HYBRID REGION MERGING FOR IMAGE SEGMENTATION USING OPTIMAL GLOBAL FEATURE WITH GLOBAL MERGING CRITERION APPROACH

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2020

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by

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Thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

February 2020

ACKNOWLEDGEMENT

Praises and thanks to the God, the Almighty for showering me with blessings to pursue this dream successfully. I would have not pen down this thesis without the continuous support from a group of special hearts.

First, and foremost, my deepest gratitude and appreciation goes to my research supervisors, Professor. Dr. Rosni Abdullah and Professor. Dr. Mandava Rajeswari for guiding me towards the path of success. Their passionate guidance has taught me on how true researchers should be. I value their insights and thoughtful advices throughout this journey.

There are not enough words to describe the encouragement from my lovely parents, Vadiveloo and Kaliammah and my siblings, Nishanthine and Selvakumaran. Without their love and blessings from my parents, this Ph.D would not be possible.

My appreciation also goes to the School of Computer Sciences, USM, and Ministry of Higher Education for providing the grant of "Image Segmentation Using Hybrid Fuzzy C-Means Clustering and Watershed Region-Based Segmentation Algorithms on General–Purpose Computing on Graphics Processing Units" with the grant account number, 203/PKOMP/6711425 and MyBrain15 scholarship, respectively.

Finally, my special thanks to my fellow lab mates, friends, Ahmad Adel, Lim Khai Yin, Vaithegy Doraisamy, Kamal Hassan, and not to mention the administrative assistant from the School of Computer Sciences, Sheela Muniandy for accompanying this research journey with good support.

TABLE OF CONTENTS

CHAPTER 4 – HYBRID REGION MERGING WITH GLOBAL MERGING CRITERION (HRM-GMC) SEGMENTATION APPROACH

CHAPTER 5 – HYBRID REGION MERGING USING OPTIMAL GLOBAL FEATURE WITH GLOBAL MERGING CRITERION (HRM-OGF-GMC) SEGMENTATION APPROACH

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

2D	2-dimensional
CSF	Cerebrospinal fluid
DRCRF	Deep randomly-connected conditional random field
DSC	Dice similarity coefficient
ED	Euclidean distance
F	F-measure
FCM	Fuzzy c-means
FP	False positive
G-HRM	Graph-based hybrid region merging
GM	Gray matter
HCC	Hierarchical correlation clustering
HRM	Hybrid-oriented region merging
HRM-GMC	Hybrid region merging with global merging criterion
HRM-OGF-GMC	Hybrid region merging using optimal global feature with global merging criterion
HSWO	Hierarchical stepwise optimization
ICM	Iterative contraction and merging
LNNG	Linear nearest neighboring graph
LRM	Local region merging
MIL	Multiple instance learning
MR	Magnetic resonance
MRI	Magnetic resonance imaging
NNG	Nearest neighboring graph

ODS	Optimal dataset scale
OIS	Optimal image scale
RAG	Region adjacency graph
ROI	Region of interest
RSME	Root square mean error
SA	Simulated annealing
SST	Shortest spanning tree
WI1OBJ	Weizmann one visual object dataset
WI2OBJ	Weizmann two visual objects dataset
WM	White matter

KAEDAH PENGGABUNGAN RANTAU HIBRID UNTUK SEGMENTASI IMEJ MENGGUNAKAN CIRI GLOBAL OPTIMA DENGAN KRITERIA PENGGABUNGAN GLOBAL

ABSTRAK

Keadah penggabungan rantau digunakan untuk mengurangkan lebihan rantau segmen yang dihasilkan oleh algoritma-algoritma segmentasi imej yang berasaskan rantau. Ia dijalankan dengan menggabungkan beberapa lebihan rantau segmen secara progresif bagi menghasilkan segmen akhir sebagai kawasan yang mempunyai sempadan tertutup. Pada kebiasaannya, penggabungan rantau dijalankan di antara dua rantau yang bersebelahan yang sepenuhnya berdasarkan kriteria penggabungan setempat. Penggabungan ini boleh menyebabkan kaedah penggabungan rantau yang sedia ada gagal untuk mengesan objek visual besar yang bukan homogen, yang mempunyai persamaan semantik global di dalam imej tetapi mempunyai pelbagai set lebihan rantau segmen. Selain itu, pemilihan maklumat ciri global yang tidak tepat oleh algoritma pengkelompokan berbahagi memberi kesan kepada penghasilan kriteria yang akhirnya menyebabkan kebocoran ke dalam rantau objek visual yang bersebelahan. Oleh itu, tesis ini bertujuan untuk menyelesaikan kedua-dua isu ini, dengan mencadangkan kaedah penggabungan rantau yang menggabungkan kesemua lebihan rantau segmen untuk menghasilkan segmen objek visual yang semantik. Pertama, kaedah penggabungan yang menggabungkan kriteria penggabungan global dalam proses penggabungan berulang untuk mengurangkan lebihan segmen. Kriteria penggabungan global ini terhasil bukan sahaja daripada dua rantau bersebelahan yang dipilih untuk penggabungan tetapi juga daripada setiap rantau yang telah berjaya digabungkan. Kedua, kaedah yang telah dicadangkan ini ditingkatkan lagi

dengan mengoptimumkan maklumat ciri global oleh pengkelompokan berbahagi secara pengaburan (FCM) dengan menggunakan algoritma simulasi penyepuhlindapan (SA) sebelum penggabungan dilakukan untuk mengelakkan kebocoran ke dalam sempadan rantau objek visual. Kaedah penggabungan rantau ini telah dinilai dengan menggunakan simulasi imej otak untuk melakukan segmentasi jirim putih (WM) dan jirim kelabu (GM) bagi sempadan rantau yang kabur. Kaedah yang dicadangkan ini menunjukkan peningkatan sebanyak 1.44% dalam nilai purata koefisien persamaan dice (DSC) dalam segmentasi sempadan rantau jirim putih (WM) dan jirim kelabu (GM) berbanding kaedah penggabungkan rantau dengan kriteria penggabungan global yang telah dicadangkan. Selain itu, kaedah penggabungan rantau yang dicadangkan ini telah dinilai pada set data semula jadi awam Weizmann untuk melakukan segmentasi bagi objek visual tunggal yang mempunyai sempadan kabur dan keamatan varians. Kaedah ini telah mengatasi tiga kaedah yang lain dengan mencatatkan purata ketepatan F-ukuran sebanyak 0.79 dalam segmentasi 100 imej objek visual tunggal ke segmen semantik. Kesimpulannya, peningkatan yang menggalakkan yang ditunjukkan oleh kaedah yang dicadangkan ini memberikan satu pemahaman terhadap penggunaan keadah ini untuk melakukan segmentasi rantau objek visual yang mempunyai sempadan yang kabur dan keamatan varians ke segmen yang semantik.

