AN IMPROVED FAST SCANNING ALGORITHM BASED ON DISTANCE MEASURE AND THRESHOLD FUNCTION IN REGION IMAGE SEGMENTATION

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Abstrak

Segmentasi adalah satu proses yang penting dan mampu memisahkan imej ke dalam sektor-sektor yang mempunyai ciri-ciri yang sama. Ini akan mengubah imej tersebut agar lebih sesuai untuk dikaji dan dinilai. Salah satu kepentingan segmentasi ialah pengenalpastian kawasan fokus dalam sesuatu imej. Pelbagai algoritma telah dicadangkan untuk segmentasi imej dan ini termasuklah Algoritma Pengimbasan Cepat *(Fast Scanning)* yang telah diaplikasikan dalam bidang makanan, sukan dan perubatan. Proses penggugusan dalam algoritma Pengimbasan Cepat dilakukan melalui penggabungan antara piksel dengan piksel yang bersempadan dengannya berdasarkan satu ambangsuai dan penggunaan Jarak Euclidean *(Euclidean Distance)* sebagai pengukur jarak. Pendekatan tersebut membawa kepada imej segmentasi yang lemah reliabiliti dan pengecaman corak. Oleh itu, kajian ini mencadangkan Algoritma Pengimbasan Cepat *(Improved Fast Scanning)* yang ditambahbaik berdasarkan pengukur jarak *Sorensen* dan fungsi ambangsuai adaptif. Fungsi ambangsuai adaptif yang dicadangkan adalah berdasarkan kepada nilai kelabu dalam piksel imej dan varians nya. Algoritma Pengimbasan Cepat yang ditambahbaik ini telah direalisasikan ke atas dua koleksi data yang mengandungi imej kereta dan alam semulajadi. Penilaian dibuat dengan mengira *Peak Signal to Noise Ratio* (PSNR) bagi algoritma Pengimbasan Cepat yang ditambahbaik dan algoritma Pengimbasan Cepat yang sedia ada. Keputusan eksperimen menunjukkan bahawa algoritma yang dicadangkan menghasilkan PSNR yang lebih tinggi berbanding algoritma Pengimbasan Cepat sedia ada. Keputusan yang sedemikian memberi indikasi bahawa algoritma Pengimbasan Cepat yang ditambahbaik adalah berguna bagi imej segmentasi dan seterusnya menyumbang kepada pengenalpastian sektor yang menarik dalam bidang pengecaman corak.

Keywords: Segmentasi imej, Algoritma Pengimbasan Cepat, ukuran jarak, fungsi ambangsuai adaptif, Peak Signal to Noise Ratio.

Abstract

Segmentation is an essential and important process that separates an image into regions that have similar characteristics or features. This will transform the image for a better image analysis and evaluation. An important benefit of segmentation is the identification of region of interest in a particular image. Various algorithms have been proposed for image segmentation and this includes the Fast Scanning algorithm which has been employed on food, sport and medical image segmentation. The clustering process in Fast Scanning algorithm is performed by merging pixels with similar neighbor based on an identified threshold and the use of Euclidean Distance as distance measure. Such an approach leads to a weak reliability and shape matching of the produced segments. Hence, this study proposes an Improved Fast Scanning algorithm that is based on Sorensen distance measure and adaptive threshold function. The proposed adaptive threshold function is based on the grey value in an image's pixels and variance. The proposed Improved Fast Scanning algorithm is realized on two datasets which contains images of cars and nature. Evaluation is made by calculating the Peak Signal to Noise Ratio (PSNR) for the Improved Fast Scanning and standard Fast Scanning algorithm. Experimental results showed that proposed algorithm produced higher PSNR compared to the standard Fast Scanning. Such a result indicate that the proposed Improved Fast Scanning algorithm is useful in image segmentation and later contribute in identifying region of interesting in pattern recognition.

Keywords: Image segmentation, Fast Scanning algorithm, Distance measure, Adaptive threshold function, Peak Signal to Noise Ratio.

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List of Abbreviations

URG	Unseeded Region Growing
UUM	Universiti Utara Malaysia
SRG	Seeded Region Growing
SAR	Synthetic Aperture Radar
LOG	Laplacian of Gaussian
1 D	One Dimensions
2 D	Two Dimensions
PC	Personal Computer
OCR	Optical Character Recognition
RGB	Red, Green and Blue
IDE	Integrated Development Environment
ROC	Receiver operating characteristic
SEM	Structural Equation Model
PSNR	Peak Signal to Nosie Ratio
MAE	Mean Absolute Error
GCE	Global Consistency Error
RI	Rand Index
VoI	Variation of Information
PRM	Precision Recall Measure
BDE	Boundary Displacement Error
LCE	Local Consistency Error
PSO	Particle Swarm Optimization
MAP-ML	Maximum and Posteriori Maximum Likelihood
JPEG	Joint Photograph Experts Group

CHAPTER ONE

INTRODUCTION

1.1 Background

There has been a substantial increase in the attention given to the challenges brought by image processing throughout the last twenty years. This attention has generated a growing demand for theoretical approaches as well as application of computer hardware with appropriate software in the design of image processing systems (Wang, 2010).

Image segmentation is one of the basic steps of the image processing and machine vision. It segments images for accurate boundaries that transform the image's representation for detail (Tawfeeq & Tabra, 2014). Its key point is: the image is divided into a number of sets that do not mutual overlapping zones; these zones either have meaning to currently mission or help to explain correspondence between them and the actual object or some parts of object (Lakshmi, 2010). Therefore, it is a process in which divide the image into disjoint regions that are meaningful with feature section and removes that relevant objects.

Image segmentation is a very interesting area in image processing field due to images are one of the most important medium to convey information in the field of computer vision (Wang, Guo, & Zhu, 2007). Yet, verifying the segment boundaries automatically remains a big challenge. Image segmentation have a wide range of applications in practice, such as: industry automation, product online detection, manufacturing and process control, remote sensing image processing, biomedical image analysis, etc (Agrawal, 2014).

Many image segmentation techniques have been developed by researchers and scientists, and these techniques can be generally classified into three major categories (Kamal, 2013). The segmentation techniques that are based on discontinuity property of pixels are considered as boundary or edges based techniques and the ones that are based on similarity or homogeneity are considered as region based techniques. On the other hand, the hybrid techniques are the ones that merge techniques from the first and second categories (Kamdi & Krishna, 2011).

The region based segmentation approach partitions an image into similar/homogenous areas of connected pixels (Kumar & Singh, 2012) . Each of the pixels in a region is similar with respect to some characteristics or computed property such as colour, intensity and/or texture. Region growing is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points (Ansari & Anand, 2007). This approach examines neighboring pixels of initial "seed points" and determines whether the pixel neighbors should be added to the region. The selection of seed points can be adaptively and fully automatic by unseeded region growing (URG). It does not depend on tuning parameters and is additionally free from manual input (Kahn, 2013).

Fast Scanning algorithm is an example of URG segmentation algorithms which consider automation in selecting the start seed. It is based on the assumption that the neighboring pixels within one region have identical value (Çamalan, 2013). The current process includes the scan on all pixels in the image and cluster each pixel by comparing one pixel with its upper and left neighbor pixels. Hence, clustering is done by merging pixels with similar neighbor based on an assigned threshold (Kanhere & Birchfield, 2008).

Threshold is a commonly used method that improves the image segmentation effect and it is simpler and easier to implement (Jianxing, Songlin, & Li, 2012).

Clustering in image segmentation capture the global characteristics of the image through the selection and calculation of the image features, which are usually based on the color or texture (Tao, Jin, & Zhang, 2007). By using a specific distance measure that ignores the spatial information, the feature samples are handled as vectors. The objective is to group them into compact, but well-separated clusters. Hence, distance measures play a critical role in clustering (Jousselme & Maupin, 2012) . Many researchers have taken elaborate efforts to find the most meaningful distance measures and numerous distance measures have been proposed in various fields (Choi, Cha, & Tappert, 2010).

This study focuses on improving the existing (standard) Fast Scanning algorithm by introducing a threshold function and determining a suitable distance measure to be used in clustering image pixels. Such an approach is executed in segmenting image of cars and nature.

1.2 Problem Statement

Image segmentation is a mechanism used to divide an image into multiple segments. It will make image smooth and easy to evaluate. Segmentation process also helps to find region of interest in a particular image (Khan, 2013). There are many techniques used for image segmentation, and some of them segmented an image based on the object while some can segment automatically. Fast Scanning Algorithm is an example for URG algorithms which does not require a seed point (Thilagamani & Shanthi, 2013). The main idea in Fast Scanning algorithm is to scan all pixels in the image and cluster each pixel according to the upper and left neighbor pixels (Ding, Kuo, & Hong, 2009).

The clustering is done by merging pixels with similar neighbor based on a pre-defined threshold. If the variance between the value of pixel which currently being scanned and the average of pixel value of the neighboring cluster is smaller than the threshold, then this pixel will be merged into the cluster. Else it will be moved into a new cluster (Ding, Kuo, Hong, Tsai, & Chen, 2013). In standard Fast Scanning algorithm, distance between pixels is identified using a fixed distance measure (i.e. Euclidean distance).

Some parts of an image may have different color distribution or properties and this will lead to a weak reliability (Çamalan, 2013). In addition, standard Fast Scanning relies on a pre-defined threshold value to segment image. A pre-defined threshold will lead to weak of shape matching in segmentation as some part of an image may have different color distribution or properties (Ding, Wang, Hu, Chao & Shau, 2011).

Such an approach creates two problem, different distance measure and a pre-defined threshold value will produce different segments. Hence, there is a need to determine a suitable distance measure for Fast Scanning algorithm and an adaptive threshold value to be used in segmenting an image.

1.3 Research Questions

1. What is the suitable distance measure that can be used in Fast Scanning image segmentation algorithm?
2. How to formulate a threshold value function for Fast Scanning algorithm?
3. How useful is the improved (distance measure and threshold function) of Fast Scanning algorithm in image segmentation?

1.4 Research Objectives

The main objective of this study is to develop an improved Fast Scanning algorithm for image segmentation. The sub-objectives of the study are as follows:

1. To determine a suitable distance measure that can be used in Fast Scanning algorithm to obtain segmented images.
2. To formulate a threshold value function that can be used in Fast Scanning algorithm.
3. To evaluate the proposed improved Fast Scanning algorithm.

1.5 Research Scope

This study focuses in segmenting images using an improved Fast Scanning algorithm. The employed datasets include the Iraqi and Saudi Arabia car plates of the private cars and public taxis. The study also utilizes nature images of Universiti Utara Malaysia (UUM) campus.

1.6 Research Significance

This study contributes a Fast Scanning algorithm for image segmentation that utilizes a suitable distance measure and adaptive threshold function. The study would be useful in pattern recognition that identifies region of interest. The following are examples of applications that benefit from pattern recognition:

1. Traffic image analysis.
2. Traffic flow control which consists of vehicle count, vehicle tracking, vehicle trajectory, vehicle classification and vehicle flow.
3. Parking management system and fruit grading system.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter consists of four parts. The first and second parts discuss the basic techniques of image segmentation, and presents image segmentation applications. The third part discusses the distance measure in image segmentation. The last part focuses on the evaluation of image segmentation algorithms.

2.2 Image Segmentation

According to Ingale, & Borkar, (2013), image processing can be described as an action involving assessment of images in order to recognise entities and evaluating its importance for handling digital images by computers. The new image data will go through a number stages of processing such as acquisition, pre-processing, segmentation, feature extraction, classification and understanding. All phases uses to remove any errors and defects thereby purifying the data. Image processing phases, as shown in the Figure 2.1.

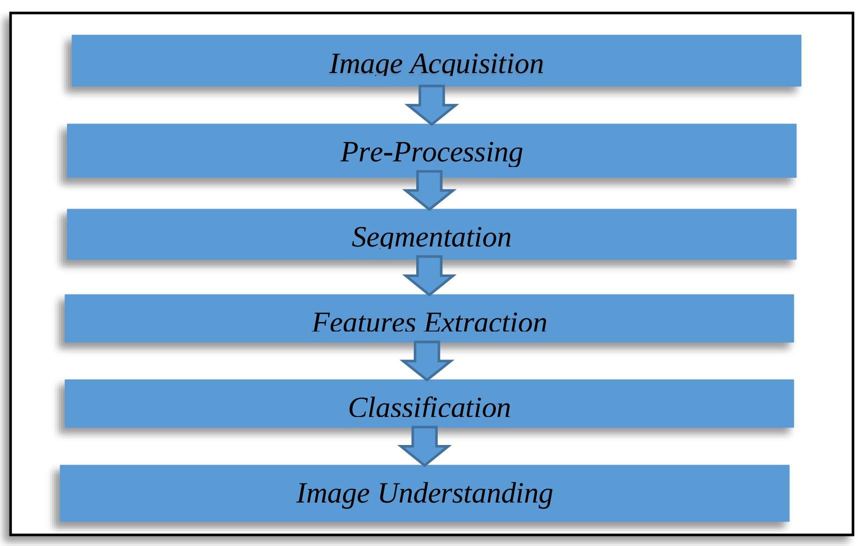

Figure 2.1. Image processing phases (Ingale, & Borkar, 2013)

Brice and Fennema have examined image segmentation as early as 1970 as the first time (Brown, Wicks, Bird, & Brown, 2014). They deliberated on a method for separating an image into atomic sections of constant intensity, and afterward utilized heuristics to link comparable sections together. The outcome was an algorithm that could distinguish entities in an image.

In computing technology, new techniques and algorithms were made. The quantity of papers in English concerning image segmentation was almost consistent at more or less 250 papers from year 1995 to year 2000. In other hand, the number multiplied to roughly 500 papers between years 2000 to 2005 (Zhang, 2006).

As expressed by Khan, (2013), one of the fundamental stages of image handling is image segmentation which partitioned segments based on feature and removes that relevant objects. Any image can be partitioned into numerous sections and every section will signify certain types of information such as colour, intensity or texture to a user.

The objective of image segmentation is to segment which has consistent attributes (colour and coarseness) and in the in the meantime to assemble the important parts at once for the comfort of recognition (Peng & Zhang, 2011). Segmentation is a fundamental necessity for recognition and categorization of items in the scene (Liu et al., 2010).

The primary objective of image segmentation is domain self-determining sectioning of an image into a series of disconnected sections. Therefore, all sections are outwardly diverse, uniformed and significant regarding some attributes or calculated characteristics, for example, dark level, coarseness or colour to allow simple image examination (Wang, Guo, & Zhu, 2007; Zuva, Olugbara, Ojo, & Ngwira, 2011). According to Khan, (2013) there are three categories of image segmentation techniques; region, edge-detection and hybrid, as illustrated in Figure 2.2.

