PARALLELIZATION OF MODIFIED GEODESIC ACTIVE CONTOUR MODEL ON HIGH RESOLUTION SATELLITE IMAGE FOR SEGMENTATION PROCESS

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DEDICATION

Dedicated to my husband, son, mak, abah and family.

Thanks for the love and supports

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ABSTRACT

A modified Sign Pressure Force (SPF) function able to enhance the existing Edge Stopping Function (ESF) in terms of simulation, visualization, and segmentation of high-resolution satellite images of Nusajaya using the Geodesic Active Contour (GAC) model. The modified SPF function is formulated by integrating both the local SPF function and the global SPF function. Next, the modified GAC model is extended to a higher-order modified GAC model. The second-order and fourth-order modified GAC models are implemented using the Finite Difference Method (FDM) and developed into a tri-diagonal and Penta-diagonal Linear System of Equations (LSE). Some numerical methods such as Second-Order Alternating Group Explicit (AGE2), Second-Order Red-Black Gauss-Seidel (RBGS2), and Second-Order Jacobi (JB2) methods are used to solve the LSE of second-order modified GAC model. Meanwhile, Fourth-Order Alternating Group Explicit (AGE4), Fourth-Order Red-Black Gauss-Seidel (RBGS4), and Fourth-Order Jacobi (JB4) methods are used to solve the LSE of the fourth-order modified GAC model. The sequential algorithm is developed using Matlab R2015a software. The indicator of numerical results is analyzed based on execution time, number of iterations, maximum error, root mean square error, and computational complexity. The actual high-resolution satellite images of Nusajaya generate a large amount of data, resulting in an enormous amount of execution time and high computational complexity. Thus, the implementation of a parallel algorithm is a reliable alternative for improving the sequential computation and reduced the execution time up to 82.23%. The parallel computation obtains an extensive large scale simulation capability for high-resolution satellite image data. The domain decomposition strategy is implemented by using the Matlab parallel computing toolbox based on the shared memory architecture. Parallel performance evaluations of numerical methods are measured based on speedup, efficiency, effectiveness, temporal performance, and granularity. As a conclusion, this investigation has proven the second-order modified GAC model could be extended to a fourth-order modified GAC model to simulate and visualize edge-region segmentation of high-resolution satellite images. Consequently, the Parallel Fourth-Order Alternating Group Explicit (PAGE4) method is an alternative solution for large sparse segmentation process of high-resolution satellite images of Nusajaya as it improves the performance up to 82.26%. Based on the numerical results and parallel performance measurements, the parallel algorithm is proved to reduce the execution time and computational complexity up to 82.23% compared to the sequential algorithm.

ABSTRAK

Fungsi *Sign Pressure Force* (SPF) yang terubah suai dapat menambah baik *Edge Stopping Function* (ESF) dari segi simulasi, visualisasi dan segmentasi imej satelit Nusajaya beresolusi tinggi menggunakan model Kontur Aktif Geodesik (GAC). Fungsi SPF yang terubah suai dirumuskan dengan mengintegrasikan kedua-dua fungsi SPF tempatan dan fungsi SPF global. Seterusnya, model GAC terubah suai diperluaskan kepada model GAC terubah suai peringkat lebih tinggi. Model GAC terubah suai peringkat kedua dan peringkat keempat berlaksana menggunakan Kaedah Perbezaan Terhingga (FDM) dan dibangunkan menjadi Persamaan Sistem Linear (LSE) Tiga Pepenjuru dan Lima Pepenjuru. Beberapa kaedah berangka seperti Kumpulan Tak Tersirat Berselang-seli Peringkat Kedua (AGE2), Gauss Seidel Merah Hitam Peringkat Kedua (RBGS2), dan Jacobi Peringkat Kedua (JB2) telah digunakan untuk menyelesaikan model GAC peringkat kedua tersebut. Manakala Kumpulan Tak Tersirat Berselang-seli Peringkat Keempat (AGE4), Gauss Seidel Merah Hitam Peringkat Keempat (RBGS4), dan kaedah Jacobi Peringkat Keempat (JB4) pula digunakan untuk menyelesaikan model GAC peringkat keempat. Algoritma berurutan dihasilkan menggunakan perisian Matlab R2015a. Penunjuk kepada keputusan berangka dianalisis berdasarkan masa pelaksanaan, jumlah lelaran, ralat maksimum, purata ralat punca kuasa dua, dan kerumitan pengiraan. Imej sebenar satelit Nusajaya beresolusi tinggi menghasilkan jumlah data yang cukup besar, masa pelaksanaan yang cukup lama dan kerumitan pengiraan yang tinggi. Justeru itu, pelaksanaan algoritma selari adalah alternatif yang boleh dipercayai untuk meningkatkan pengiraan berurutan dan mengurangkan masa perlaksanaan hingga 82.23%. Pengiraan selari mempunyai keupayaan simulasi berskala besar yang luas untuk data imej satelit beresolusi tinggi. Strategi penguraian domain berlaksana menggunakan kotak alat pengkomputeran selari Matlab berdasarkan seni bina ruang ingatan berkongsi. Ukuran prestasi selari untuk kaedah berangka adalah berdasarkan kepada kepantasan, kecekapan, keberkesanan, prestasi sementara, dan pembutiran grid**.** Kesimpulannya, penyelidikan ini telah membuktikan bahawa model GAC terubah suai peringkat kedua boleh diperluaskan kepada model GAC terubah suai hingga ke peringkat keempat untuk menyelesaikan dan menggambarkan segmentasi kawasan pinggir imej satelit beresolusi tinggi. Oleh itu, kaedah Selari Kumpulan Tak Tersirat Berselang-seli Peringkat Keempat (PAGE4) adalah penyelesaian alternatif untuk proses segmentasi berskala besar bagi imej satelit Nusajaya beresolusi tinggi kerana berupaya meningkatkan prestasi hingga 82.26%. Berdasarkan keputusan berangka dan ukuran prestasi selari, algoritma selari terbukti dapat mengurangkan masa pelaksanaan dan kerumitan pengiraan hingga 82.23% berbanding algoritma berurutan.