HYBRID REGION MERGING FOR IMAGE SEGMENTATION USING OPTIMAL GLOBAL FEATURE WITH GLOBAL MERGING CRITERION APPROACH

ABSTRACT

Region merging approach is used to reduce over segmented regions produced by region-based image segmentation algorithms. It is performed by merging the over segmented regions progressively to produce the final segmentation as spatially contiguous regions with closed boundaries. Predominantly, region merging is performed between two neighboring regions solely on a local merging criterion. This may fail most existing region merging approaches to detect large non-homogeneous visual objects that have global semantic similarity but consist of diverse set of over segmented regions. Besides that, improper selection of global feature information by partitional clustering algorithm in turn affects the merging criterion derivation in region merging eventually causing leakages into adjacent visual object regions. Consequently, this thesis aims to solve these two issues by proposing a region merging approach to merge the over segmented regions producing semantic segments of visual objects regions. Firstly, the proposed region merging approach incorporates a global merging criterion in the iterative merging process in order to reduce over segmentation. The global merging criterion is derived not only from two neighboring regions chosen for merging but also from each successively merged region. Secondly, the proposed approach is further enhanced by performing optimization on the global feature information by fuzzy c-means (FCM) partitional clustering using simulated annealing (SA) algorithm before the merging is performed to prevent leakages into visual objects region boundaries. The proposed region merging approach is evaluated on the simulated brain images dataset to segment

white matter (WM) and gray matter (GM) ambiguous boundary regions. The approach showed an improvement by 1.44% in average dice similarity coefficient (DSC) in segmenting WM and GM boundary regions against the proposed region merging approach with global merging criterion. In addition to that, the proposed approach has also been evaluated on the Weizmann public benchmarked natural images dataset to segment one visual object with ambiguous boundary and intensities variances. This approach has outperformed three established state-of-the-art approaches by producing an average of 0.79 of F-measure accuracy in delineating 100 images of one visual object into semantic segments. In conclusion, promising improvement produced by the proposed region merging approach provides an insight on its applicability to perform delineation on the visual objects regions with ambiguous boundary and intensities variances into semantic segments.

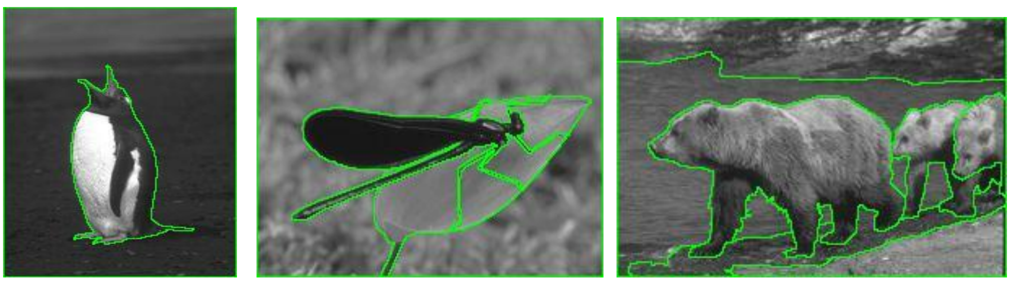
CHAPTER 1

INTRODUCTION

1.1 Background

The definition of segmentation in image processing can be perceived as the process of partitioning an image into non-intersecting regions. The goal of segmentation is to identify or delineate the image into visual objects. In this context, visual objects refer to objects that are perceived as distinguishable image components. The objects are inherently associated to regions, R_i, and the idea of segmentation is explained as, $(R_1 \cup R_2 \cup \ldots, R_n) = \Omega$ where $R_i \cap R_j = \emptyset$ for $i \neq j$ and Ω is all pixels in an image, $R_i \subset \Omega$.

Human perceptual system is able to naturally extract visual objects from an image. In Figure 1.1 for instance, human perceptual system perceives the highlighted regions as visual objects or regions of interest (ROIs).



(A) (B) (C)

Figure 1.1 Visual objects perceived by human perceptual system.

Wertheimer (1938) proposed gestalt theory in psychology which explains the human perceptual system extracting visual objects by a set of grouping laws of proximity, similarity, and continuity. In computer vision, the set of grouping law on similarity has implied to some well-defined formulations in segmentation techniques. Successful segmentation may be achieved if the objects have similar image properties. In most real-world applications of image segmentation, researchers' biggest interest is to extract the visual object/s from the image. However, using methods that plainly offer local similarity constraint on image feature properties, for instance intensity are less meaningful in visual object/s segmentation, especially when there are adjacent objects regions sharing similar intensities but belonging to semantically different classes. These methods may cause some regions of the visual objects being segmented with adjacent objects that have similar intensity. Once this happens, the visual objects are failed from being segmented accurately.

Image segmentation algorithms can be classified into three categories. The first category, Category 1 comprises of algorithms that label individual pixels. Examples of this category algorithm are thresholding- and clustering-based algorithms. While Category 2, is the algorithms that label syntactic components. These include edge or boundary detection. The final category, Category 3, contains algorithms that label the regions. This covers all region-based segmentation algorithms. The algorithms in Category 1 are of generally non-contextual techniques, in which pixels are simply grouped together by the intensity value of pixels without considering spatial information of the image into account. This may result in a large number of small segments, known as over segmentation. These small segments may not have any visual semantic meaning and in order to overcome this over segmentation problem to some extent, noise smoothing or morphological post-processing methods are imposed to remove the noisy fragments in the segmented image. In addition to that, the segmentation algorithm itself can be modified to include a spatial component. The segmentation algorithms in Category 1, assign a label to each pixel at the end of segmentation, in which they do not guarantee a closed connected segments. In practical segmentation applications, however, region labeling is necessary. For example, in natural image analysis, regions need to be delineated as the main interest lies in producing either coarser or finer details of segmented visual object regions subjective to users' preferences (Syu et al., 2017). Therefore, region labeling is more desirable than pixel labeling since it ensures the regions are produced with closed connected segments.