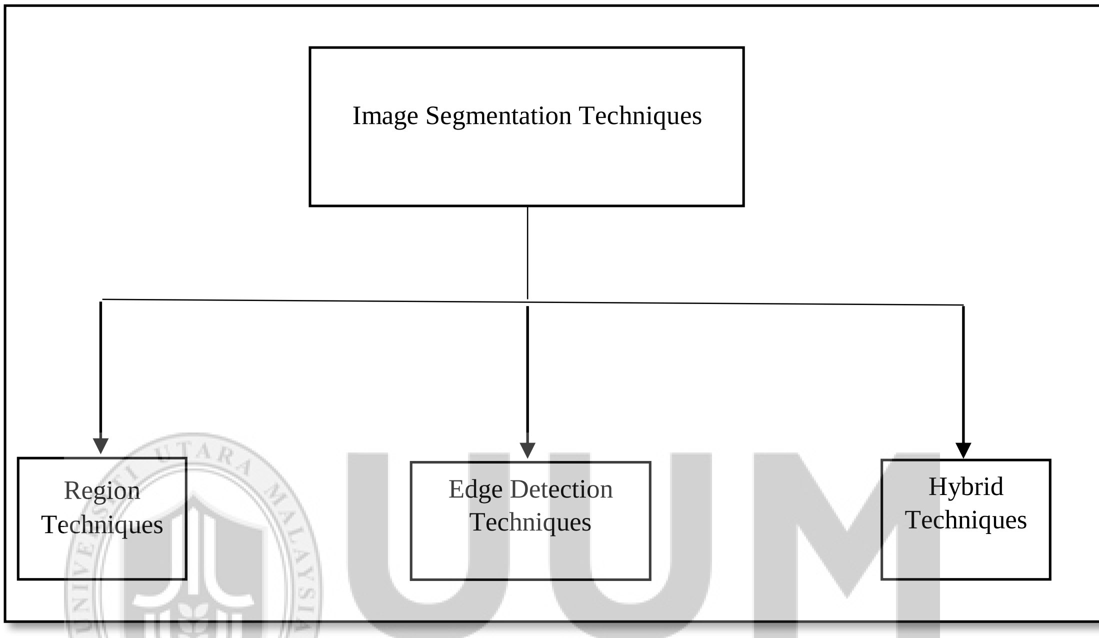

Figure 2.2. Categorization of image segmentation techniques (Khan, 2013)

2.2.1 Region Techniques

Region techniques is easier to implement compared to other techniques and it is noise resilient. Images are separated into distinctive sections based on pre-defined standard, namely, colour, intensity, or entity (Kee, Souiai, Cremers, & Kim, 2014). It tries to partition an image into comparable regions by means of standard or set of standards based on their resemblance or uniformity. Some conditions are typically enforced on the regions: the mean criteria values are different for each region and the regions are typically characterized by a Gaussian distribution of the pixel criteria within them (Brown et al., 2014).

In the region-based segmentation, pixels that match an entity are jointly classified and symbolized in the region-based segmentation. It also needs the utilization of suitable tress holding techniques (Seuerha, 2013). The important principles are value similarity (which includes gray value differences and gray value variance) and spatial proximity (which consists of Euclidean distance and compactness of a region). The region-based segmentation techniques are classified into five groups, i.e. region growing, region merging and splitting, data clustering, mean shift and threshold (Kulkarni, Khandebharad, Khope, & Chavan, 2012). It is indicated in Figure 2.3.

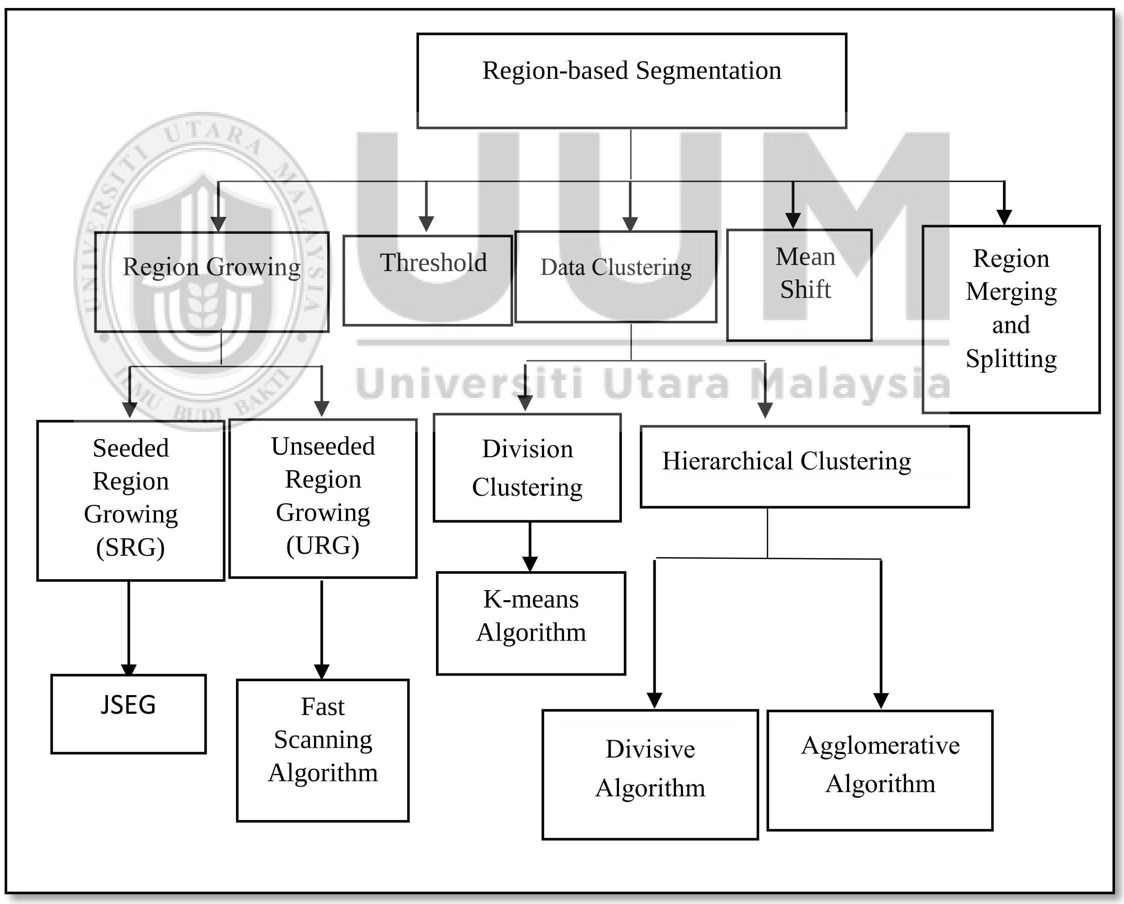

Figure 2.3. Region based image segmentation techniques (Seuerha, 2013)

The idea of the region growing techniques involves choosing sections that have few pixels and getting uniformity. The pixels nearby that have similarity between each other; the pixels are counted as equivalent (Kamdi & Krishna, 2011). The procedure goes on until the entire pixels are similar. The principal target of the region growing is to represent distinct pixel named seeds in the input image to a series of pixels known as the region (Adams & Bischof, 1994). The process of growing and iterations are shown in Figure 2.4.

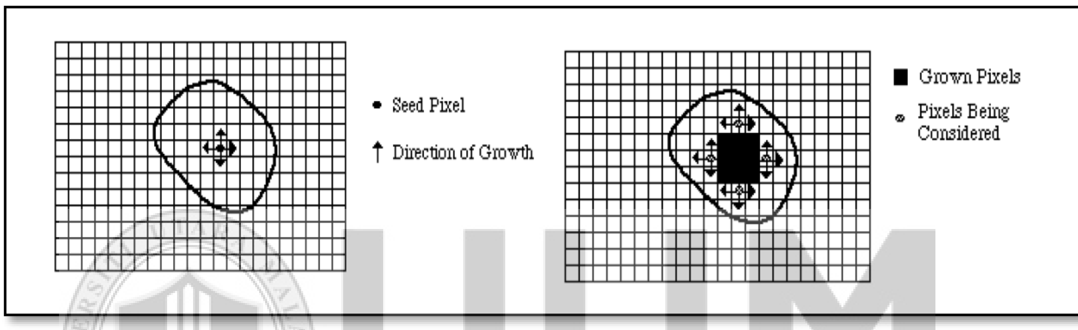

Figure 2.4. Start of grown region and process after iterations (Kamdi & Krishna, 2011)

This technique investigates adjacent pixels of first seed points. It determines if the pixel's neighbours ought to be added to the area or not, and this procedure is repeated. It is shown in Figure 2.5.

For every pixel *I(x,y)* in the image, if *I(x,y)* does not belong to any region

1. Take *I(x,y)* as starting point and label it.
2. Initialize a new queue and add the neighbors that don't belong to any region to the queue.
3. While the queue is not empty
    a. Pop the first value from the queue
    b. If the adjacency criterion is satisfied
        - Add the pixel to the region (label it).
        - Obtain the neighbors that are nit in the queue and don't belong to any region.
4. Increase the label of the region.

Figure 2.5. Region growing process (Ramos & Rezaei, 2010)

Region growing techniques are generally better in noisy images, where borders are extremely difficult to detect. Homogeneity is an important property of the regions and used as a main segmentation criterion in the region growing. Therefore, the basic idea is to divide an image into zones of maximum homogeneity

However , this algorithm presents many problems such as :

- How to select the nearby pixels ?
- How to describe the resemblance or combination standard and what features of the section should be utilized as the standard ?

Seeds are pixel with perfect features that fits to section of interest of the relevant section. Since the region growing outcome was responsive towards the first seeds, precise seed collection is very critical for appearance. The selection of seeds is subject to the type of the problem. The traditional seed selection technique is done in a collaborative way, that is, this technique is not programmed. (Kulkarni et al., 2012)

Numerous works can be found regarding automatic seed selection. These works can be classified on three areas. First, the work that is based on region extraction approach. The principle of these work is the extraction of regions using segmentation algorithms and the selection of seeds. Second, the work based on feature extraction approach that have two steps. In the first step, region features are calculated (Ilea & Whelan, 2011). In the the second step, a test is performed: if region features values match with some fixed features values, a seed is placed in the region.

The third work are studies related to edge extraction and these works applied edge detection methods like gradient calculation, active contour and many others, to prepare the seed point (Mustafa, Mat-Isa, & Mashor, 2009).

Additionally,it could categorized into two, namely seeded region growing method (SRG) and unseeded region growing method (URG) . The major difference between the two is that while SRG is semi-automatic type, the URG is a complete automatic type (Khan, 2013). Both SRG and URG work by adding every pixel one after the other in the region and enable the region to be bigger. The JSEG and Fast Scanning algorithm are examples of the SRG and URG respectively (Çamalan, 2013).

In SRG, an algorithm utilized for image segmentation was first recommended by Adams and Bischof, (1994) and from that point it has been utilized for image segmentation in both grey scale and colour images (Verma et al., 2011). The first seeds are chosen based ona number of standards and then the region growing procedureis utilized for segmentation. The region growth is done by contrasting the seed pixel with all the nearby pixels with a limit and pixels which are higher than the limit are combined to make only one region (Mirghasemi, Rayudu, & Zhang, 2013).

The region growing procedure is carried out until every pixel values are combined in any one of the region. The first seeds can be one pixel or combination of pixels called clusters. After combination because incidence of noise then over segmentation can occur and this can be averted by the region merging process (Kamdi & Krishna, 2011). The general steps in SRG algorithm are given as follows:

1. Determine seeds to initiate the segmentation process. In this approach initially the seeds are to be specified by the user. A seed is a test pixel with ideal characteristic that belongs to the region interested in and should be the part of the region interest. The choice of seed is very crucial since the overall success of the segmentation is dependent on the seed input. The seed set may have one or more members and is users choice.
2. Determine standard to be used for growing the region and if there are more than one regions, then distinct features of the regions have to be stated in order to avoid any uncertainty that can position any pixel in a specific region.
3. The entrant pixels have to be included in the region and it must be attached to not less than one of the pixel in the region.
4. Proper verification have to be done to ensure pixels undergo test for allocation and label accordingly.
5. Two distinct regions with identical should be joined together

URG is an automatic segmentation method and is taking into account propose of pixel similitude's inside regions. URG does not depend on tuning parameters and is additionally free from manual inputs. This approach easily assimilates the advance knowledge of the image and is extremely significant for the selection of region statistics. Assimilation of fundamental versatile filtering techniques have demonstrated some great results practically (Khan, 2013).

URG is a versatile and fully automatic segmentation technique suitable for multispectral and 3D images (Kaur & Randhawa, 2014). URG still has a few problems because of the absence of earlier understanding of what the image stand for. The most critical problems are:

1. The choice of threshold value (T) heavily effects on the segmentation results.
2. There is a bias towards growing regions discovered earlier.

A new technique was described by Palus, (2006) for URG which is typical bottom-up technique. It is based on the concept of region growing with-out seeded needed to start the segmentation process. At the beginning of the algorithm each pixel has its label (one – pixel regions) (Uemura, Koutaki, & Uchimura, 2011).

Fast Scanning algorithm is an example for the URG (Kaur, Singh, & Bhandari, 2014; Thilagamani & Shanthi, 2013). It's applications in nature images, medical images and food images. Seed point is not required in Fast Scanning algorithm (Ding, Wang, Hu, Chao, & Shau, 2011). Clustering involves joining of pixels with comparable neighbor based on allocated threshold value. If the threshold value is greater than the difference between the average value of the cluster and the pixel, usually the pixel will be joined with the cluster. Else, the pixel will be produced as a fresh cluster. The following depicts the steps in Fast Scanning algorithm.

