...]
f140=[-2.35168294376097,-1.59250257881616,-2.93282281259576,...]
%(Note that TRAINING IMAGE FEATURE EXTRACTION is applied to 70 homogeneous
images and 70 Speckled images to obtained 140 TRAINING IMAGE FEATURES)%

%------------------------------TRAINING IMAGES----------------------------%
Training = cat(1,f1,f2,f3...,f138,f139,f140);
Group = [0;0;0;...;1;1;1];
ImageTrain = svmtrain(Training,Group);

%-------------------------------TESTING IMAGES----------------------------%
disp ('Please key in image name. Example : Sample1.tif')
prompt = 'Image Name: ';
Image0 = input (prompt, 's');

ImageT = imread(Image0);
ImageGrayT = rgb2gray(ImageT);
[cA,cH,cV,cD] = dwt2(ImageGrayT,'db1');
fT = mean(cA);

%-------------------------------CLASSIFY IMAGES---------------------------%
Class = svmclassify(ImageTrain,fT);

if Class==0;
disp ('This Cell is categorized as Homogeneous');
else
disp ('This Cell is categorized as speckled');
end
```

b. MATLAB CODING FOR ICA

```
%----------------------TRAINING IMAGE FEATURE EXTRACTION------------------%
clc; clear all;close all;
Image = imread('C:\Users\thania\Documents\MATLAB\PICS\Trial 2\h1\1.png');
Resize=imresize (Image, [50 50]);
ImageGray = rgb2gray(Resize);
[A,B,C] = fastica(ImageGray);
f = min(A);

%---------------------------TRAINING IMAGE FEATURES ----------------------%
f1=[-2.93719038623652,3.81923624976847,3.03076330372642,...]
f2=[6.50361403430190,-4.86194339580985,3.16984194753601,...]
f3=
[2.84389717603174,4.88846923531903,2.00389873283500,2.84763029388523...]
...
...
...
f138=[-4.13852288976711,-3.94270229576542,-3.80392810860021,...]
f139=[1.06308350556614,-4.66862294415928,-3.68781534335114,...]
f140=[-2.35168294376097,-1.59250257881616,-2.93282281259576,...]
%(Note that TRAINING IMAGE FEATURE EXTRACTION is applied to 70 homogeneous
images and 70 Speckled images to obtained 140 TRAINING IMAGE FEATURES)%

%-------------------------------TRAINING IMAGES---------------------------%
Training = cat(1,f1,f2,f3...,f138,f139,f140);
Group = [0;0;0;...;1;1;1];
ImageTrain = svmtrain(Training,Group);

%-----------------------------TESTING IMAGES-------------------------------%
disp ('Please key in image name. Example : Sample1.tif')
prompt = 'Image Name: ';
Image0 = input (prompt, 's');

ImageT = imread(Image0);
ImageGrayT = rgb2gray(ImageT);
[AT,BT,CT] = fastica(ImageGrayT);
fT = mean(AT);

%------------------------------CLASSIFY IMAGES----------------------------%
Class = svmclassify(ImageTrain,fT);

if Class==0;
disp ('This Cell is categorized as Homogeneous');
else
disp ('This Cell is categorized as speckled');
end
```

c. MATLAB CODING FOR WAVELET AND ICA WITH GRAPHICAL USER INTERFACE

```
function varargout = WaveICA(varargin)
% WAVEICA MATLAB code for WaveICA.fig
%      WAVEICA, by itself, creates a new WAVEICA or raises the existing
%      singleton*.
%
%      H = WAVEICA returns the handle to a new WAVEICA or the handle to
%      the existing singleton*.
%
%      WAVEICA('CALLBACK',hObject,eventData,handles,...) calls the local
%      function named CALLBACK in WAVEICA.M with the given input arguments.
%
%      WAVEICA('Property','Value',...) creates a new WAVEICA or raises the
%      existing singleton*.  Starting from the left, property value pairs
are
%      applied to the GUI before WaveICA_OpeningFcn gets called.  An
%      unrecognized property name or invalid value makes property
application
%      stop.  All inputs are passed to WaveICA_OpeningFcn via varargin.
%
%      *See GUI Options on GUIDE's Tools menu.  Choose "GUI allows only one
%      instance to run (singleton)".
%
% See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to help WaveICA

% Last Modified by GUIDE v2.5 03-Dec-2013 14:29:23

% Begin initialization code - DO NOT EDIT
gui_Singleton = 1;
gui_State = struct('gui_Name',       mfilename, ...
                   'gui_Singleton',  gui_Singleton, ...
                   'gui_OpeningFcn', @WaveICA_OpeningFcn, ...
                   'gui_OutputFcn',  @WaveICA_OutputFcn, ...
                   'gui_LayoutFcn',  [] , ...
                   'gui_Callback',   []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
% End initialization code - DO NOT EDIT