1.2 Over Segmentation in Region-Based Segmentation

The main aim in region-based segmentation algorithms is to produce non overlapping homogeneous labeled regions with closed boundaries. These regions satisfy a given similarity of image features properties. The regions maybe associated with full or partial visual objects in an image (Kaur & Goyal, 2013; Lalaoui et al., 2013; Gould et al., 2009). Watershed, region growing, and region splitting and merging are the classical segmentation algorithms that belong into this category (Hanburry, 2008; Pal & Pal, 1993).

These aforementioned algorithms have gained great attention and are used extensively in image segmentation. However, the major drawback of these algorithms is that they suffer from producing over segmented regions (Yang et al., 2017; Ji et al., 2016). Many small partitions of regions are produced by these algorithms in the final segmentation result as shown in Figure 1.2. This is due to the existence of excessive local minima or seed points. Since a partition of region is created for each local minima or seed point, presence of excessive points produce many small regions (Roerdink & Meijster, 2000). In addition to that, these algorithms are also sensitive to noise. This too contributes to over segmentation (Arbeláez et al., 2011; Roerdink & Meijster, 2000).

(A) (B)

Figure 1.2 The over segmented regions produced by the region-based segmentation algorithm. (A) The target image. (B) The over segmented regions produced by immersion watershed algorithm. The white lines represent the watershed label that acts as the boundary pixels separating the regions produced (Peng et al., 2011).

Many approaches have been proposed over the years in order to reduce the over segmentation issue in the aforementioned algorithms. However, *post-processing* has been the most habitual approach used to reduce over segmentation (Freixenet et al., 2002).

Generally in the *post-processing* approach, the over segmented regions produced are merged progressively to produce the final segmentation as spatially contiguous regions with closed boundaries. This approach is known as region merging. Region merging on the over segmented regions is performed iteratively between two similar neighboring regions using a merging criterion and guided by a stopping rule (Alshehhi & Marpu, 2017; Zhang et al., 2013). Neighboring regions refer to the spatially adjacent regions that share a common boundary while ***merging criterion*** *indicates the similarity between two neighboring regions and the decision in merging them* as illustrated in Figure 1.3. This merging criterion between the local neighboring regions is derived from feature value that is extracted locally and or globally. It is important to note that, the feature selection is crucial in producing accurate merged regions. In general, region merging approach produces a good segmentation of merged regions by reducing the over segmentation problem. However, the *merging criterion* plays an important role in obtaining the desired results (Shui & Zhang, 2014)

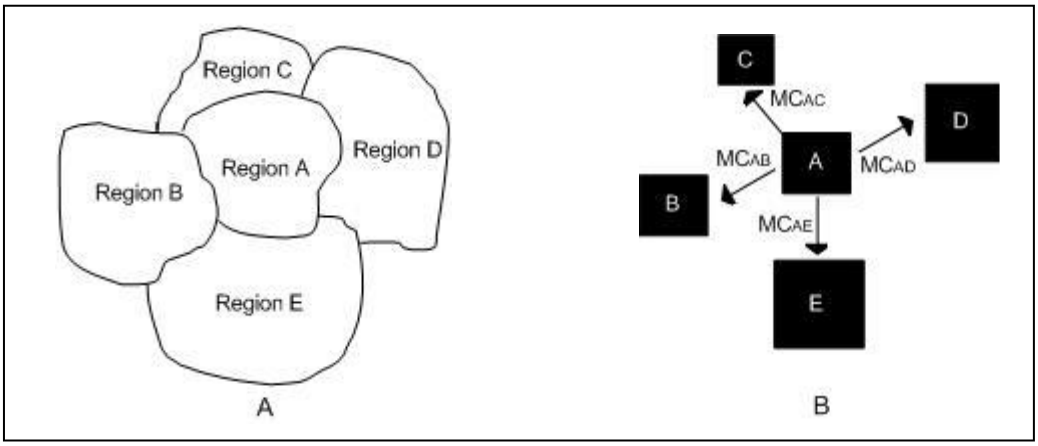


Figure 1.3 Representation of the over segmented regions in the region merging approach. (A) The over segmented regions produced by the region-based algorithm. (B) Illustration of (A) with neighboring regions and merging criterion (MC) between them.

1.3 Problem Statement

Generally, region merging is classified into three categories based on the merging strategy. They are global-, local-, and hybrid-oriented methods. Global-oriented method performs merging iteratively by globally searching for the most similar pair of neighboring regions using merging criterion and is guided by a stopping rule (Zhang et al., 2014). While local-oriented method chooses the similar merging pair of neighboring region at a local scale (Tarabalka et al., 2012) and the hybrid-oriented method combines both the global- and local-oriented merging strategies (Zhang et al., 2014).

In each of the aforementioned region merging strategy, the merging criterion is always derived from two neighboring regions to verify their similarity in order to merge them. This process continues iteratively until the merging stops when the merging criterion does not satisfy the stopping rule defined (Rantalankila et al., 2014; Zhang et al., 2014; Arbeláez et al., 2011). In this case, the merging criterion derivation becomes *local*. This eventually leads most existing region merging approaches fail in producing a global solution of merging result. They may fail to detect large non-homogeneous visual objects that have global semantic similarity but consist of diverse set of over segmented regions. Thus, this may cause some regions of the visual objects getting merged with the adjacent object that have almost similar feature properties but belong to semantically different classes. Or in some cases the regions may not get merged into semantic visual objects segments due to dissimilar feature properties. Once this happens, the visual objects fail from being segmented accurately. As a result, the final segmented regions produced, are either over or under merged or in some cases resulting to both (Rantalankila et al., 2014). Therefore, in order to solve this main challenge, merging between two neighboring regions that exhibit some global similarity property is needed to be incorporated into the existing region merging approach to improve the segmentation results.