Algorithm 2.1

Fast Scanning Algorithm (Camalan, 2013)

Input image *E* = (n,m)

1: Assign upper left pixel of is assigned as the first pixels *Ci* and first cluster of the *E*
Assign next pixels as *Cj* with set pre-determined threshold value *Th*

2: In first row the pixel [1, 1 +1] is scanning of the *E*
  if / *Cj – mean Ci* / ≤ *Th*
    Cj merged into *Ci* then ave *of Ci* calculated
  Else
    / *Cj – mean Ci* / >*Th* set *Cj* as new cluster
  end if

3: Repeat Step 2 for all first row pixels in *E*

4: Scan pixel (x+1, 1) in the next row and set the upper cluster as *Cu*
  if / *Cj – mean Cu*/ ≤ *Th*
    Cj merged into *Cu* then ave *of Cu* calculated
  Else
  Generate *Cn* as new cluster
  end if

5: Scan next pixel (x+1, 1+1) in *E*
  if / *Cj – mean Cu*/ ≤ *Th and / Cj – mean Ci* ≤ *Th*

    Cj is merged to *Cu* or *Ci* also *Cu* an *Ci* merged into *Cn* then calculate mean of *Cn*
  Else
  if / *Cj – mean Cu*/ ≤ *Th and / Cj – mean Ci* > *Th*
    Cj merged into *Cu* and calculate mean of *Cu*
  Else
  if / *Cj – mean Cu*/ > *Th and / Cj – mean Ci* ≤ *Th*
    Cj is merged to *Cu* and calculate mean of *Ci* or adjust *Cn*
  end if
  end if
  end if

6: Repeat steps 4 and 5 of all pixels on *E*

7: Remove the smaller regions *R*

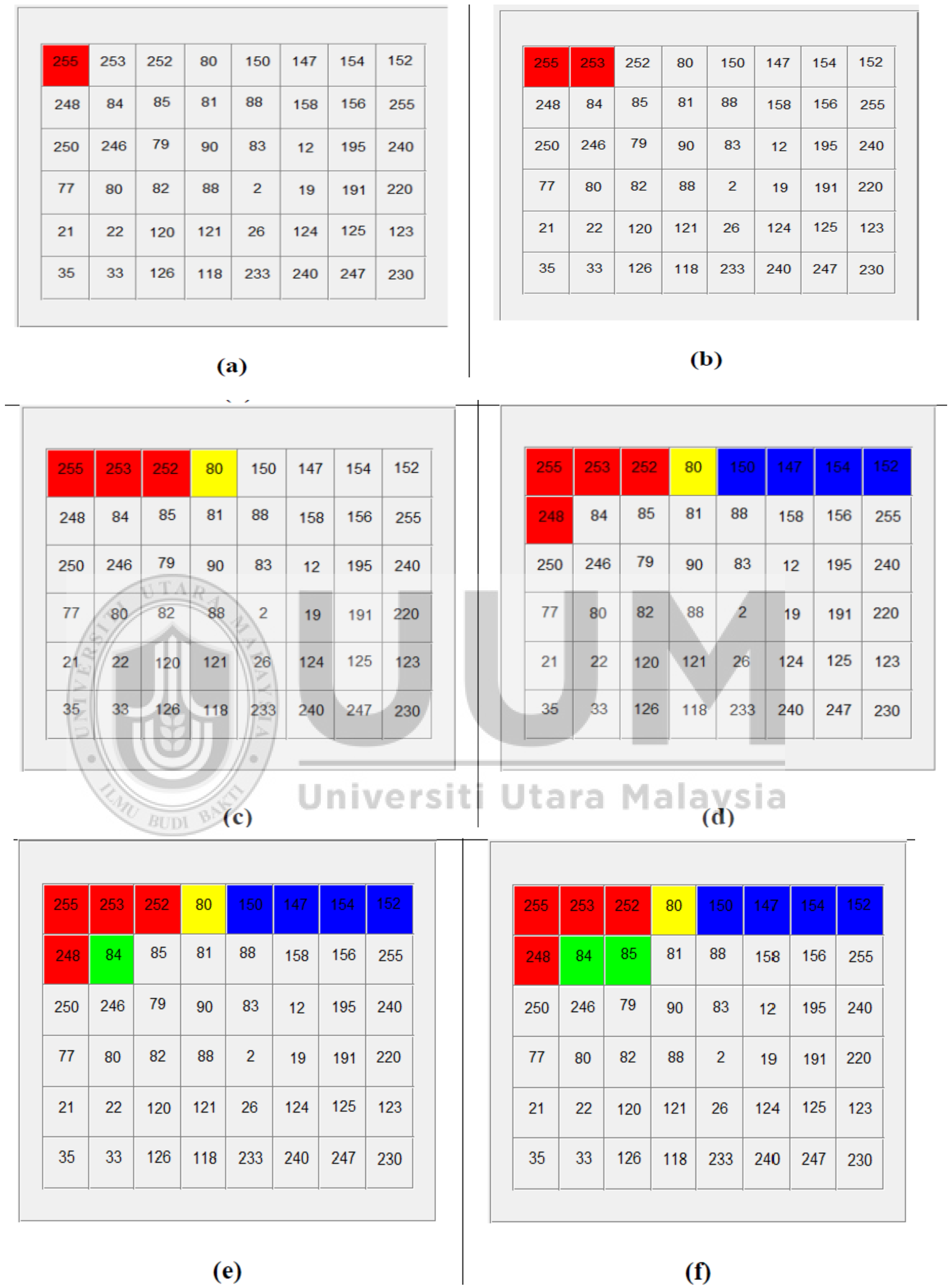

Figure 2.6 (a-f). Pixels by fast scanning algorithms representation (part 1)

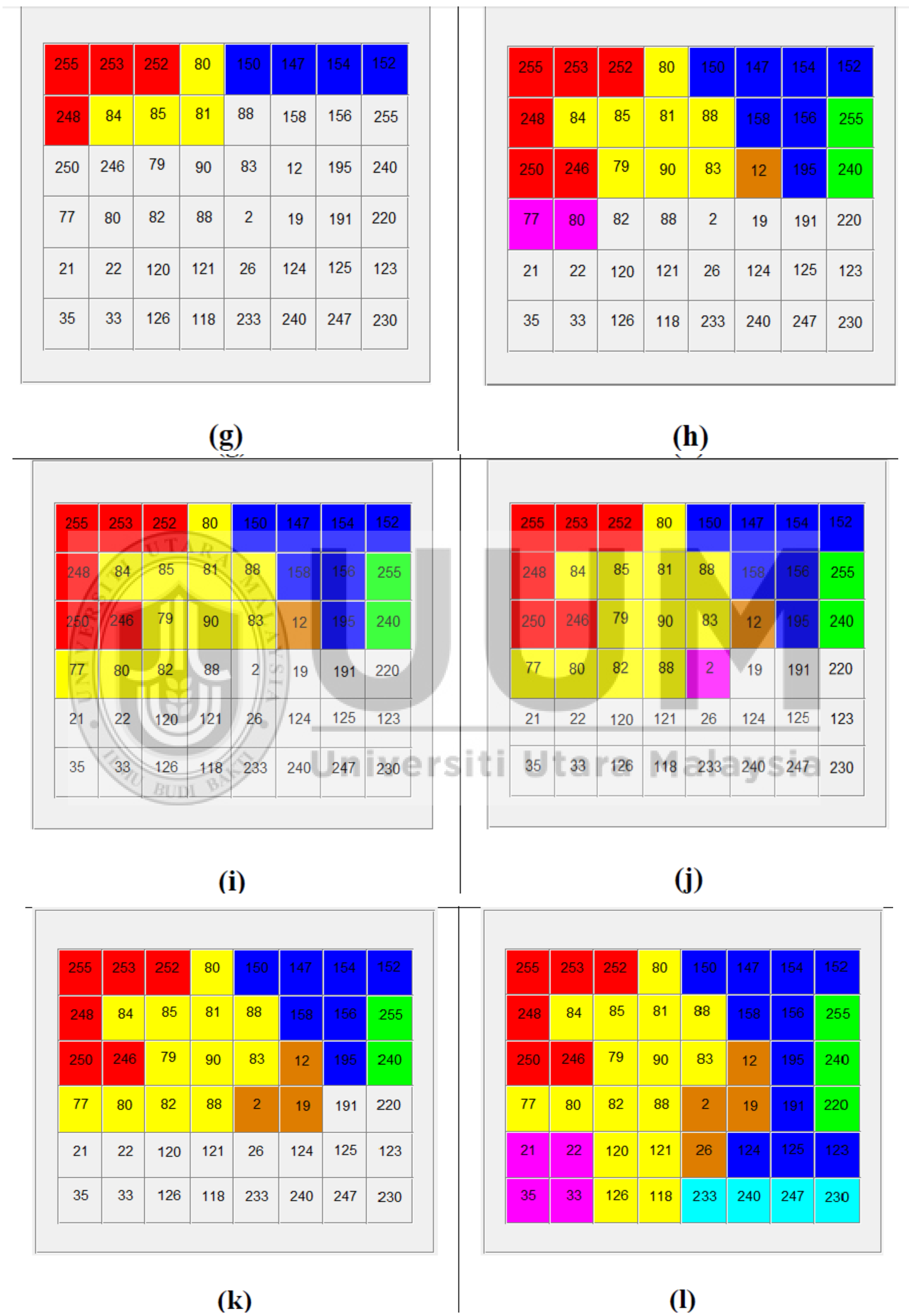

Figure 2.6 (g-l). Pixels by fast scanning algorithms representation (part 2)

The Figures 2.6 (a), 2.6(b), 2.6(c), 2.6(d), 2.6(e) and 2.6(f) respectively show the first four steps of algorithm. As seen the first pixel is assigned as the first cluster. Because the difference between the mean of first cluster and the second pixel is less than 45, the second pixel is also assigned to the first cluster. However, the distance between the fourth pixel and the mean of the first cluster is higher than 45, fourth pixel is assigned as a new cluster. First pixel of the second row of the image is assigned to the first cluster which is the cluster of upper pixel because the distance is less than 45. (Ding, Kuo, Hong, Tsai, & Chen, 2013).

In Figures 2.6(g), 2.6(h) 2.6(i), 2.6(j), 2.6(k) and 2.6(l) show the last three steps of algorithm, distance between the pixel that is being currently clustered and the means of the both upper pixel cluster and left pixel cluster is greater than 45. So, the current pixel is assigned as new cluster. Also, distance between the pixel that is being currently clustered and the both upper pixel cluster and left pixel cluster is less than 45. Therefore, the current pixel and both the clusters of upper and left pixels are assigned as a new cluster. The number of the pixels are checked of each cluster is less than delta. The value of delta is calculated by (Δ = (height x width) / size). Here, the size of the image is 6 x 8, with 128 the delta is 0,375. Thus, the number of the pixels for each cluster is at least 3 and it is greater than delta, there is not any removed cluster (Çamalan, 2013). For the color images, each pixel has three channels red, green and blue. Euclidean distance is used to measure the distances between the pixels. The flow chart of Fast Scanning algorithm steps are shown in Figure 2.7.

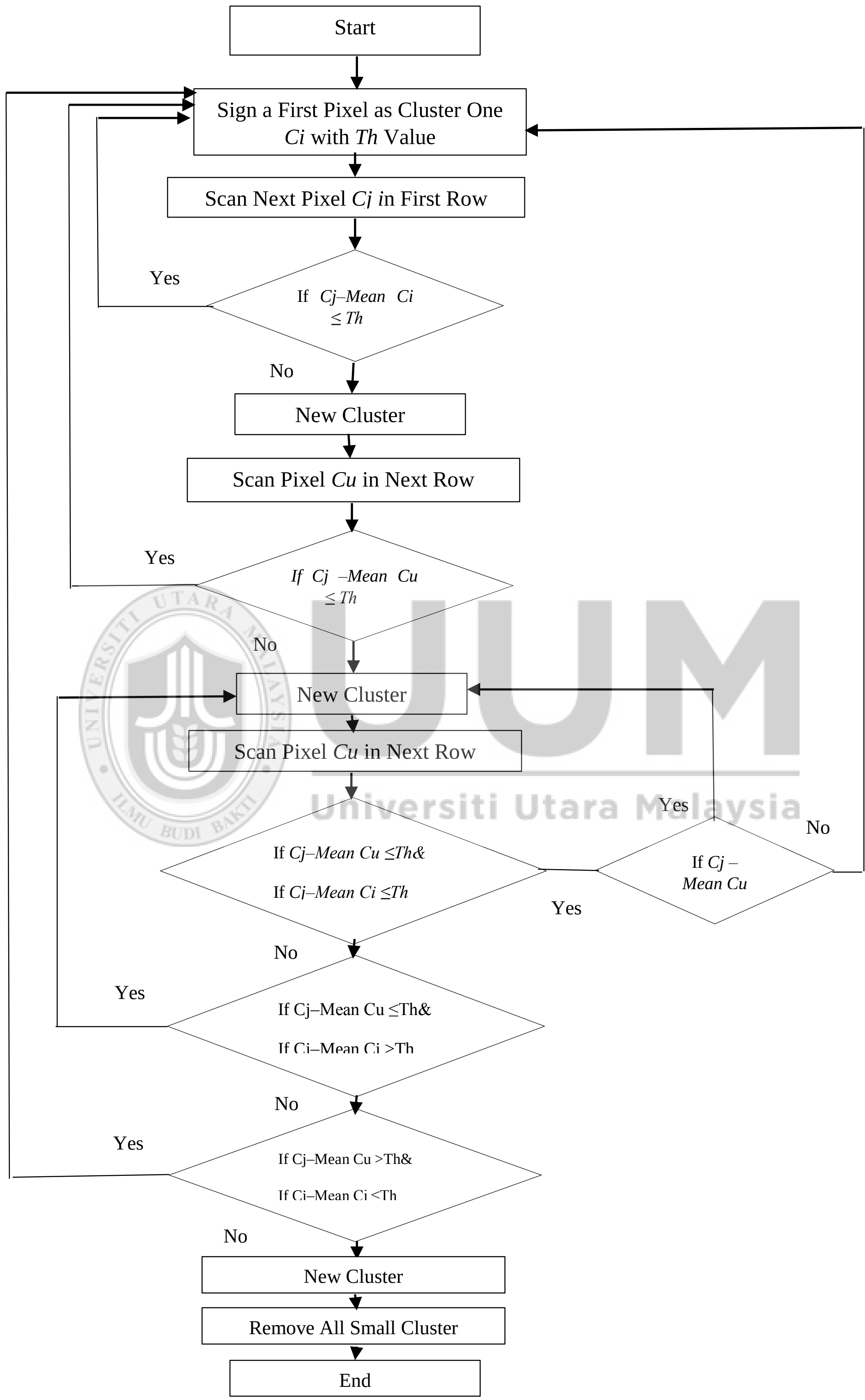

Figure 2.7. Flow chart of Fast Scanning algorithm

In Ding et al. (2011) Fast Scanning algorithm was used for muscle image segmentation. The selection of Fast scanning algorithm is due to the fact that it is faster than other existing segmentation algorithm. Besides, its advantages are that each cluster is connected and has similar pixel value. Based on the segmentation results to segment the image of mouse muscle could directly find the healthy muscle fiber and the unhealthy muscle fiber in the ultrasound image. Also, derive the injury score (Ding et al., 2013).

A good image segmentation algorithm should have the following three advantages: (1) fast speed, (2) good shape connectivity, and (3) good shape matching (Khan, 2013). Fast scanning algorithms have been applied on Gray-level and colour images. Also, three candidate popular algorithms have been applied like region growing, K-means and watershed for this kind of role. However, none of the three algorithms have these three characteristics at the same time. On otherwise, fast scanning algorithm considered a useful for segmenting due to its speed and good shape connectivity in segmenting results. It has a problem in shape matching. Table 2.1 shows the comparison of Fast Scanning algorithm to other three algorithms.