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LIST OF ABBREVIATIONS

1D	-	One-Dimensional
2D	-	Two-Dimensional
ADI	-	Alternating Direction Implicit
AGE	-	Alternating Group Explicit
AGE2	-	Second-Order Alternating Group Explicit
AGE4	-	Fourth-Order Alternating Group Explicit
AGE4-PENTA	-	Penta-Diagonal Fourth-Order Alternating Group Explicit
AOS	-	Additive Operator Splitting
API	-	Application Programming Interface
CPU	-	Central Processing Unit
CV	-	Chan Vese
ESF	-	Edge Stopping Function
FDM	-	Finite Difference Method
FEM	-	Finite Element Method
FVM	-	Finite Volume Method
GAC	-	Geodesic Active Contour
GE	-	Group Explicit
GGAC	-	Generalized Geodesic Active Contour
GSPF	-	Global Signed Pressure Force
IADE	-	Iterative Alternating Decomposition Explicit
JB	-	Jacobi
JB2	-	Second-Order Jacobi

JB4	-	Fourth-Order Jacobi
LAC	-	Localized Active Contour
LSE	-	Linear System of Equation
LU	-	Lower and Upper
ME	-	Maximum Error
MIMD	-	Multiple Instruction Multiple Data
MISD	-	Multiple Instruction Single Data
MPI	-	Message Passing Interface
MS	-	Mumford-Shah
ODE	-	Ordinary Differential Equation
PAGE2	-	Parallel Second-Order Alternating Group Explicit
PAGE4	-	Parallel Fourth-Order Alternating Group Explicit
PCT	-	Parallel Computing Toolbox
PCW	-	Parallel Command Window
PDE	-	Partial Differential Equation
PJB2	-	Parallel Second-Order Jacobi
PJB4	-	Parallel Fourth-Order Jacobi
PPE	-	Parallel Performance Evaluations
PRBGS2	-	Parallel Second-Order Red Black Gauss-Seidel
PRBGS4	-	Parallel Fourth-Order Red Black Gauss-Seidel
PVM	-	Parallel Virtual Machine
RBGS	-	Red Black Gauss-Seidel
RBGS2	-	Second-Order Red Black Gauss-Seidel
RBGS4	-	Fourth-Order Red Black Gauss-Seidel
RE	-	Relative Error

RMSE	-	Root Mean Square Error
RSF	-	Region-Scalable Fitting
SAGE2	-	Sequential Second-Order Alternating Group Explicit
SAGE4	-	Sequential Fourth-Order Alternating Group Explicit
SBGFRLS	-	Selective Binary and Gaussian Filtering Regularized Level Set
SIMD	-	Single Instruction Multiple Data
SISD	-	Single Instruction Single Data
SJB2	-	Second-Order Sequential Jacobi
SJB4	-	Sequential Fourth-Order Jacobi
SLE	-	System of Linear Equations
SOR	-	Successive Over Relaxation
SPF	-	Signed Pressure Force
SRBGS2	-	Second-Order Sequential Red Black Gauss-Seidel
SRBGS4	-	Sequential Fourth-Order Red Black Gauss-Seidel