To propose a local region merging approach that effectively incorporates *optimal global merging criterion* to improve the segmentation of visual objects regions, the following questions need to be answered:

i. **How to incorporate global merging criterion into the local region merging approach in order to reduce over segmentation?**

   In the literature, region merging approaches are classified into statistics-, graph- and marker-based region merging (Yang et al., 2017; Ji et al., 2016;

Peng et al., 2011). Currently, enormous research interest has focused on reducing over segmentation using any of the aforementioned approaches. However, in order to incorporate global similarity property into region merging approach, the initial effort is taken by infusing global feature information to derive the merging criterion between two neighboring regions to perform merging (Hasanzadeh & Kasaei, 2010; Makrogiannis et al., 2005). However, in these approaches the merging process is found to be *local* since the merging criterion is always determined from two neighboring regions to perform the iterative merging. Several studies have proposed a global pre-processing approach before performing graph-based region merging (Syu et al., 2017; Arbeláez et al., 2011). However, in these studies the merging process is still local since the merging criterion is always derived locally. In several other approaches, in order to incorporate global similarity property in the graph-based region merging approach, the effort is taken by deriving the merging criterion, globally (Zhang et al., 2014; Zhang et al., 2013; Peng et al., 2011). The merging criterion is derived from non-adjacent regions pairs iteratively to exhibit the global similarity property. However, in these approaches the global merging criterion is not achieved during each iterative merging. In some iteration, if the chosen regions for merging are neighbors, then the merging criterion becomes local and does not exhibit the global similarity. Hence, local region merging approach that incorporates global merging criterion during the iterative merging process may be beneficial to reduce over segmentation.

ii. How optimized global feature information on the over segmented regions is of assistance for merging criterion derivation in local region merging approach to prevent leakages into adjacent object regions?

Feature selection in deriving the merging criterion is critical in producing accurate final segmentation results. In the existing works in region merging, *partitional clustering algorithms* are commonly used to obtain the global feature information in deriving the merging criterion (Derivaux et al., 2010; Zhang et al., 2007). This is because clustering algorithms are efficient in finding salient global feature information in images (Makrogiannis et al., 2005). Generally, in the clustering algorithms, clusters represent the visual objects for a given dataset and cluster centers are the global feature information of each defined clusters. However, the main issue in most existing partitional clustering algorithms is that the generated cluster centers values tend to get trapped in local optima solutions. This is due to improper selection of initial cluster centers values that may result in non optimal result during the clustering process (Popat & Emmanuel, 2014). This in turn, affects the derivation of the merging criterion if these cluster centers values are used as the global feature information and eventually may not produce accurately merged object regions. The problem is more pronounced when performing segmentation on visual objects with ambiguous boundary. This may cause *leakage* at the visual objects regions boundaries if the adjacent object/s have almost similar feature properties. Figure 1.4 illustrates example of the ambiguous boundary phenomenon in a natural image that consists of a building as the foreground visual object region while the sky as the background object region. The colored shape (pointed by the arrow) is the potential ambiguous boundary regions where pixels with similar intensity in the foreground and background regions are found. Hence, obtaining optimal cluster centers values on the over segmented regions is pertinent to be studied in order to enhance the region merging approach to produce semantic segments of objects regions.

(A) (B)

Figure 1.4 Example of ambiguous boundary in visual objects of natural image. (A) The target image (Alpert et al., 2012). (B) The illustration of ambiguous boundary phenomenon. The colored shape (pointed by the arrow) represents the regions with this phenomenon.

1.4 Research Objectives

The objectives of this research are as follows.

1. To propose a local region merging approach that incorporates global merging criterion in the iterative merging process to reduce over segmentation.
2. To propose a local region merging approach that optimizes the global feature information from partitional clustering on the over segmented regions to prevent leakages into adjacent objects regions.

1.5 Research Scope

The scope of this thesis is limited to the following constraints:

- The datasets being used in this work is limited to grayscale images focusing on simulated magnetic resonance (MR) brain images as well as natural images that consist of single and double visual objects.
- The work of this thesis focuses on semantic delineation. Hence, the natural images dataset being used consists of only single and double visual objects. Moreover, the semantic segmentation is being performed using grey level feature information.
- The rules derivation in the visual object/s segmentation identification is based on the common understanding (or experts' opinion) on the test datasets. Experts' opinion is required in the segmentation identification of soft tissues regions in simulated MR brain images.

1.6 Research Contributions

The main contributions of this thesis are detailed as follows:

1. A local region merging approach that incorporates global merging criterion in the iterative merging process to reduce over segmentation.
2. A local region merging approach is established by optimizing the global feature information from partitional clustering on the over segmented regions to prevent leakages into adjacent objects regions.

1.7 Operational Definition

The operational definition of important concepts or terms are being used in the context of this thesis are detailed in Table 1.1 as follows:

Table 1.1 Operational definition of important concepts or terms

Concept/term	Operational definition
Global/local feature information	In region merging approach, the global feature implies the global image feature information while local feature is the feature information extracted locally from the over segmented regions itself.
Region	In region-based segmentation algorithms, regions consist of image pixels that are grouped together based on the similarity of the chosen feature values of the pixels and also by considering spatial information of the pixels into account.
Semantic segment/s	In natural image segmentation, semantic segment/s refer to the delineation of the visual objects in the image into non overlapping regions as perceived by human perceptual system or gold standard provided.
Local merging criterion	In region merging approach, local merging criterion refers to the statistical similarity that is always derived from the feature values of two local neighboring regions. This is to verify their similarity in order to merge the regions.
Global merging criterion	In region merging approach, global merging criterion refers to the statistical similarity that is derived from the feature values of non-adjacent regions pairs in the over segmented regions plane. This is to verify the similarity of two local neighboring regions chosen for merging in the over segmented regions plane.
Merging scheme	In region merging approach, merging scheme refers to the merging criterion, merging order, and region model.
Global similarity property	In region merging approach, global similarity property indicates the similarity of the global statistical feature values of the regions in the over segmented regions plane.
Optimal global feature	In region merging approach, optimal global feature refers to the compactness of a global feature value with respect to the associated regions. Compactness defines that a region should be close to its associated global feature value but being well separated from other defined global feature values.

1.8 Thesis Outline

This thesis is organized into six chapters as follows:

Chapter 2 provides a brief description on region-based segmentation and critical review of state-of-the-art over segmentation reduction approaches focusing on region merging approach. In addition to that, it also covers discussion on the state-of-the-art approaches used for evaluation purpose.

Chapter 3 delivers an overview of the methodology adapted in this thesis for region merging approach. This chapter also covers detailed information on the datasets and evaluation measures used in this research.

Chapter 4 presents the first phase of this research, which is the region merging with global merging criterion segmentation approach. This chapter covers detailed explanation on the proposed approach and is validated with supporting experiments and comparisons with the sate-of-the-art approaches.

Chapter 5 describes the second phase of this research on how to enhance the region merging approach from the first phase in detail. The segmentation results are evaluated and compared with the state-of-the-art approaches.