Table 2.1

Comparison of Algorithms (*Ding et al., 2011)*

	Fast Scanning	**Region growing**	**K-means**	**Watershed**
Speed	Much Faster	Much Slower	little Slower	little Slower
Shape Connectivity	Good Performances	Good Performances	Good Performances	Good Performances
Shape Matching	not good shape matching	not good shape matching	not good shape matching	more bad shape matching

Efficient image segmentation based on one-time fast scanning and upper-left Merging algorithms were proposed. It based on apply the techniques of fast scanning, the adaptive region mean, and the vertical / horizontal difference but, each pixel is processed only once. The proposed Fast Scanning algorithm can also be applied to the colour image. With these techniques, the segmentation results of their method are as well as those of the region growing method, but the computation time is less (Ding et al., 2013).

It considers fast and its result of segmentation intact with good connectivity. In otherwise, the matching of physical object is not good It can be improved by morphology and geometric mathematic. There are some morphological operations used to improve fast scanning algorithm like erosion, dilation, thinning, opening, closing (Ding, Kuo, & Hong, 2009).

Threshold technique is used to separate foreground from background by selecting a threshold value T, Any pixel(x, y) is selected as a part of foreground if its intensity is higher than or equal to threshold value i.e. $f(x, y) \geq T$, else pixel points to background" (Seerha, 2013). It can be categorized into two classes: global threshold and local (adaptive) threshold. (AL-amri & Kalyankar, 2010). Currently, Threshold is popular and simplest technique of region based segmentation (Dhivyaa & Suganya, 2014). Lastly, there are various threshold techniques e.g. the Mean, P-Tile, Histogram Dependent, EMT and Visual Technique (Zuva et al., 2011)

The clustering based techniques are those techniques in which the image is segmented into clusters that have pixels with comparable features. (Abed, Ismail, & Hazi, 2010). Specifically, clustering is done based on diverse properties of an image namely, size, colour, texture etc. (Cao & Wang, 2011).

Also, clustering technique consists of two essential classes namely Hierarchical Technique and Partition based Technique (Kaur & Kaur, 2014). Also, there are variety of algorithms which fall in the middle of these two techniques that are used to find clusters (Dehariya, Shrivastava, & Jain, 2010).

Nevertheless, mean Shift is viewed as a strong technique utilized for image segmentation, visual tracing and so on (Cao & Wang, 2011). Mean shift technique is a repetitive mode detection algorithm in the density distribution space or an instrument for discovering modes in a series of data samples. This technique is given as follows (Tao, Jin, & Member, 2007).

- Find a window around every data point.

- Calculate the mean of data inside the window.
- Translate density assessment window.
- Shift the window to the mean and repeat until convergence.

However, a number of segmentation algorithms may generate an excess of small regions as a result of division of one big region in the view. In such circumstance, the minor regions required to be joined in view of comparison and compression of the minor regions (Agrawal, 2014). Splitting and merging can be merged together for segmenting such complicated outlooks. The most well-known technique make use of the quad tree which is type of tree that have nodes with precisely four posterity (Kamal, 2013; Kaur & Kaur, 2014).

2.2.2 Edge Detection Techniques

Edge-based segmentation endeavors to subdivide an image in light of the presence of edges in the image. An edge in an image can be described as a discontinuity in various pixels in a collinear course. These edges describe entities in the image and can be created utilizing numerous techniques (Maini & Aggarwal, 2009). Furthermore, edge detection is an essential instrument for image segmentation. It change primary image into edge images take advantages from the grey tones in the image (Muthukrishnan & Radha, 2011).

There are numerous Techniques in the in the previously written texts utilized for edge detection and few of them are based on fault reduction, expanding function of an entity, fuzzy logic, wavelet approach, morphology, genetic algorithms, neural network, Bayesian approach and watershed (Patel, Patel, & Shah, 2013). The grouping of the detection algorithms taking into account the behavioral investigation of edges regarding operators (Lakshmi, 2010).

Based on the previous paragraphs, there are many algorithm used for edge detection which have been discussed in many scholarly literature for image segmentation. The most commonly used are. Watershed, Roberts Detection, Sober Edge Detection, Prewitt, Zero Crossing, Robinson, Laplacian of Gaussian (LoG) and Canny Edge Detection. These are applied to segmentation of various SEM images for comparison, which is used to split the primary image into two regions; foreground region and background region. The introduced method showed the accuracy of 94% for 1D image type and accuracy of 98% for 2D image type (Lee & Yoo, 2008).

2.2.3 Hybrid Techniques

Numerous techniques are used for an fault-free image separation as histogram-based which stand for the simple probability distribution function of intensity values of any image (Tripathi, Kumar, Singh, & Singh, 2012). Edge based techniques is used for detection utilizing differential filter in order of image gradient or laplacian and then classified them into contours that represents the surface. In the region-based segmentation technique, this segment the image into a series of uniform regions then joined them based on specific decision guidelines. In hybrid segmentation Technique the goal is to offer an enhanced answer for the segmentation problem by bringing together Techniques of the previous classes. Most of them are based on the amalgamation of edge-based and region-based Methods. Again the Methods are derived from integration of the edge and region based Methods information (Wang et al., 2007). Firstly image is divided into regions and they are then joined using divide and join method and after contours are detected by using edge-based technique (Patil & Deore, 2013).

Besl and Jain, (1985) were at first divided images into regions utilizing surface arc sign and, then, a variable-order surface fitting repetitive regions joining the procedure is originated. Whereas Pavlidis and Liow at first segmented the image utilizing region-based separate and-join method and then, the detected contours are purified utilizing edge information (Haris, Efstratiadis, Maglaveras, & Katsaggelos, 1998).

There are numerous demanding issues like advancement of an integrated methodology to image segmentation which can be utilized all sort of images even the choice of appropriate method for a specific kind of image is a troublesome issue. Accordingly, despite quite a few years of investigation, there is no generally accepted technique for image segmentation for all classes of images and in this way it stays as a problem in picture handling and PC imagination (Agrawal, 2014).

In general, the significance of image segmentation's techniques can't be ignored on the grounds that it is utilized in nearly of all areas of science that is eliminating noise from an image, therapeutic images, satellite imaging, machine vision, PC vision, biometrics, military, image recovery, isolating attributes and identifying entities from the given images (Lakshmi, 2010).

A high level of consideration has been given to investigation on image segmentation for several years. Huge number of diverse segmentation techniques are available in the present situation, however there is not by any means a solitary technique which can be viewed as appropriate for distinctive images, all techniques are not similarly relevant for a specific kind of image (Yasmin, Mohsin, & Sharif, 2012). Table 2.2 illustrates the principal contrasts between the major segmentation techniques.

Table 2.2

Principal Contrasts between Major Segmentation Techniques

Segmentation Technique	Description	Advantages	Disadvantages
Edge Detection	Based on the discontinuity Detection	Good for images having better contrast between objects	Not suitable for wrong detected or too many edges
Region	Based on dividing image into homogeneous regions	More impervious to noise, useful when it is simple to define similarity criteria	Expensive techniques in terms of time and memory
Hybrid	Based on combining techniques especially region and edge detection Methods	Offering an improved solution to the segmentation problem by combining Methods of the previous categories	Need prior knowledge

2.3 Image Segmentation Applications

Segmentation is bridges the gap between low-level image processing and high-level image processing (Abed, 2011; Seerha, 2013). Some kinds of segmentation technique will be found in any application involving the detection, pattern recognition, and measurement of objects in images. In addition, there are several application for segmentation like Industrial inspection, optical character recognition (OCR) tracking of objects in a sequence of images, classification of terrains visible in satellite images, detection and measurement of bone in medical images, tissue, detection interesting regions, etc (Deb, Lim, & Jo, 2009).

Hamdey, (2009) proposed a national system for car identification that depends on license plate recognition using the simply algorithm for segmentation. The obtained results is quite satisfactory and could be evidently expanded to other applications such as in Input - output transport system, ship, trains, etc. The algorithm was examined for many images captured by digital camera and test done for 25 images of car. The result is showed that 20 images, is indicate 80 % of them are useful recognition. Process of the Simply algorithm is shown in Figure 2.8.

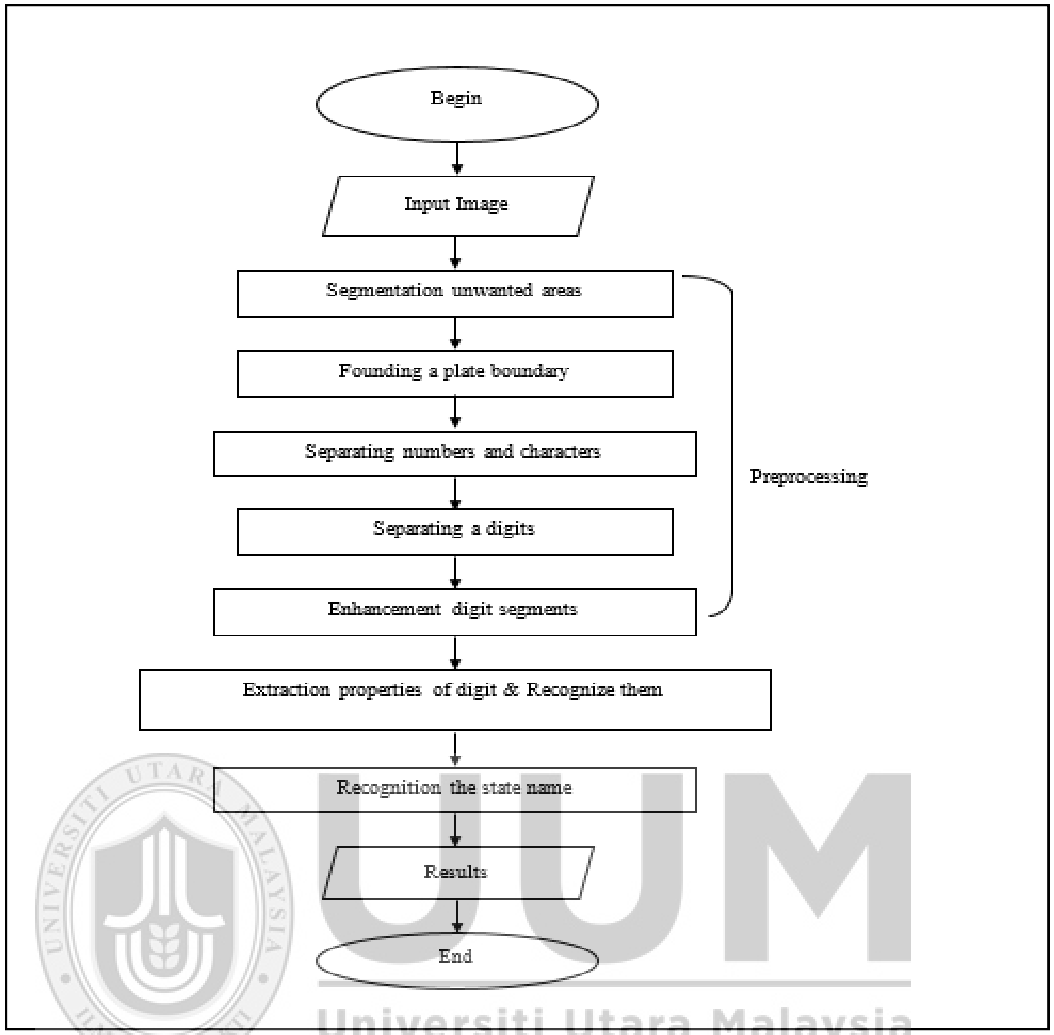

Figure 2.8. Simply algorithm process (Hamdey, 2009)

Several image segmentation's algorithms and techniques were used and applied for nature images. The researchers were focused on determine nature background as interesting things (Jie & Peng-Fei, 2003). A new algorithm segmentation has proposed for nature images which contains trees and flowers. It uses a principled information-theoretic approach to join cues of image texture and boundaries. In details, the texture and boundary information of each texture region is encoded using a Gaussian distribution and adaptive chain code, respectively.

The segmenting of an image is applies by an agglomerative clustering process. The experiments have showed that the proposed algorithm betters than other existing algorithms in terms of region-based segmentation indices rand index and variation of information (Mobahi et al., 2011).

Therefore, a new approach was presented for image segmentation that is depended on low-level characteristics for color and texture. It is aimed at segmentation of nature images in which the color and texture of each segment does not typically display regular statistical features (Chen, Pappas, Mojsilović, & Rogowitz, 2005).

The new approach presented by (Chen, Pappas, Mojsilović, & Rogowitz, 2005) joins knowledge of human perception with an understanding of signal characteristics in order to segment natural images into perceptually/semantically same regions. The experiments were as following below Figure 2.9.

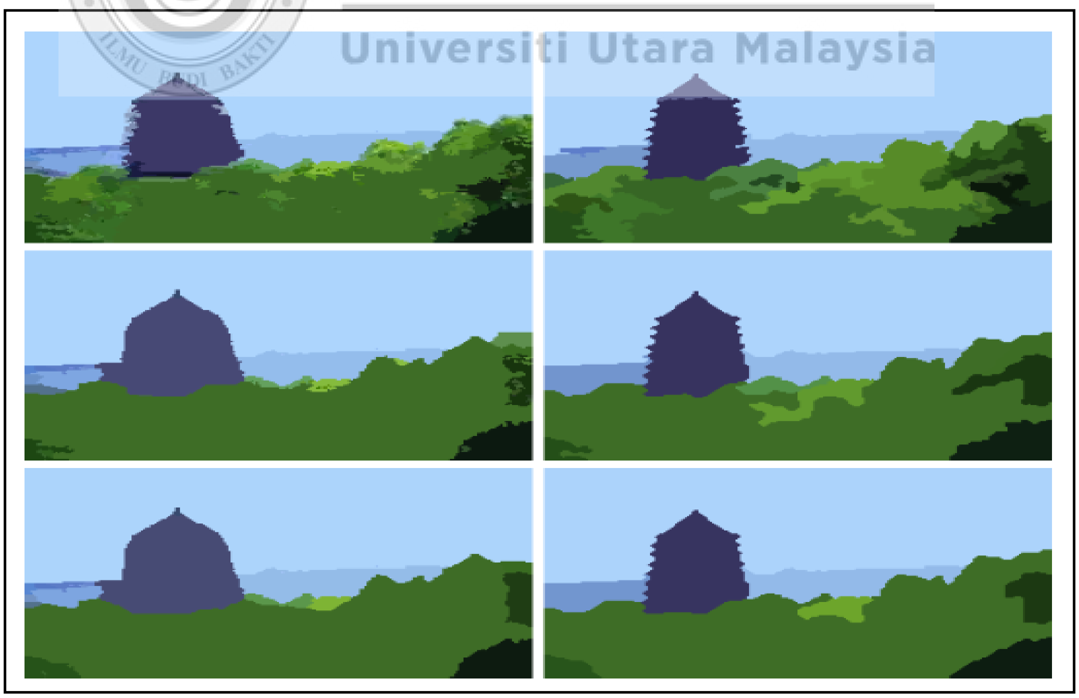

Figure 2.9. Experiments results

A new method for nature color image segmentation using integrated features is investigated. Edges are first detected in term of the high phase congruency in the gray-level image. K-means cluster is used to label long edge lines based on the global color information to estimate roughly the distribution of objects in the image, on other hand short ones are merged depended on their situation and its color differences to remove the negative passion reason whether texture or other trivial information in image (Chao, 2009). Region growing technique is employed to apply the final segmentation results. The investigated method integrates edges, both the whole and local color distributions, and the spatial characteristics to solve the natural image segmentation problem (Jie & Peng-Fei, 2003).