% --- Executes just before WaveICA is made visible.
function WaveICA_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
```

```
% varargin   command line arguments to WaveICA (see VARARGIN)

% Choose default command line output for WaveICA
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes WaveICA wait for user response (see UIRESUME)
% uiwait(handles.figure1);


% --- Outputs from this function are returned to the command line.
function varargout = WaveICA_OutputFcn(hObject, eventdata, handles)
% varargout  cell array for returning output args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;


% --- Executes on button press in pushbutton.
function pushbutton_Callback(hObject, eventdata, handles)
% hObject    handle to pushbutton (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
[fn pn] = uigetfile('*.tif','select tif file');
complete = strcat(pn,fn);
ImageT = imread(complete);
axes(handles.axes1);
imshow(ImageT);
axes(handles.axes2);
ImageGrayT = rgb2gray(ImageT);
imshow(ImageGrayT);
NegativeImageT = 255-ImageGrayT;
StretchedImageT = imadjust(NegativeImageT, stretchlim(NegativeImageT), []);
EqualizedImageT = histeq(NegativeImageT);
FilteredImageT = medfilt2(EqualizedImageT,[5 5]);
SharpT=imsharpen(FilteredImageT);
imshow(SharpT);
axes(handles.axes10);
[cAT,cHT,cVT,cDT] = dwt2(SharpT,'db1');
mT = mean(cAT);
plot(cAT);
axes(handles.axes11);
plot(cDT);
axes(handles.axes12);
plot(cHT);
axes(handles.axes13);
plot(cVT);
```

```
m1=[437.484000000000,455.556000000000,450.500000000000,...];
m2=[311.720000000000,336.596000000000,334.736000000000,...];
m3=[383.560000000000,416.836000000000,413.232000000000,...];
...
...
...
m139=[449.156000000000,465.364000000000,460.680000000000,...];
m140=[399.656000000000,412.880000000000,408.808000000000,...];

Training1 = cat(1,m1,m2,m4,m5,m7,m8,m10,m11,m13...,m139,m140);
Group1 = [0;0;0;0;0;0;0;0...;1;1;1];
ImageTrain1 = svmtrain(Training1,Group1);

Class = svmclassify(ImageTrain1,mT);

if Class==1;
str={'Speckled'};
else
str={'Homogeneous'};
end

set(handles.edit1,'String',str);

axes(handles.axes7);
[AT,BT,CT] = fastica(SharpT);
mBT = mean(BT);
plot(AT);
axes(handles.axes8);
plot(BT);
axes(handles.axes9);
plot(CT);

B1=[-2.93719038623652,3.81923624976847,3.03076330372642,...];
B2=[6.50361403430190,-4.86194339580985,3.16984194753601,...];
...
...
...
B139=[1.06308350556614,-4.66862294415928,-3.68781534335114,...];
B140=[-2.35168294376097,-1.59250257881616,-2.93282281259576,...];
Training2 = cat(1,B1,B2,B4,B5,B7,B8,B10,B11,B13,...B139,B140);
Group2 = [0;0;0;0;0;0;0;...;1;1;1;1]
ImageTrain2 = svmtrain(Training2,Group2);

Class2 = svmclassify(ImageTrain2,mBT);

if Class2==1;
str={'Speckled'};
else
str={'Homogeneous'};
end

set(handles.edit3,'String',str);
```

```
function edit1_Callback(hObject, eventdata, handles)
% hObject    handle to edit1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit1 as text
%        str2double(get(hObject,'String')) returns contents of edit1 as a
double

% --- Executes during object creation, after setting all properties.
function edit1_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function edit2_Callback(hObject, eventdata, handles)
% hObject    handle to edit2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit2 as text
%        str2double(get(hObject,'String')) returns contents of edit2 as a
double

% --- Executes during object creation, after setting all properties.
function edit2_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function edit3_Callback(hObject, eventdata, handles)
% hObject    handle to edit3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit3 as text
%        str2double(get(hObject,'String')) returns contents of edit3 as a
double
```

```matlab
% --- Executes during object creation, after setting all properties.
function edit3_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end



% --- Executes on button press in pushbutton2.
function pushbutton2_Callback(hObject, eventdata, handles)
% hObject    handle to pushbutton2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
Axeshandles=[handles.axes1, handles.axes2, handles.axes7,
handles.axes8,handles.axes9,handles.axes10,handles.axes11,handles.axes12,ha
ndles.axes13];
for h = Axeshandles;
cla(h);
set(handles.edit1,'String','');
set(handles.edit3,'String','');
end



% --- Executes on button press in pushbutton3.
function pushbutton3_Callback(hObject, eventdata, handles)
% hObject    handle to pushbutton3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
close all;
```