Chapter 6 summarizes this research and draws conclusion from the results produced. Limitations as well as the recommendations for future research are also presented.

CHAPTER 2

LITERATURE REVIEW

This chapter briefly discusses region-based segmentation followed by critical discussion on the current state-of-art approaches in reducing over segmented regions produced by region based segmentation algorithms. Specifically, the reviews focus on the region merging approaches which are known as the post-processing approach in reducing the over segmented regions. This chapter also does highlight the research gap and the direction of the work in this thesis. Finally, it is concluded with a discussion on the state-of-the-approaches that are used for comparison purpose.

2.1 Region-Based Segmentation

Region-based segmentation algorithms produce non overlapping homogeneous regions with closed boundaries that satisfy a given similarity of image feature properties such as grey level, shape, texture, size, and etc (Kaur & Goyal, 2013; Hanburry, 2008). The regions are built either by grouping neighboring pixel to form regions or by starting with a single region and successively subdividing it into partitions of regions. The classical region-based segmentation algorithms that belong into this category are watershed (Meyer, 1994; Vincent & Soille, 1991), region growing (Zucker, 1976), and region splitting and merging (Ojala et al., 1999). In addition to these algorithms, clustering algorithms such as mean shift (Comaniciu & Meer, 2002) and super pixel (Ren & Malik, 2003) too produce segmented regions as the final segmentation results.

In comparison to the aforementioned algorithms, watershed has gained great attention and has been used extensively in region segmentation to produce over segmented regions. Although this algorithm generates severe over segmented regions however, the major advantage of watershed is that it is simple and generates quasi-homogeneous regions with closed boundaries (Romero-Zaliz et al., 2018; Roerdink & Meijster, 2000). In comparison to watershed, mean shift and super pixel clustering algorithms produce a more sophisticated over segmented regions. However, these algorithms require predefined parameters before performing the segmentation (Carreira-Perpiñán, 2015; Achanta et al., 2012). The choice of the parameters values is crucial and poor selection may produce over segmented regions with incorrect boundaries which affects the final segmentation results. Similarly with region-based multi-thresholding algorithm; poor selection of the threshold values may too produce over segmented regions with incorrect boundaries (Ji et al., 2016). While, region growing algorithm is computationally expensive and sensitive to initial seeds selection in comparison to watershed (De et al., 2016). Many approaches have been proposed (Hanburry, 2008; Freixenet et al., 2002) over the years in order to reduce the over segmentation in the aforementioned algorithms. Detailed discussion on this is given in the following section.

2.2 Over Segmentation Reduction Approaches

The approaches on reducing the over segmentation projects three main genres, based on how the over segmented regions have been reduced and segmented into accurate visual objects regions in an image. These are *in-algorithm modification*, *pre-processing*, and *post-processing* as referred in Figure 2.1 (Hanburry, 2008; Freixenet et al., 2002).

In the *in-algorithm modification* approach, to reduce the over segmentation in region-based segmentation algorithms, graph-based searching algorithms have been adapted to identify only the distinct local minima points. Graph-based algorithms such as directed graphs, shortest spanning tree, shortest path, minimum spanning

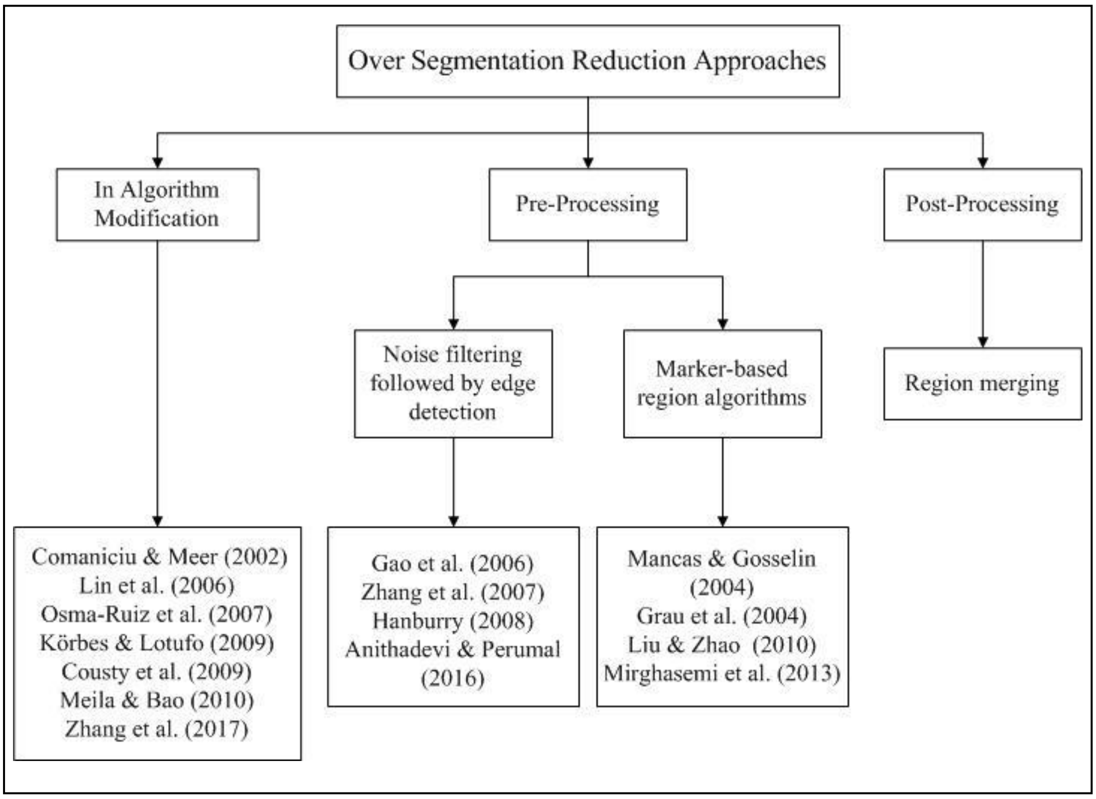


Figure 2.1 Taxonomy of over segmentation reduction approaches.

forest, breadth first search, and depth first search have been adapted into region-based algorithms in order to reduce the over segmentation (Körbes & Lotufo, 2009; Cousty et al., 2009; Osma-Ruiz et al., 2007; Lin et al., 2006). While in mean shift and super pixel algorithms, the in-algorithm modification is performed by optimizing their objective function. This is done by proposing alternative kernel density estimation (KDE) or distance space in order to obtain better segmented regions (Zhang et al., 2017; Meila & Bao, 2010; Comaniciu & Meer, 2002). The in-algorithm modification approach has to some extent reduced the over segmentation problem, but however it is unable to fully eliminate it.