2.4 Distance Measures in Image Segmentation

Distance-based approaches calculate the distance from each point to a particular point in the data set (Jaworska, Nikolova-Jeliazkova & Aldenberg, 2005). In image analysis, the distance transform measures the distance of each object point from the nearest boundary and is an important tool in computer vision and image processing. There have been considerable efforts in finding the appropriate measures among such a plethora of choices because it is of fundamental importance to pattern classification, clustering, and information retrieval problems (Seung-Seok, Sung-Hyuk, & Tappert, 2010).

Distance to the mean, averaged distance between the query point and all points in the data set, and maximum distance between the query point and data set points, are examples of the many available options (Kaur, 2014).

Since the performance of clustering relies on the choice of an appropriate measure, many researchers have taken elaborate efforts to find the most meaningful distance measures. Numerous binary distance measures and similarity measures have been proposed in various fields. There are different color distance measures used in the literature today depending on the color space. Extracting useful information for color image segmentation directly from the red, green and blue (RGB) space is not well defined. However, given that images are easily available in the RGB space, most research has been done in that domain. There has been some research done on combining distance measures in color image processing (Androutsos, Plataniotiss, & Venetsanopoulos, 1998).

There are several distance measures have used in color image processing. As well as, each color image have three colors representing by blue, green and blue colors then by merging the three matrices will produced the real colors (Eldahshan, Youssef, Masameer, & Hassan, 2015). There are two types for color's domain in images which are double and unit8. The color's value in double domain was restricted between [0,1] where 0 represents the black color's value and 1 represent the color's value for one of three colors. Therefore, color's gradients have restricted between two values and smaller from 1 for example (0.234, 0 560, etc.) as in the Figure 2.10.

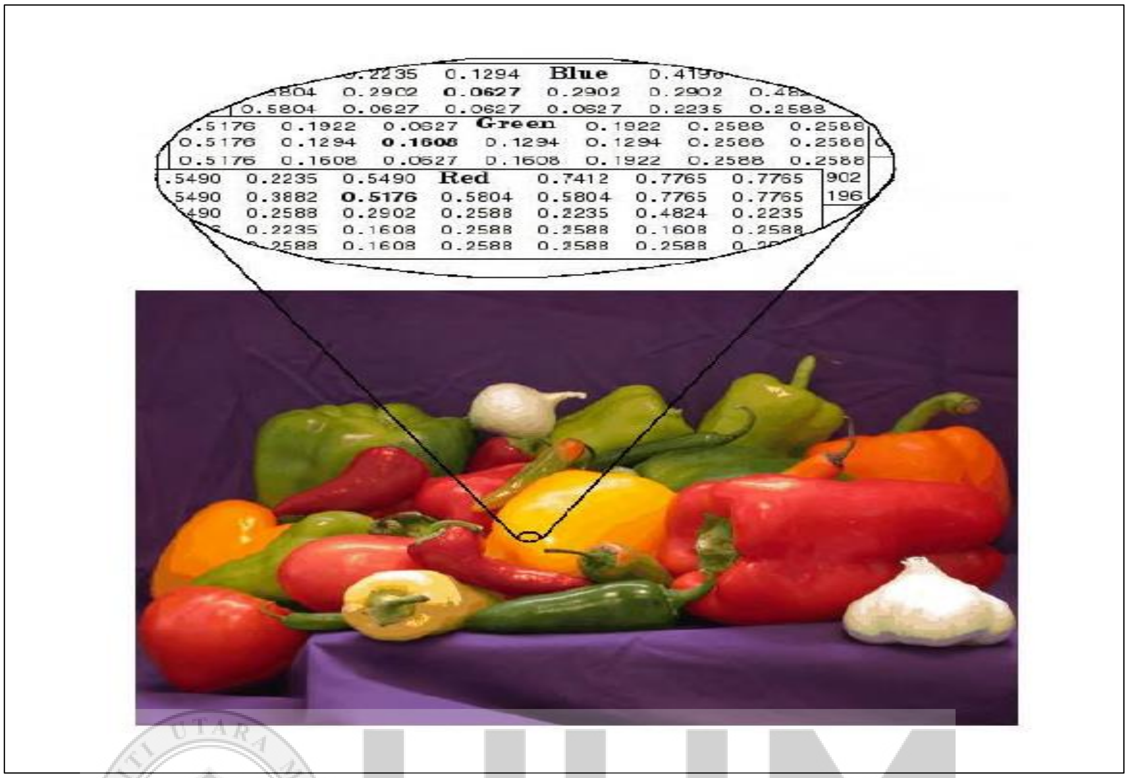

Figure 2.10. RGB color double domain

The unit8 domain have an integer values ranged between [0,255] black color have a 0 value and 255 to color's values and other gradients in middle as Figure 2.11.

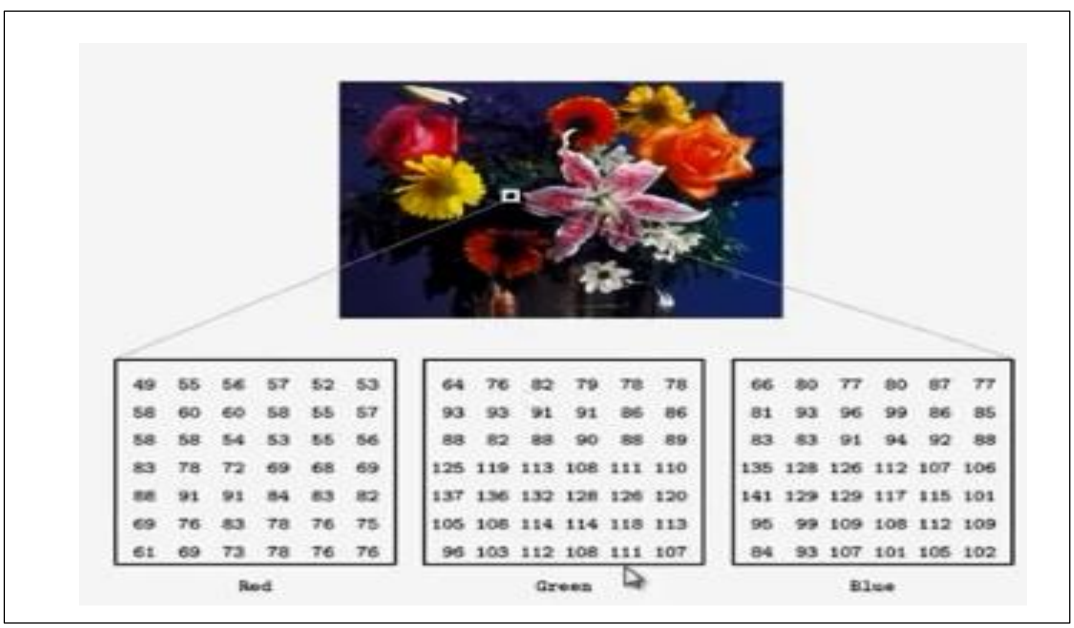

Figure 2.11. RGB color unit8 domain

2.4.1 Euclidean Distance

A couple of thousand years ago, Euclid stated that the shortest distance between two points is a line and thus is predominantly known as Euclidean distance. It was often called Pythagorean metric since it is derived from the Pythagorean Theorem (Cha, 2007). The Euclidean distance (D_{ECU}) measure is usually used to compute distance is defined as:

$$D_{ECU} = \sum_{i=1}^{d} \sqrt{|P_i - Qi|^2} \tag{2.1}$$

$$D_{ECU} = \sqrt{(p_{1,1} - q_{2,1})^2 + (p_{1,2} - q_{2,2})^2 + (p_{1,3} - q_{2,3})^2} \tag{2.2}$$

Where the P and Q are two points. In a three- color space P with the coordinates *(p1, p2, p3)*, Q with the coordinates *(q1, q2, q3)* (Wesolkowski, 1999). The d refers to dimensions and i is point counter.

2.4.2 City Block Distance

The City Block distance t is produced by Hermann Minkowski in late of the 19th century (Barlow, 1996). Also, it has other names for like rectilinear distance, taxicab norm, and Manhattan distance. It is named according to the distance a car would drive in a city laid out in square blocks, like Manhattan. According to Jaworska, Nikolova-Jeliazkova and Aldenberg, (2005) city block distance assumes a triangular distribution and it is particularly useful for discrete descriptors. In addition , Notice that the city block distance (D_{CB}) depends on the choice on the rotation of the coordinate system, but does not depend on the translation of the coordinate system or its reflection with respect to a coordinate axis (Finch, 2005). It is defined as:

$$D_{CB} = \sum_{i=1}^{d} |P_i - Q_i| \qquad (2.3)$$

$$D_{ECU} = (p_{1,1} - q_{2,1}) + (p_{1,2} - q_{2,2}) + (p_{1,3} - q_{2,3}) \qquad (2.4)$$

Where the *P* and *Q* are two points. In a three- color space *P* with the coordinates *(p1, p2, p3), Q* with the coordinates (*q1, q2, q3)*. The *d* refers to dimensions and *i* is point counter.

2.4.3 Dice Distance

This index was first proposed by Dice in 1945 as a measure of distance / similarity by derived from Dice's coincidence index. It has separately developed by the botanists Thorvald Sørensen and Lee Raymond Dice, and then they have published in 1948 and 1945 respectively. It is more regarding to the Jaccard coefficient, with further weight being given to cases of mutual agreement. The dice distance (D_{DICE}) measure is usually used to compute distance is defined as:

$$D_{DICE} = \frac{2\sum_{i=1}^{d} PiQi}{\sum_{i=1}^{d} Pi^2 + \sum_{i=1}^{d} Qi^2} \qquad (2.5)$$

$$D_{DICE} = \frac{2\,(p1\ 1\ q2\ 1) + (p1\ 2\ q2\ 2) + (p1\ 3\ q2\ 3)}{(p1\ 1)^2 + (p1\ 2)^2 + (p1\ 3)^2 + (q1\ 1)^2 + (q1\ 2)^2 + (q1\ 3\ )^2} \qquad (2.6)$$

Where the *P* and *Q* are two points. In a three- color space *P* with the coordinates *(p1, p2, p3), Q* with the coordinates *(q1, q2, q3)*. The *d* refers to dimensions and *i* is point counter.

2.4.4 Sorensen Distance

It is similar to Jaccard's index and it is also named as Sorensen coefficient. Its equation comes from Thorvald Sorensen, a turn-of-the-century Danish botanist and it consider as very easy to calculate. Its applications are familiar in several fields especially in ecology (Cha, 2007).

Sorensen distance is a settlement method that views the space as grid similar to the city block distance. It has a good property that if all coordinates is positive; its value is between zero and one. The dice distance (D_{DICE}) measure is usually used to compute distance is defined as: settlement is done using absolute difference divided by the combination (Kaur, 2014) as the below equation:

$$D_{sor} = \frac{\sum_{i=1}^{d} /Pi - Qi/}{\sum_{i=1}^{d} (Pi + Qi)} \qquad (2.7)$$

$$D_{sor} = \frac{/(p_{1,1} - q_{2,1}) + (p_{1,2} - q_{2,2}) + (p_{1,3} - q_{2,3})/}{(p_{1,1} + q_{2,1}) + (p_{1,2} + q_{2,2}) + (p_{1,3} + q_{2,3})} \qquad (2.8)$$

Where the *P* and *Q* are two points. In a three- color space *P* with the coordinates *(p1, p2, p3)*, *Q* with the coordinates *(q1, q2, q3)*. The *d* refers to dimensions and *i* is point counter.

In clustering, Kuar, (2014) implement K-means clustering with three different measures that includes Euclidean distance, Canberra and Sorensen distance. These measures were used to forecast the fault vulnerability at premature phase of software life process along with available data that may help the software practitioners to erect more accurate projects. The experimental results shows that K-means clustering with Sorensen distance is better than Euclidean and Canberra distances.

According to (Crausbay, Martin, & Kelly, 2015) the determine a rate of compositional change in vegetation and they conducted rate-of-change analysis on adjacent pollen/spore percentages. Receiver operating characteristic (ROC) was identified by calculating the Sørensen distance between sequent pollen/spore samples and dividing by the time elapsed between samples and have produced a suitable results.

2.5 Evaluation of Image Segmentation Algorithms

The evaluation of image segmentation algorithms and techniques is important in determining which characteristics of which algorithms work well, and in what circumstances. It is an open subject in today's image processing field and it has not reached maturity, in the sense of reliability and consistency (Borsotti, Campadelli, & Schettini, 1998). Related work on quantitative segmentation evaluation includes both standalone evaluation methods, which do not make use of a reference segmentation, and relative evaluation methods employing ground truth (Zhang, 2002). For standalone evaluation of image segmentations metrics for intra-object homogeneity and inter-object disparity have been proposed in (Levine, 1985). Performance evaluation parameters presented by (Sharma, 2010) includes the Rand Index (RI), Variation of Information (VoI), global consistency error (GCE) ,boundary displacement error (BDE), segmentation accuracy , precision recall measure (PRM) ,convergence rate ,mean absolute error (MAE), peak signal to noise ratio (PSNR), hamming distance ,local consistency error (LCE), structural similarity index measure and entropy (Sardana, 2013). Researchers also investigate which parameter is suitable for which type of segmentation. It is learned that the most popular measure for region based segmentation is the

- Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio (PSNR) represents region homogeneity of the final partitioning. The higher the value of PSNR the better the segmentation is (Sowmya & Rani, 2011). PSNR in calculated in decibels (dB) is obtained using:

$$\text{PSNR} = 20\log_{10}\left(\frac{255}{MAE}\right) \tag{2.9}$$

$$\text{MAE} = \frac{1}{MN}\sum\sum\left|F(i,j) - f(i,j)\right| \tag{2.10}$$

Where, *255* is max of pixels' number and *MAE* is abbreviation of t mean- absolute error, is *F (i, j)* - segmented image, *f (i, j)* - source image that contains *M by N* pixels. The higher PSNR, the better quality of the output image when PSNR value approaches infinity the mean absolute error (MAE) approaches zero; this shows that a higher PSNR value provides a higher image quality. On the other end, a small value of the PSNR implies high numerical differences between images (Almuhairi, 2010). In image segmentation PSNR values have been used to evaluate the segmented images and results within the quantitative evaluation type.