LIST OF SYMBOLS

E_{int}	-	Internal Energy
E_{ext}	-	External Energy
v	-	Positive Real Constant or Balloon Force
$\vec{N}$	-	Normal Vector of the Curve
Γ_t	-	Euclidean Heat Flow
$v\vec{N}$	-	Constant Velocity
g	-	Stopping Function
$\hat{I}$	-	Smoothed Version
$I(x)$	-	Image
Ω	-	Bounded Open Subset of R^2
G_σ	-	Gaussian Kernel
σ	-	Standard Deviation
$*$	-	Convolution Operator
$H(\phi)$	-	Heaviside Function
f_1, f_2	-	Weighted Averages of Image Intensities
c_1, c_2	-	Intensity Averages of Regions Inside or Outside
$\lvert\nabla u\rvert$	-	Gradient of The Image

spf_{GL}	-	Global SPF Function
spf_{LC}	-	Local SPF Function
spf_{LCGL}	-	Modified SPF Function
u	-	Desired Image
τ	-	Time Step
$\Delta x, \Delta y$	-	Step Size in x and y Axis
$M \times N$	-	Size of Image
$\overline{\mathrm{H}}^{k}(\Omega)$	-	Hilbert Space
p	-	Number of Processors
∇^{2}	-	Laplace Operator
∇	-	Gradient Operator
$S(p)$	-	Speedup
T_0	-	Total Time Spent
T_1	-	Execution Time on One Processor
T_p	-	Execution Time on Several Processor
$E(p)$	-	Efficiency
$F(p)$	-	Effectiveness
$L(p)$	-	Temporal Performance
G	-	Granularity

T_{comp}	-	Computation Time
T_{comm}	-	Communication Time
$T_{startup}$	-	Start-up Time
$T_{startup}$	-	Data Time
T_{idle}	-	Idle Time
ε	-	Epsilon
ω_1, ω_2		Adaptive Filter

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CHAPTER 1

INTRODUCTION

1.1 Research Background

High-resolution satellite images provide enormous amounts of important and useful data, especially for people who are involved in urban planning, security, mapping, and environmental monitoring. However, the human eye is not sufficiently sensitive to detect small changes in satellite images, making manual inspection unsuitable for exploring hidden information in satellite images (Ganesan et al., 2015). This manual process is also a time-consuming and challenging way of retrieving information from huge quantities of data due to the complexity and abundant textures of high-resolution satellite images.

Image segmentation process is the most important and difficult task in image analysis (Gamba and Aldrighi, 2012; Ganesan and Rajini, 2014). Image segmentation is highly useful for detecting changes in land usage as well as road and building extraction. One part of the segmentation process is the partitioning process, in which a digital image is divided into several segments (pixels). Image segmentation can reduce image complexity to ease analysis process. More precisely, the aim of image segmentation process is to detect objects and image boundaries. The image segmentation process extracts an image into a set of contours.

There are several image segmentation techniques such as threshold-based segmentation, edge-based segmentation, region-based segmentation, and clustering-based segmentation. Threshold-based segmentation is one of the earliest and easiest methods in image segmentation and works as a tool to differentiate objects from the background. Some examples of threshold-based applications are to extract the region of mass in mammography (Makandar and Halalli, 2016), to detect glaucoma in fundus images and to segment the optic disc and cup from a fundus image (Issac et al., 2015a, b).

Threshold-based segmentation works well in segmenting images with homogeneous intensity. Homogeneous intensity is defined by the difference in intensity between the object and the background. On the contrary, inhomogeneous intensity means that both the object and the background have a common intensity in the image (Al-amri et al., 2010). However, threshold-based segmentation produces mediocre results in segmenting images with high level of noise (Makandar and Halalli, 2016).

Later, edge-based segmentation technique is introduced for segmenting specific objects in an image and to overcome the limitation of the threshold-based segmentation. Edge-based segmentation works well with images that have clear edge information. However, this method produces poor outcomes in segmenting images with low gradient and weak edge information (Akram et al., 2015). This is because edge-based segmentation depends on the clear edge information or influenced by the visibility of edges in an image. Therefore, threshold-based and edge-based segmentations have similar limitations. Both segmentation techniques aim to detect objects that have clear and meaningful edge information, thus, when the image has unclear edge information or lots of noise, the segmentation will not be successful. To overcome this limitation, region-based segmentation method is introduced.

Region-based segmentation approach is better than edge-based segmentation because it occupies more pixels in an image (Saini et al., 2013). Compared to edge-based segmentation, region-based segmentation uses both pixel intensity and image gradient. On the other hand, edge-based segmentation uses gradient of the image only. However, region-based segmentation produces unsatisfactory results for images with intensity inhomogeneity. In other words, the region-based method does not produce a successful outcome when both the object and background have common intensities.