The *pre-processing* approach is divided into two categories. They are noise filtering followed by edge detection and marker-based region algorithms. In the former approach, the aim of noise filtering is to reduce the number of insignificant local minima as most local minima are often caused by noise (Hanburry, 2008).

Filters such as median with stationary wavelet transform (Anithadevi & Perumal, 2016), morphological opening and closing reconstruction (Zhang et al., 2007) H-minima (Gao et al., 2006) are used to smooth the target images to preserve the boundaries of the objects regions. This is followed by performing the region-based algorithms on the smoothened image to obtain improved segmentation result (Anithadevi & Perumal, 2016; Zhang et al., 2007). However, in order to further enhance the boundaries of the visual objects regions, edge detection algorithm such as morphological gradient and canny edge detector are first performed on the smoothened image to deliver a gradient image (Hanburry, 2008). The region-based algorithms are then performed on this gradient image in order to produce more defined and accurate boundaries of segmented objects regions. Although this noise filtering followed by edge detection approach has produced regions with accurate boundaries but however, it did not overcome the over segmented regions and in some cases it causes a more severe over segmentation.

While in the marker-based region segmentation, it starts with a local minima point, referred to as a marker. Marker is identified either manually or automatically for each expected region. In general, the result produced in this approach is dependent on the accuracy and preciseness in the marker generation and positioning. The simplest way of obtaining markers is to manually draw the markers on the target or gradient image using mouse clicks or strokes (Mancas & Gosselin, 2004). Interactive markers specifications tend to produce the best segmentation. However, it is very time consuming and labor intensive especially in high resolution and complex images. Hence, many automatic marker generation approaches have been proposed in the recent years. Prior information is needed to automatically generate the markers for both background and foreground objects regions. These markers are then used as the local minima points in the region-based segmentation algorithms to delineate the foreground objects regions from the background regions. Generally the prior information to generate markers is obtained from the target image using several approaches such as atlas knowledge (Grau et al., 2004), morphological opening and closing reconstruction (Liu & Zhao, 2010), and particle swarm optimization (PSO) (Mirghasemi et al., 2013). The segmentation result obtained from the automatic marker-based approaches is quite promising. However, obtaining perfect automatic markers from the prior information is very crucial. Losing even one marker may cause under segmentation where inhomogeneous regions are segmented as a single region or in some cases the over segmentation may still remains.

Thus, the most habitual approach (Freixenet et al., 2002) to reduce over segmentation is the *post-processing* approach. Generally in this approach, the over segmented regions are merged progressively to produce the final segmentation as spatially contiguous regions with closed boundaries. This approach is known as region merging. Region merging on the over segmented regions is performed iteratively between two similar local neighboring regions using merging criterion and guided by a stopping rule. The merging criterion indicates the similarity between two neighboring regions and the decision in merging them while the stopping rule is a predefined threshold value that is normally derived from the merging criterion. If the merging criterion between two chosen neighboring regions is less than the stopping rule, the regions are merged into one growing region or otherwise no merging occurs. If the regions are merged, the false boundaries between these two regions are removed to merge them into growing region. After each successive merging, the merging criterion between the growing region and its neighboring regions are dynamically updated before the subsequent merging is performed. This merging process continues iteratively until the merging criterion between the chosen neighboring regions satisfies the threshold value. Generally, in region merging, the merging between region pairs is performed based on a merging strategy. This merging strategy refers to how the most similar local neighboring region pairs are searched to perform the iterative merging. Detailed discussion on this is given in the following section.

2.3 Global, Local, and Hybrid-Oriented Region Merging

In general, region merging is classified into three categories based on the merging strategy. They are global, local, and hybrid-oriented region merging. Global-oriented region merging or widely known as hierarchical stepwise optimization (HSWO) algorithm is performed iteratively by globally searching for the most similar pair of neighboring regions for merging. HSWO was proposed by Beaulieu & Goldberg (1989) to globally segment similar neighboring pixels into homogeneous object regions which later has been extended to perform merging on the over segmented regions.

In HSWO, the globally most similar neighboring region is identified by the merging criterion and if their merging criterion is less than the predefined stopping rule, these regions are merged as shown in Figure 2.2. (A) shows the over segmented regions produced by the region-based or clustering segmentation algorithm. (B) is the illustration of the over segmented regions in (A) with the merging criterion (MC) values between two local neighboring regions. (C) presents that $Region\,C$ and $Region\,E$ have the lowest MC value in the region plane, thus the $Region\,C$ and E are chosen and merged into one growing region since their MC value is lower than the predefined threshold value. The MC value between the growing region comprised of $Region\,C$ and E and its neighborhood regions are updated. (D) shows that in the next merging, the globally most similar pair, $Region\ B$ and $Region\ D$ is chosen for merging since their MC value is the lowest in the region plane and it is lower than the predefined threshold value. Thus, these regions are merged. This global merging process continues iteratively until the merging criterion between the chosen neighboring regions satisfies the threshold value. The computational complexity of HSWO is $O(hn + n\beta log_2 B)$ where n represents the number of iterations to perform merging; h represents the computational time required to update the merging criterion between two neighboring regions after each merging; $n\beta log_2$ is the computational time required to update priority queue, B that stores the merging criterion values in ascending order after each merging (Zhang et al., 2014).