- Global Consistency Error (GCE)

The Global Consistency Error (GCE) measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentations which are related are considered to be consistent, since they could represent the same image segmented at different scales. The formula for GCE is as follows,

$$\mathrm{GCE} = \frac{1}{n}\min\{\sum_i E(s1, s2, pi), \sum_i E(s2, s1, pi)\} \quad (2.11)$$

Where, *S1* and *S2* as two input images segmentation error measure takes two segmentations *S1* and *S2* as input, and produces a real valued output in the range [0::1] where zero signifies no error. For a given pixel pi consider the segments in S1 and S2 that contain that pixel (Xess & Agnes, 2014).

- Rand Index (RI)

The Rand index (RI) between test and ground-truth segmentations S and G is given by the sum of the number of pairs of pixels that have the same label in S and G and those that have different labels in both segmentations, divided by the total number of pairs of pixels (Arbelaez, Maire, Fowlkes, & Malik, 2011). The RI is given as:

$$RI = \frac{a+b}{a+b+c+d} = [\binom{n}{2}[0.5\{\sum_i(\sum_j n_{ij})^2 + \sum_j(\sum_i n_{ij})\}^2 - \sum\sum n_{ij}^2]] \Big/ \binom{n}{2} \qquad (2.12)$$

Where, *a*, the number of pairs of elements in *S* that are in the same set in *U* and in the same set in *V ; b,* the number of pairs of elements in *S* that are in different sets in *U* and in different sets in *V; c*, the number of pairs of elements in *S* that are in the same set in *U* and in different sets in *V; d*, the number of pairs of elements in *S* that are in different sets in *U* and in the same set in *V*. is the number of objects in the *ith* cluster in *U* and *jth* cluster in *V*, and *n/2* is the binomial coefficient, which gives the number of distinct pairs found in a set of n objects (Xess & Agnes, 2014).

- Variation of Information (VoI)

The Variation of Information (VoI) metric defines the distance between two segmentations as the average conditional entropy of a segmentation given the other, and thus roughly measures the amount of randomness in a segmentation which cannot be explained by the other (Fan, Zeng, Body, & Hacid, 2005). Lower the VoI value better is the result. The VoI is defined as:

$$VI(c, c') = H(c) + H(c') - 2I(c, c')$$

Where, *H(c)* and *H(c`)* are the entropies associated with cluster *c* and *c*`; is *I(c, c`)* the mutual information between the associated random variables.

Three image segmentation algorithms namely FCM, region growing and watershed are discussed by (Xess & Agnes, 2014) and their segmentation results are evaluated. Comparative analysis shows that region growing algorithm has more de-noising capability with highest PSNR value. Measures suitable for evaluating FCM algorithm are (RI, VoI and GCE), where GCE for FCM is zero indicating better segmentation result. Also PSNR is suitable for evaluating Watershed algorithm. Thus, different image segmentation algorithm can be evaluated with suitable performance metric based on its application.

In the work by Yadav & Meshram, (2013). The quality of segmented image is measured by statistical parameters: (RI, GCE and VOI) and boundary displacement error (BDE).The modified maximum a posteriori and the maximum likelihood (MAP-ML) algorithm has implemented by (Karlis, 2014) which gives comparable results with the original MAP-ML algorithm performing the image segmentation. The experimental results have successfully shown that the modified MAP-ML algorithm takes less time to execute as compared to the original MAP-ML algorithm giving nearly same results as the original algorithm.

A according to (Sathya & Kayalvizhi, 2010) a new multilevel thresholding technique based on Particle Swarm Optimization (PSO) is proposed which enables in determining the optimal threshold values by maximizing tsallis objective function. Experiments with several standard test images have proved the robustness of the proposed method, evaluated through the PSNR measure and the objective function. Comparison with the genetic algorithm method showed that the proposed method more stable.

A function of PSNR has used by (Rao, Goardham & Badashah, 2011) along with the execution time for evaluating the segmented images. A statistical approach to evaluate the variance among the PSNR and the execution time in output image is also incorporated. Similar metric is also employed in (Anitha & Nagabhushana, 2012).

A histogram based and graph theory based image segmentation has been proposed by (Ukunde & Shrivastava, 2012). The proposed algorithms have been evaluated using PSNR values. From the results it can be seen that histogram based segmentation technique suffers from lower PSNR values. Also, (Sardana & Haryana, 2013) have present Qstu technique, watershed technique and k-means clustering for image segmentation. Then evaluation of these method is done using PSNR value. The experiments results have showed that watershed technique is better by producing highest values.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodology implemented in this study. The phases incorporated of four major tasks; Data Collection, Determine Suitable Distance Measure, Formulate Threshold Function and Evaluation. The simplified form of the methodology implemented is illustrated in Figure 3.1

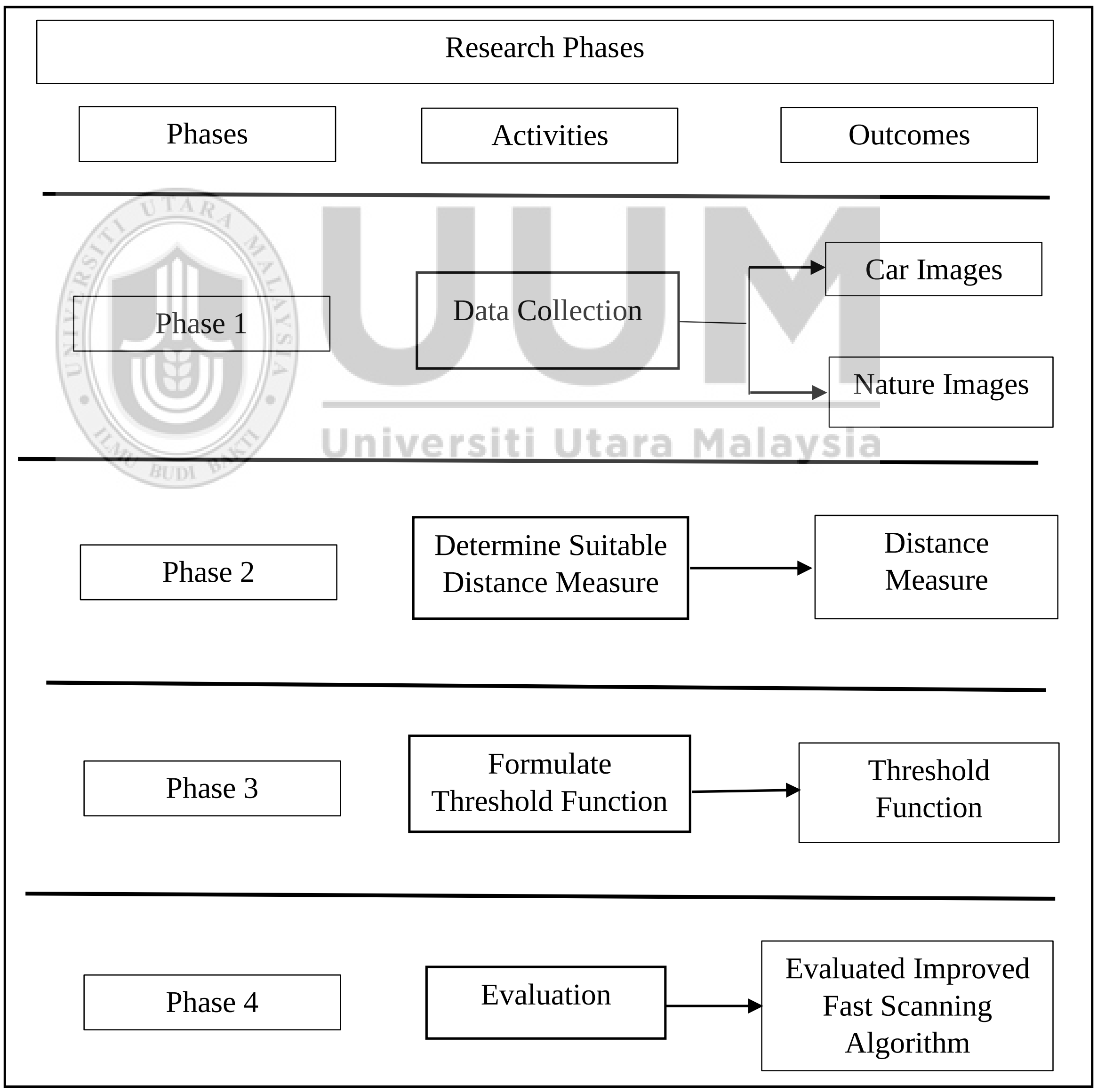

Figure 3.1. Research methodology

3.2 Data Collection

This section presents the datasets used in this study. The datasets consist of two major types, Dataset 1 and Dataset2.

3.2.1 Dataset 1

The first dataset used in this study includes image of Middle East cars. It includes a collection of Iraqi and Saudi Arabia car images which have interesting regions. Specifically, it contains several region like numbers and characters (Arabic and English) in its plate which could be recognized. This dataset is utilized due to the importance of segmentation in car plate recognition system. If a good segmentation is performed than a higher chance is obtained in recognizing the letters and numbers in the plate.

The collection of Iraqi cars images are captured using a digital camera while images of Saudi Arabia cars are downloaded from the internet (http://sa.waseet.net). All images are stored with red, green and blue (RGB) as color space and dimensions of 600×600 pixels and totally, there are 25 images included in the first dataset (Hamdey, 2009). Examples of the images are as shown in Figure 3.2.

Figure 3.2. Examples of images

3.2.2 Dataset 2

The second dataset is a collection of nature images which refers to images taken outdoors and devoted to displaying nature l elements such as landscapes, wildlife and plants. The collection is built upon images of trees and flowers as the focal points and were captured using a digital camera in gardens, public parking and streets inside Universiti Utara Malaysia (UUM) campus. The aim is that the segmentations could be used in location tracking system that benefits from pattern recognition. In total, there are 15 images as a suitable number with RGB color space and dimensions of 600×600 pixels. Figure 3.3.includes examples of the dataset.

Figure 3.3. Examples of images in dataset 2

3.3 Determine Suitable Distance Measure

This study determines the suitable distance measure for grouping pixels in Fast Scanning algorithm. In this study the RGB space color have been used as input dataset and four distance measures are evaluated ; Euclidean Distance (Liao, Xu, & Zeng, 2014) , City Block Distance (Paul & Gupta, 2013) , Dice (Avants *et al.*, 2011) and Sorensen Distance (Cha, 2007). In detail, this study determined 25 adjusted pairs of pixels as sample for each image in both datasets. The four distance measure have evaluated and used to calculate the distance between pixel and its neighbor pixel in each image to produce smaller distance. Therefore, evaluated using the four measures as shown in the Figure 3.4.

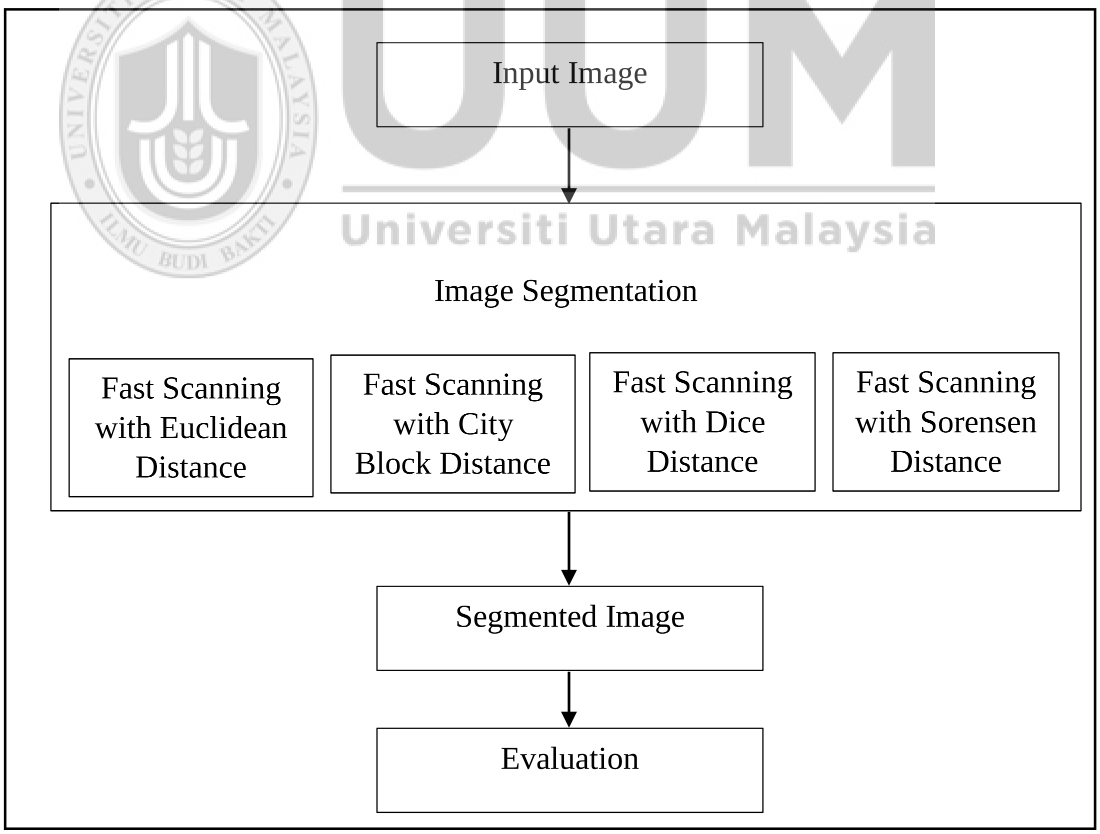

Figure 3.4. Experimental design for distance measure of fast scanning algorithm

3.4 Formulate Threshold Function for Fast Scanning Algorithm

The study also proposes adaptive threshold that is calculated by following function:

$$\text{Adaptive Threshold} = 1/\text{n x m} \sum_{\substack{1\le i\le n \\ 1\le j\le m}} (\text{Gray}(i,j) - \text{Mean}(\text{Gray}))^2 \quad \text{Image } [i, j] = \begin{cases} 1 \text{ if Gray } (i\text{ , }j) > \text{Threshold} \\ 0 \text{ if Gray } (i\text{ , }j) \le \text{Threshold} \end{cases}$$

Where (n x m) : Size of image.