Local-oriented region merging, earns its name by choosing the similar merging pair at a local scale. In each iteration, only the neighbors of the growing region are chosen as the merging pair using merging criterion and the merging is also controlled by a stopping rule as shown in Figure 2.3. (A) presents the over segmented regions produced by the region-based or clustering segmentation algorithm. (B) is the illustration of the over segmented regions in (A) with the merging criterion (MC) values between two local neighboring regions. In (C) the merging starts from the left to right according to the region's scanning order, where $Region\ B$ is chosen as the starting region. Since $Region\ D$ has the lowest MC value among other neighboring regions of $Region\ B$, and this MC value is lower than the predefined threshold, thus $Region\ D$ and $Region\ B$ are merged. The MC values

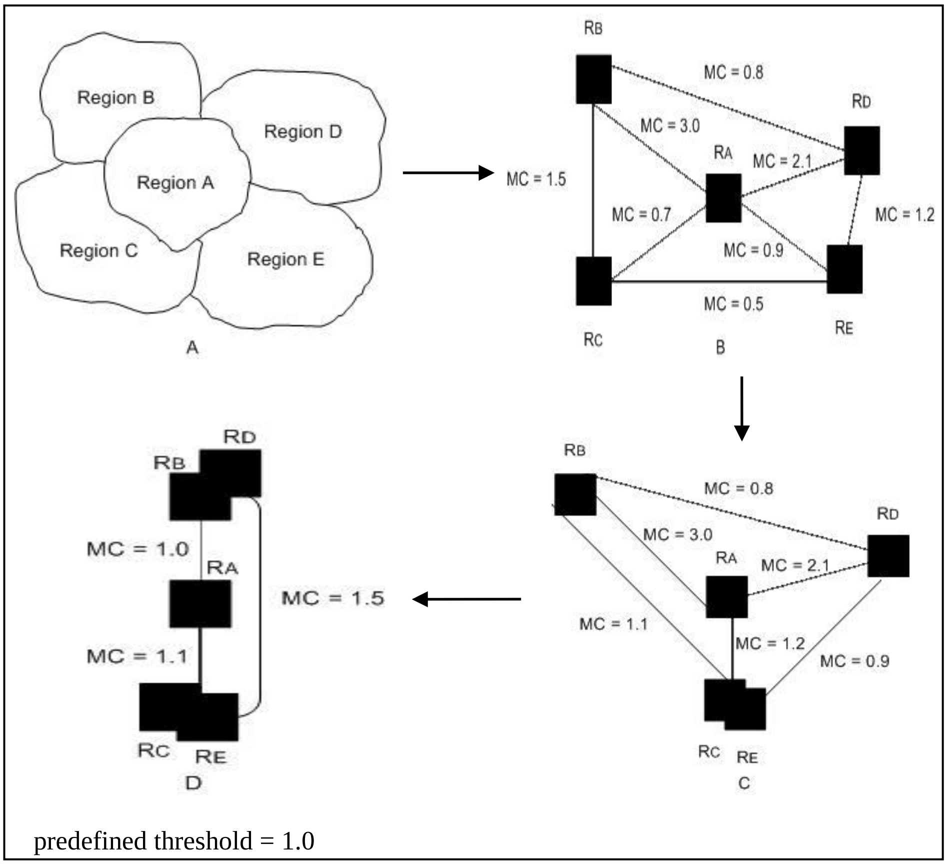


Figure 2.2 Global-oriented region merging strategy.

between the growing region comprised of $Region\ B$ and D and their neighboring regions are updated. While in (D), the merging continues by selecting the neighboring region in the growing region's neighborhood for merging. Since neighboring $Region\ E$ has the lowest MC value in the neighborhood which is also lower than the threshold value, thus $Region\ E$ is merged into the growing region. This local merging process continues iteratively until the merging criterion between the growing region and its neighboring regions satisfies the threshold value. The computational complexity of local-oriented region merging is $O(hn)$ where n represents the number of iterations to perform merging while h represents the computational time required to update the merging criterion between two neighboring regions after each merging (Zhang et al., 2014).

As such, in comparison with the global-oriented merging, the local-oriented merging strategy requires lower computational time complexity (Zhang et al., 2014) and is influenced by the regions local structure context (Tarabalka et al., 2012). The issue in this merging strategy is the difficulty in determining the proper starting point of the growing region to perform merging. This is because the starting point is an initial region that is usually determined by the regions' scanning order (Zhang et al., 2014).

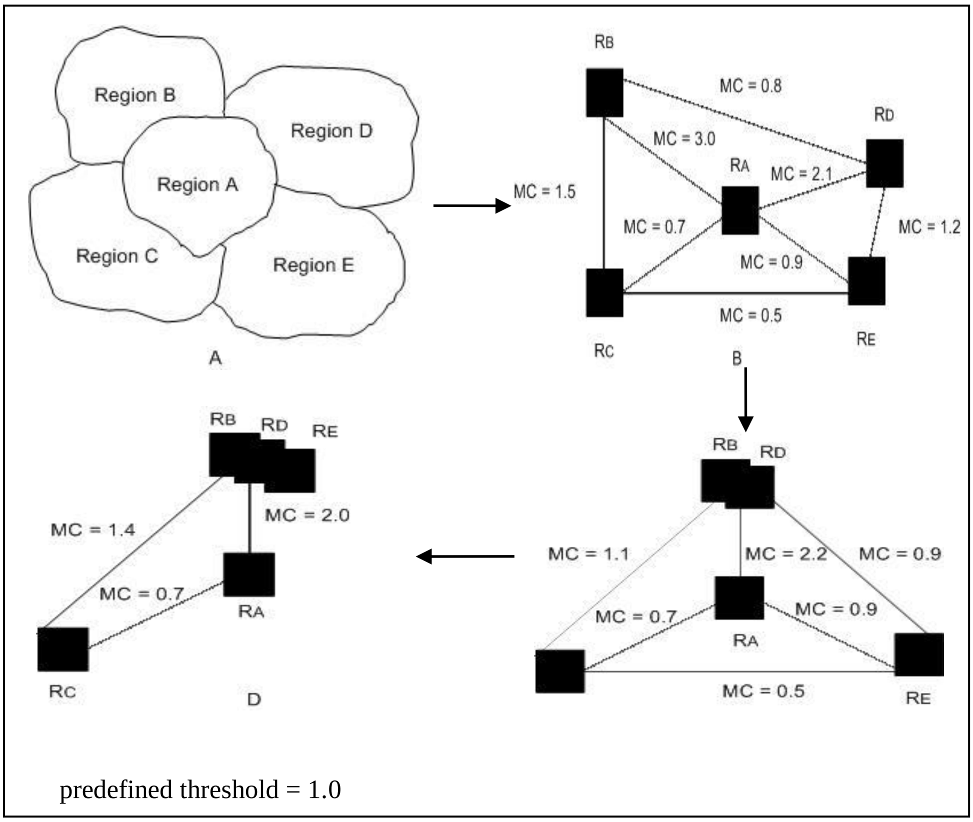


Figure 2.3 Local-oriented region merging strategy.

In order to make use of the advantages and to compensate the flaws of both global and local-oriented merging strategies, Zhang et al. (2014) proposed hybrid-oriented region merging (HRM) strategy. HRM combines both the global and local-oriented region merging strategies. In HRM, the global-oriented merging strategy determines the starting point of a growing region by merging the globally most similar pair of neighboring regions. This is followed by performing the local-oriented merging strategy by merging the most similar region neighbors of the growing region. As usual they are guided by the stopping rule. Figure 2.4 shows the illustration of this merging strategy (Zhang et al., 2014). (A) shows the over segmented regions produced by the region-based or clustering segmentation algorithm. (B) illustrates of the over segmented regions in (A) with the merging criterion (MC) values between two local neighboring regions. (C) presents the hybrid merging starts by selecting the globally most similar pair of regions for merging. $Region\ C$ and $Region\ E$ have the lowest MC value in the region plane, thus these regions are chosen and merged into one growing region since their MC value is lower than the predefined threshold value. The MC value between the growing region comprised of $Region\ C$ and E and its neighborhood regions are updated. (D) illustrates that in the next iteration, the merging is performed locally between the growing region and its neighboring regions. Since neighboring $Region\ D$ has the lowest MC value in the neighborhood of the growing region, which is also lower than the threshold value, thus $Region\ D$ is chosen and merged with the growing region. This local merging in (D) stops when the MC value between the growing region and its neighboring regions is higher than the threshold value. The merging then continues again to (C) and the similar merging process as described above is performed, iteratively. The merging stops when the MC value between the globally chosen neighboring regions is higher than the threshold value.

This hybrid merging strategy outperforms the former two merging strategies by enhancing the global optimization ability that is neglected in the local-oriented merging strategy and is constrained by regions local structure context unlike in the global-oriented merging strategy. The merging process of HRM is faster as compared to the global strategy but is slower than the local merging strategy (Zhang et al., 2014).

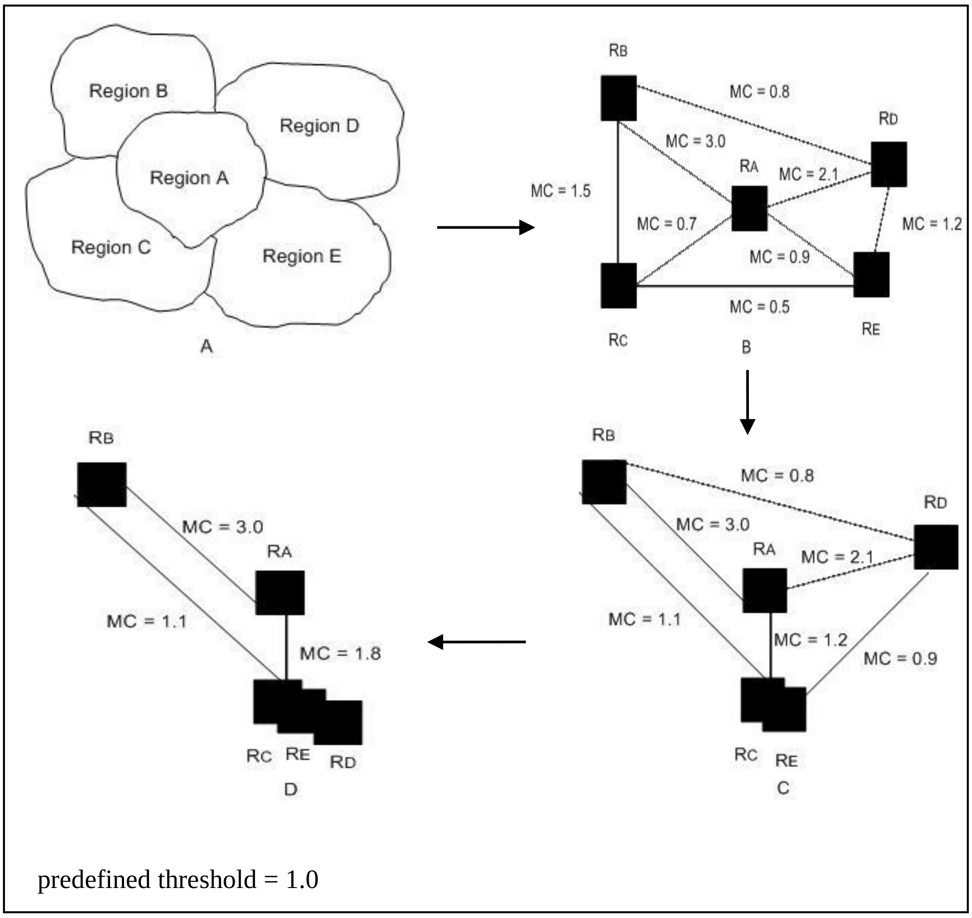


Figure 2.4 Hybrid-oriented region merging strategy.

Nevertheless, a region merging approach based on the three merging strategies is influenced by three factors (Shui & Zhang, 2014). The first factor is the merging criterion which indicates the similarity between two neighboring regions and the decision in merging them. Second factor is the merging order which is not only the starting point to perform merging but also is the sequence of merging the regions during the merging process. Since merging is performed between one pair of neighboring region at a time, the starting merging point and the sequence of regions being merged affects the final segmentation results. The third factor is the region model, which is the representation of the over segmented regions in the merging process, for instance by representing the regions in a graph plane to perform merging. Among these three factors, the *merging criterion* plays an important role in region merging to obtain the desired segmentation results (Shui & Zhang, 2014). Generally, the improvements on the region merging approach in reducing over segmented regions lie within these three factors using the aforementioned three merging strategies; global-, local-, and hybrid-oriented merging. These region merging approaches can be classified into statistics-, graph- and marker-based region merging (Peng et al., 2011) as illustrated in Figure 2.5. The following discusses each of these approaches in detail.

2.3.1 Statistics-Based Region Merging

Statistics-based region merging approach performs region merging by progressively merging similar neighboring regions according to the merging criterion normally derived from statistical properties. These statistics are determined from the local and/or global feature values. They are defined by determining the difference of the chosen feature values from two neighboring regions to verify the regions similarity for merging. Local features are extracted from the over segmented regions itself while global features imply the global image feature information (Zha et al., 2013; Tilton et al., 2012; Wang et al., 2006). In general, the feature selection in deriving the merging criterion is critical in producing accurate final segmented of merged regions in the region merging approach (Makrogiannis et al., 2005).

In the statistics-based region merging, adjacent region size (Wang et al., 2006) of four or eight is used depending on the over segmented regions plane