(i, j) : i and j are the pixel coordinates i ∈ Image (rows) and j ∈ Image (columns).

Threshold: threshold value, Grey (i,j) grey level.

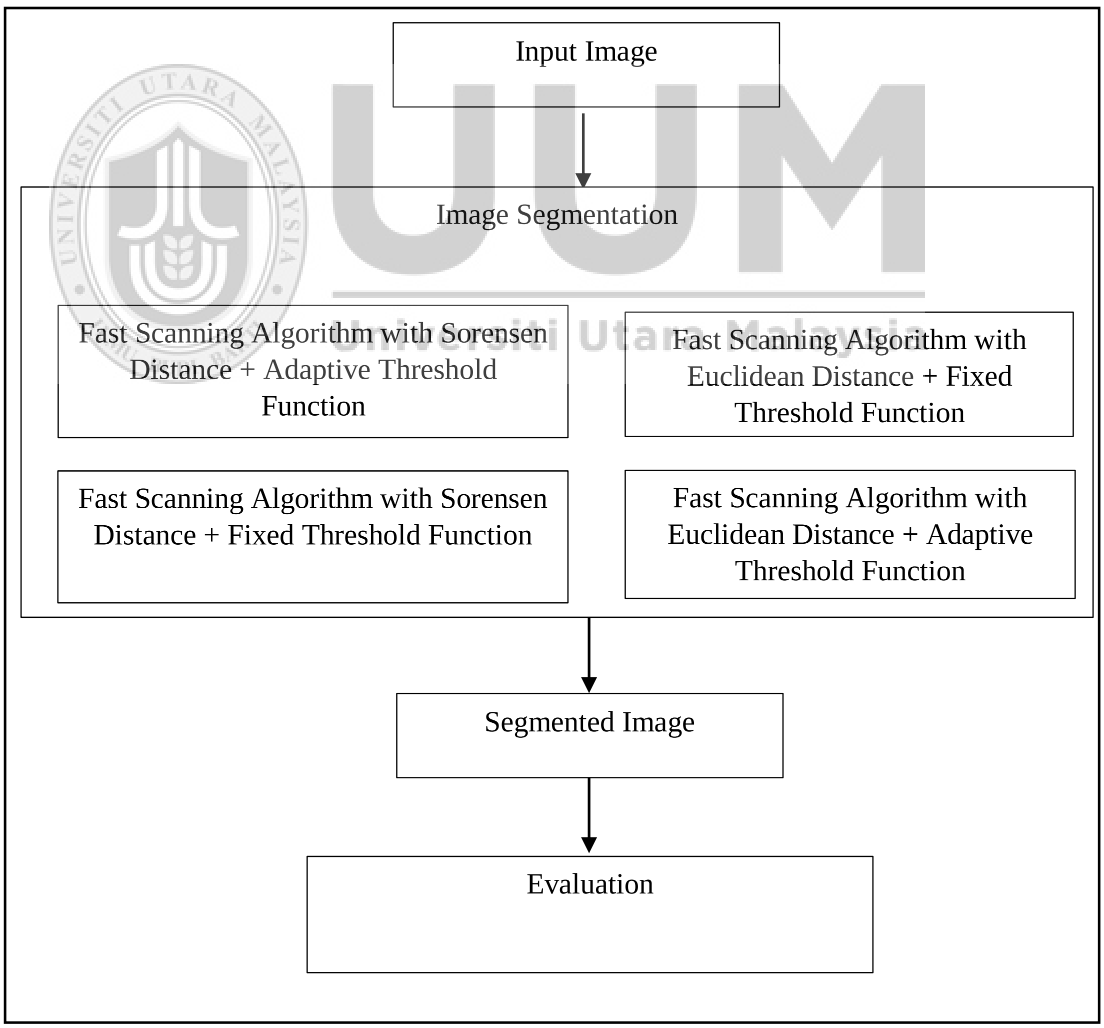

Figure 3.5. Experimental design for objectives 2 and 3

Besides, this study proposed an improved Fast scanning algorithm for image segmentation. The proposed algorithm is composed of the following steps:

Algorithm 3.1

Proposed of IFSA

```
   Input image E = (n,m)
1: Assign upper left pixel of is assigned as the first pixels P of the E
   Where pixel [1, 1] as first Region = R1.
2: Set R [1, 1] as R1, n and m =1, i and j = 1.
3: Scan all pixels in E begin from upper left pixel as first one
4: Cluster pixels using Sorensen distance measures as S
    where p1 = x1 and p2 = x2
    where S =( sum (P1 – P2)) / (sum (P1 + P2))
5: Calculate adaptive value ,Th1, to segment E
   Where Th = sum ((Gray (i,j) - mean (Gray))
6: Th1 = Th ^ 2
7: for i = 1 to 600
       for j = 1 to 600
           if P(i,j) ≤ Th1
               P(i,j) = 0
          else
          P(i,j) = 1
          end if
       end for
   end for
```


The algorithm 1.2 has used Euclidean distance to cluster pixels and predefined threshold value in its segmentation process. On other hand the IFSA in algorithm 3.1 uses Sorensen distance to group pixels and calculates threshold value adaptively as clear in algorithm 3.1 in step 5.

3.5 Evaluation

The final phase in this study is the evaluation of the proposed IFSA for image segmentation. This done by comparing results obtained from the standard Fast Scanning algorithm and the IFSA by calculate the PSNR value for both algorithms. The flow chart

3.6 below illustrates steps of calculate PSNR value. As seen in the flow chart that the first steps begins with reading the data for both images. After that moves to do a checking for their size. If they are concede, moves to another examining which type, if not have to resizing one of them and starting again. As in the previous test if both images have the same type, will go back to the beginning. Otherwise, Calculation and reading Max Pixels for both will be done in the stage. The final two steps are just computing MAE and PSNR for the Images.

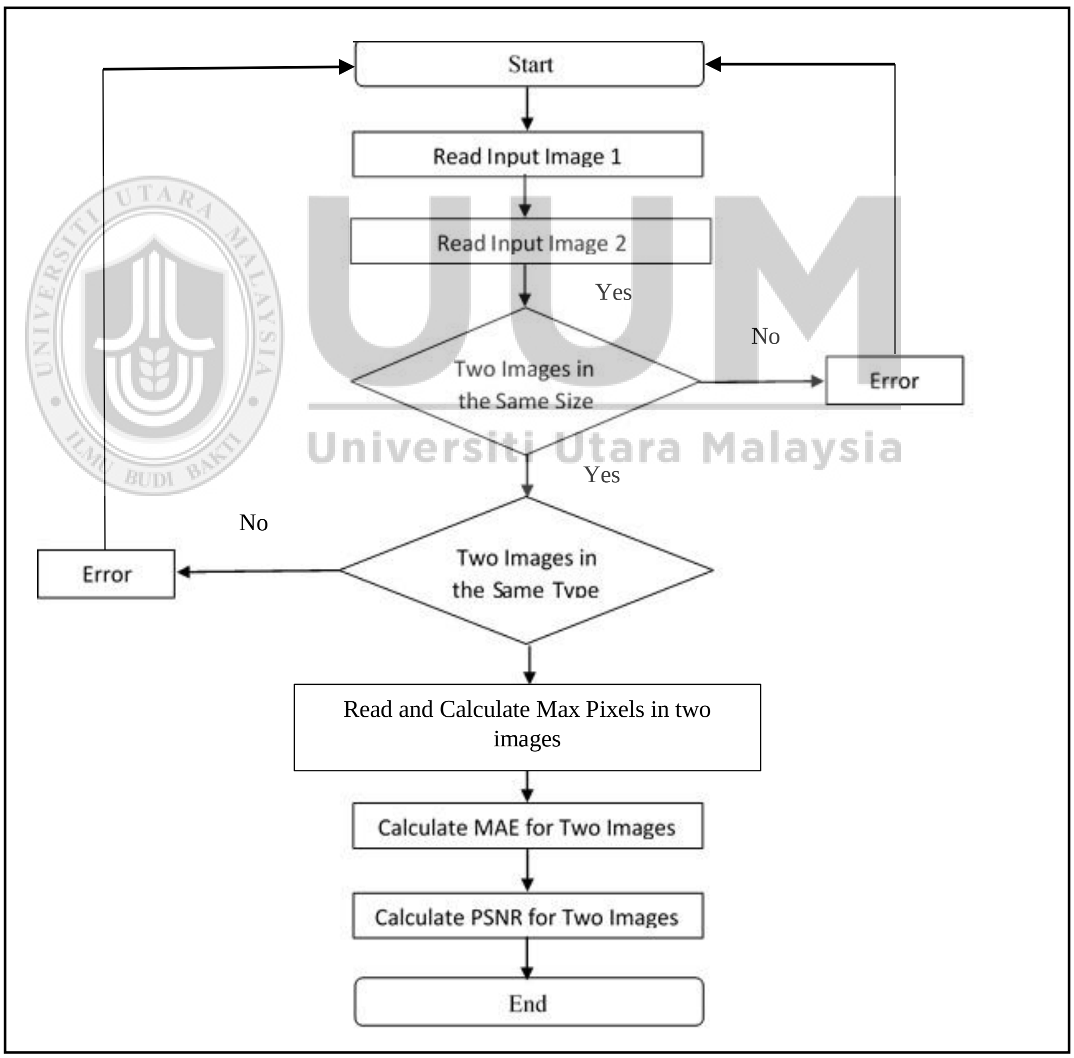

Figure 3.6. Flow chart for calculate the PSNR

The employed PSNR equation have used to evaluate the effectiveness of the algorithms is as below (Xess & Agnes, 2014):

$$\text{PSNR} = 20\log_{10}\left(\frac{255}{MAE}\right) \qquad (3.1)$$

$$\text{MAE} = \frac{1}{MN}\sum\sum |F(i,j) - f(i,j)| \qquad (3.2)$$

Where F (i, j)

Segmented image, f (i, j).

Source image that contains M by N pixels.

3.6 Summary

This chapter explains the methodology for the study. The methodology consists of four phases: data collection, determine suitable distance, formulate threshold function and evaluation. Data collection consists of two types of datasets; Dataset1 which includes Iraqi and Saudi car's images while dataset2 includes nature images in UUM campus. Determine suitable distance includes four distance measures which are Euclidean Distance, City block Distance, Dice Distance and Sorensen Distance. Formulate threshold function phase focus on formulate adaptive threshold for segmentation of improved algorithm. For evaluation phase, the improved algorithm is compared with standard algorithm by PSNR measure as described earlier.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter discusses the results obtained from the series of experiments conducted. The study results have been presented according to phases described in Chapter Three. The objective of the undertaken experiments is to determine suitable distance measure for clustering pixels and formulate an adaptive threshold function in Fast Scanning algorithm.

4.2 Results of Distance Measure for Standard Fast Scanning

This study determines the suitable distance measure for grouping pixels in Fast Scanning algorithm. In detail, 25 adjusting pair of pixels for each image were evaluated using the four measures; Euclidean Distance (D_{EUC}), City Block Distance (D_{CB}), Dice Distance (D_{SOR}) and Sorensen Distance (D_{DIC}). As shown in figure 4.1 it can noted that images produced by Sorensen distance is more clear and better compared to images produced by other three distance measures.

Figure 4.1. Samples of images of Fast Scanning with Sorensen distance measure

Illustration in Figure 4.2 shows samples of image produced by Fast Scanning algorithm using the four distance measures.

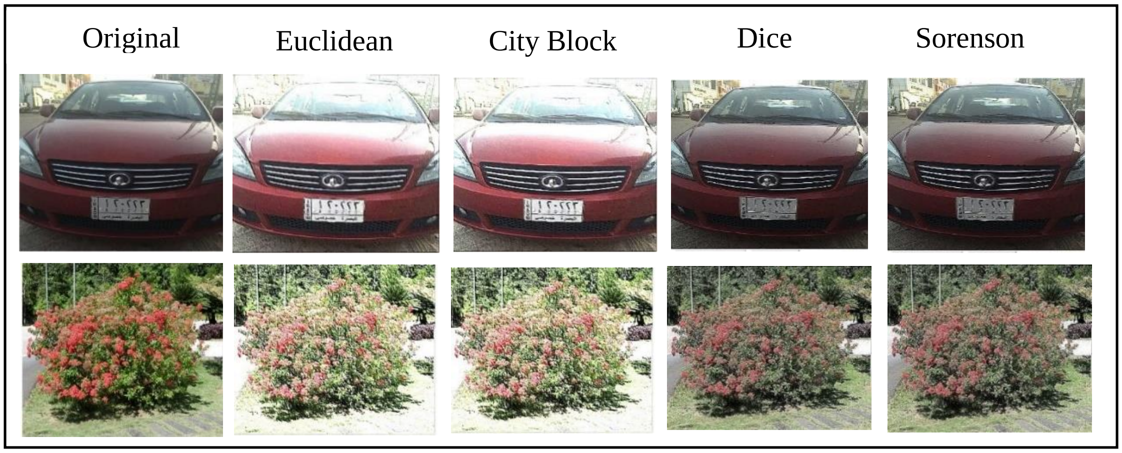

Figure 4.2. Samples of images of Fast Scanning with four distance measures

Table 4.1

Average Value of 25 Pixels Pairs for Dataset1

Image NO.	D EUC	D CB	D DIC	D SOR
1	52.81 %	86.16 %	0.962 %	0.088 %
2	25.90 %	42.68 %	0.991 %	0.062 %
3	2.04 %	3.24 %	0.999 %	0.005 %
4	15.05 %	23.08 %	0.994 %	0.018 %
5	3.18%	14.6 %	0.998 %	0.004 %
6	10.70 %	18.44 %	0.998 %	0.017 %
7	20.07 %	34.64 %	0.989 %	0.050 %
8	2.05 %	3.12 %	0.999 %	0.002 %
9	7.94 %	12.68 %	0.983 %	0.029 %
10	7.46 %	12.24 %	0.998 %	0.015 %
11	5.93 %	9.08 %	0.998 %	0.009 %
12	2.04 %	3.32 %	0.999 %	0.001 %
13	2.74 %	4.84 %	0.999 %	0.003 %
14	24.44 %	41.52 %	0.992 %	0.039 %
15	16.62 %	28.4 %	0.983 %	0.066 %
16	2.76 %	4.8 %	0.998 %	0.003 %
17	21.32 %	34.4 %	0.995 %	0.032 %
18	6.05 %	9.8 %	0.998 %	0.009 %
19	2.84%	4.46 %	0.998 %	0.016 %
20	3.29 %	5.28 %	0.996 %	0.024 %
21	7.01 %	10.8 %	0.999 %	0.011 %
22	10.15 %	16.08 %	0.995 %	0.043 %
23	13.43 %	30.72 %	0.998 %	0.061 %
24	1.83 %	2.92 %	0.998 %	0.001 %
25	24.30 %	40.44 %	0.980 %	0.050 %

Depending on numerical examples which shown in Table 4.1 all four distance measures (D_{EUC}, D_{CB}, D_{SOR}, D_{DIC}) produce different (average) values of distances for the pair of pixels of for images in dataset1. As seen in the table above the Sorensen distance have produced the smallest distance average of 25 pixels pairs for all dataset 1 images. The values of 25 pixels'pairs for each image is presented in Appendix A.

Table 4.2

Average Value of 25 Pixels Pairs for Dataset2

Image NO.	D_{EUC}	D_{CB}	D_{DIC}	D_{SOR}
1	53.07 %	94.84 %	0.836 %	0.257 %
2	21.56 %	32.96 %	0.968 %	0.050 %
3	61.34 %	89.71 %	0.882 %	0.187 %
4	8.56 %	13.32 %	0.997 %	0.009 %
5	43.46 %	69.28 %	0.931 %	0.130 %
6	49.32 %	63.28 %	0.998%	0.114 %
7	42.70 %	69.61 %	0.997 %	0.060 %
8	41.23 %	71.48 %	0.856 %	0.263 %
9	36.37 %	63.52 %	0.996 %	0.108 %
10	33.62 %	57.48 %	0.951 %	0.137 %
11	48.01 %	77.84 %	0.969 %	0.094 %
12	54.40 %	96.16 %	0.871 %	0.255 %
13	90.26 %	91.45 %	0.742 %	0.319 %
14	71.47 %	95.39 %	0.849 %	0.227 %
15	33.02 %	54.28 %	0.902 %	0.175 %

The same pattern is also found for dataset 2 and it depicted in Table 4.2 the Sorensen distance has again produced the smallest distance average of 25 pixels pairs for all images. The values of 25 pixels’pairs for each image is presented in Appendix B.

4.3 Results of Adaptive Threshold Function for Fast Scanning

This section present the results of produced by Fast Scanning algorithm that uses fixed threshold and adaptive threshold function. Segmented images samples of dataset1 are presented on Figure 4.3 by the left column for original image and the second column is located to fast scanning with Euclidean and fixed threshold (SFSA) while third one for Fast Scanning with Euclidean and adaptive threshold.

Figure 4.3. Samples results of adaptive threshold function for dataset 1

Table 4.3

Comparison of PSNR for Adaptive Threshold Function on Dataset1

Image No	Fast Scanning with Euclidean and fixed Threshold	Fast Scanning with Euclidean and Adaptive Threshold
1	19.9925 dB	22.3267 dB
2	18.7005 dB	20.9571 dB
3	18.5984 dB	22.6875 dB
4	18.2427 dB	24.4341 dB
5	19.1123 dB	20.7392 dB
6	17.0871 dB	22.2288 dB
7	17.7572 dB	23.4403 dB
8	17.0322 dB	21.5217 dB
9	17.6921 dB	21.3919 dB
10	19.5745 dB	23.4721 dB
11	18.5048 dB	24.0230 dB
12	19.0127 dB	23.9077 dB
13	20.9669 dB	24.9842 dB
14	19.6572 dB	23.1338 dB
15	17.2267 dB	20.5870 dB
16	19.3332 dB	23.6166 dB
17	16.1129 dB	20.4396 dB
18	18.2495 dB	21.5516 dB
19	20.0297 dB	26.5983 dB
20	21.2196 dB	26.9025 dB
21	17.5420 dB	21.2291 dB
22	16.5062 dB	22.9223 dB
23	16.2346 dB	20.9021 dB
24	17.8567 dB	22.2408 dB
25	17.6323 dB	21.6995 dB

Table 4.3 above shows the PSNR value obtained by the Fast Scanning with Euclidean and fixed threshold and Fast Scanning with Euclidean and adaptive threshold for dataset1. The higher value of PSNR means that the quality of the image is better. For all

the images, the performance of the adaptive threshold is better than the fixed threshold, since their value of PSNR measure are higher. With the same configuration of previous table, segmented images samples by of dataset 2 are showed below on Figure 4.4.

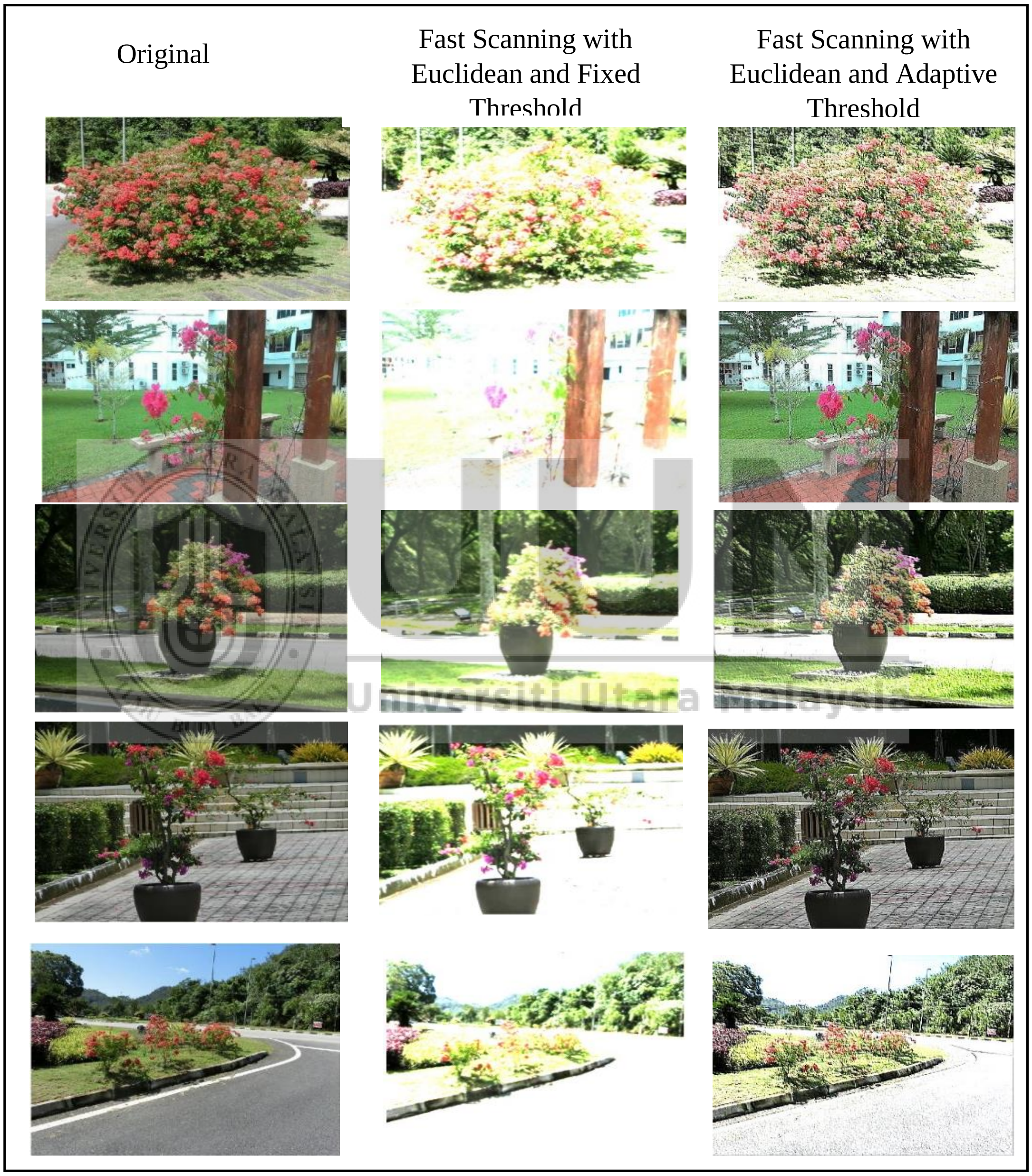

Figure 4.4. Samples results of adaptive threshold function for dataset 2

Table 4.4

Comparison of PSNR for Adaptive Threshold Function on Dataset2

Image No	Fast Scanning with Euclidean and Fixed Threshold	Fast Scanning with Euclidean and Adaptive Threshold
1	18.4389 dB	19.2851 dB
2	16.6063 dB	21.3856 dB
3	17.7734 dB	23.0423 dB
4	18.9735 dB	22.7416 dB
5	17.8571 dB	20.1945 dB
6	17.7367 dB	20.5176 dB
7	16.5971 dB	20.7758 dB
8	22.0024 dB	25.6732 dB
9	16.6385 dB	20.2329 dB
10	17.4656 dB	20.3763 dB
11	17.5168 dB	19.3211 dB
12	19.1655 dB	23.8784 dB
13	19.9089 dB	20.5087 dB
14	18.5585 dB	20.8741 dB
15	20.0692 dB	20.7905 dB

Table 4.4 shows the PSNR of Fast Scanning with Euclidean and fixed threshold along with Fast Scanning with Euclidean and adaptive threshold of dataset 2. This shows PSNR of adaptive threshold is higher than fixed threshold. So using, PSNR conclude that adaptive threshold is better than fixed threshold.

Depending on previous comparison that fast scanning with Euclidean and fixed threshold has segmented both datasets images in low PSNR. In other hand, the fast scanning with Euclidean and adaptive threshold segments all datasets images in low PSNR values.

4.4 Results of Improved Fast Scanning for Image Segmentation

This section presents samples of results produced by IFSA that uses Sorensen distance and adaptive threshold function. Figure 4.5 shows produced images by IFSA for dataset1.

Figure 4.5. Samples results of IFSA for dataset 1

Table 4.5

Comparison of PSNR for IFSA on Dataset1

Image No	Fast Scanning with Sorensen and fixed Threshold	Fast Scanning with Sorensen and Adaptive Threshold
1	15.0431 dB	40.8659 dB
2	15.5191 dB	42.0770 dB
3	12.8340 dB	43.5071 dB
4	14.7908 dB	44.4744 dB
5	16.5615 dB	46.2370 dB
6	13.3296 dB	46.6260 dB
7	15.8471 dB	38.9482 dB
8	14.1482 dB	48.2959 dB
9	14.0465 dB	47.7655 dB
10	15.9569 dB	33.6031 dB
11	12.8321 dB	45.8519 dB
12	16.4339 dB	42.7739 dB
13	16.7595 dB	43.1586 dB
14	17.0459 dB	51.4769 dB
15	13.5316 dB	47.3067 dB
16	16.6462 dB	41.9966 dB
17	13.3166 dB	50.2132 dB
18	14.1030 dB	43.1609 dB
19	14.4107 dB	43.9811 dB
20	15.8494 dB	42.1207 dB
21	14.7311 dB	43.4534 dB
22	13.8785 dB	43.7182 dB
23	13.0974 dB	44.0606 dB
24	13.2485 dB	40.8380 dB
25	15.2304 dB	39.3502 dB

Based on Table 4.5 above for dataset1 , comparative analysis have showed that the IFSA have produced higher PSNR value for segmented images when compared with fast scanning with Sorensen and fixed threshold.

In Figure 4.6 below shows samples of segmentation results of the IFSA for dataset 2 and Fast Scanning with Sorensen and fixed threshold.

Figure 4.6. Samples results of IFSA for dataset 2

Table 4.6

Comparison of PSNR for IFSA on Dataset 2

Image No	Fast Scanning with Sorensen and fixed Threshold	Fast Scanning with Sorensen and Adaptive Threshold
1	12.2068 dB	31.1203 dB
2	12.5568 dB	40.5773 dB
3	12.7836 dB	38.3768 dB
4	15.1863 dB	40.3908 dB
5	13.1520 dB	40.8489 dB
6	13.9470 dB	34.0051 dB
7	12.5404 dB	38.1250 dB
8	15.9089 dB	40.9082 dB
9	12.0332 dB	31.9010 dB
10	12.5521 dB	30.0403 dB
11	12.9152 dB	31.1044 dB
12	13.2520 dB	40.5523 dB
13	14.3688 dB	40.3087 dB
14	12.5913 dB	32.0211 dB
15	14.1110 dB	29.1993 dB

Table 4.6 shows comparative analysis for dataset 2, as clearly seen IFSA have produced higher PSNR value for segmented images when compared with fast scanning with Sorensen and fixed threshold.

4.5 Summary

This chapter discussed the results obtained upon completing a series of experiment on distance measures and adaptive threshold function for FSA and IFSA. The evaluation is based on PSNR value. Based on the obtained results, it can be concluded that IFSA is a better image segmentation algorithm compared to the standard Fast Scanning for both datasets. Numerical results depicted that the all PSNR values of the improved algorithm were higher and is between (30, 0000 – 50, 0000 dB) where larger values indicates better segmentation. . Hence, the IFSA is better in terms of shape matching.

CHAPTER FIVE

CONCLUSION

5.1 Introduction

This chapter provides the highlight on the proposed algorithm. The first section in this chapter recaps the achievement of the study while the following section includes the future work.

5.2 Achievement

The goal of this study is to improve the standard Fast Scanning algorithm for image segmentation. This is achieved by determining a suitable distance measure and formulating an adaptive threshold function in clustering the pixels of image under analysis.

Experimental results on the first objective of this study indicate that the Sorensen distance measure is the best to be used as compared to the other three measures (Euclidean, City Block and Dice) as it produced a smaller and closeness values between pixels pairs (as shown in Table 4.1 and Table 4.2).

The second objective of the study is achieved by proposing an adaptive function based on the average grey value and its variance. The proposed function produced betters image segmentations and this is presented in Tables 4.3 and 4.4.

Both of the distance measure and adaptive threshold function were utilized in Fast Scanning and later employed as improved Fast Scanning algorithm in Figure 3.7. Experimental results on the third objective of this study showed that the proposed IFSA produced better image segmentations and this is presented in Tables 4.5 and 4.6.

5.3 Recommendations for Future Work

In this study, several recommendations for future work is presented. Even though this research has shown that the proposed algorithm is able to produce better image segmentations, further research needs to be done to improve or support the proposed algorithm. Among the suggestions are the following:

1. Implementation of the improved algorithm on other types of images, such as food, medical and sports.
2. The segmented images by IFSA should be employed in pattern recognition in order to evaluate its capability in identifying region of interest.
3. The utilization of swarm intelligence in formulating the adaptive threshold function may provide reliable shape matching in pattern recognition especially in noisy images. .

In general, this study is has achieved the proposed objectives of improving the standard Fast Scanning algorithm by determining a suitable distance measure and formulating an adaptive threshold function. The improved Fast Scanning algorithm is proved to perform better than the standard algorithm.

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