Further research in image segmentation field results in the development of another type of image segmentation technique that is clustering-based segmentation. Clustering is a process by which objects or patterns are classified so that the samples are more similar in the same group than those in different groups (Choy et al., 2017; Ji et al., 2012). Clustering-based segmentation directly incorporates local spatial information into the segmentation process. The basic process of this technique is to replace the pixels with image patches. As a consequence, it provides an efficient way to reduce noise effects and sustain information when segmenting image. However, this technique is very sensitive to initialization condition of cluster number and center. Table 1.1 shows the advantages and disadvantages of each image segmentation technique.

Table 1.1 Summary of image segmentation techniques.

Techniques	**Characteristics**	**Advantages**	**Disadvantages**	**Methods/Models**
Threshold-based segmentation	Differentiates objects from the background.	Prior information of the image is not needed and computationally inexpensive.	Highly noise sensitive and selection of threshold is crucial.	Otsu Threshold Method (Makandar and Halalli, 2016)
Edge-based segmentation	Only uses the gradient of the image.	Works for images with intensity inhomogeneity.	Gives very poor results for images with noise and weak edges.	Geodesic Active Contour (GAC) Model (Zubaidin, 2013)
Region-based segmentation	Uses both the intensity of the pixel and also the gradient of the image.	Performs better on images with weak or blurred edges.	Produces unsatisfactory results for images with intensity inhomogeneity.	Chan-Vese (CV) Active Contour Model (Korfiatis et al., 2015)

Techniques	Characteristic	Advantages	Disadvantages	Methods/Models
Clustering-based segmentation	Basically used in exploratory data analysis.	Eliminates noisy spots obtain more homogenous regions.	Sensitive to initialization condition of cluster number and center.	Deep Clustering (Hershey et al., 2015), K-Means Clustering (Deepika and Vishnu, 2016)

1.2 Active Contour Model (ACM)

Another approach in image segmentation is Partial Differential Equation (PDE)-based segmentation technique. In image segmentation, PDE-based segmentation has been developed into an important tool in computer vision and has been applied to a wide variety of problems such as edge detection and region segmentation (Zubaidin, 2013). A well-known PDE-based segmentation is the active contour model (Zhang et al., 2017). Existing active contour models can be classified into edge-based (Liu et al., 2017; Pratondo et al., 2017) and region-based models (Soudani and Zagrouba, 2018; Liu et al., 2017).

The edge-based model and region-based model each has their own advantages and disadvantages as shown in Table 1.1. The choice between an edge-based model and region-based model depends on the variance of the images taken into account. Edge-based model creates an edge indicator that forces the development contour to object boundaries (Akram et al., 2013; Akram et al., 2014; Akram et al., 2015). However, this model has difficulty converging to the right boundaries when it works on images with extreme noise or weak edges. Geodesic Active Contour (GAC) model is one example of an edge-based model (Zhang et al., 2017; Shafiq et al., 2015).

Region-based model is much better than edge-based model at dealing with blurred edges. The region-based model is not sensitive and can efficiently detect object boundaries. A well-known region-based model is the Chan-Vese (C-V) model, which has been extensively used for image segmentation (Korfiatis et al., 2015; Mukherjee and Acton, 2015). Although in some aspects the region-based model is better than edge-based model, there are limitations when images are intensively inhomogeneous. In other words, both the object and background have common intensities.

In real images, intensity inhomogeneity can commonly appear especially in high-resolution satellite images. One effective way to work with images with intensity inhomogeneity is by taking the local information of the segmented image into account (Yuan et al., 2014; Shi et al., 2014; Liu et al., 2013). Li et al. (2008) proposed a Region-Scalable Fitting (RSF) active contour model that handles intensity inhomogeneity by using local intensity means as constraints. Due to its complicated procedures, the RSF model incurs high computational costs which limits the use of such method in practice.

To enhance the performance of the region-based model, several researchers have proposed a hybrid model that combined local and global image intensities (Yuan et al., 2017; Akram et al., 2017; Soomro et al., 2016). This hybrid model is known as the Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) model. The signed pressure force (SPF) function is used in SBGFRLS for statistical information both inside and outside contours. However, this model does not work with inhomogeneous images (Dong et al., 2013; Wang et al., 2012). Therefore, the combination of local and global intensity information can evade contour evolutions being captured by a local minimum (Wang et al., 2012). SBGFRLS is sensitive to contour initialization and intense noise. It is clear that the global-based model is unable to be implemented with inhomogeneous images. On the other hand, the local-based model is easily affected by initialization, which may cause leaking at object boundaries.

Numerous PDE-based segmentation algorithms have been recently proposed to solve the problems of image segmentation, noise removal, image enhancement, and image restoration in high-resolution satellite images. Many researchers have proved PDE-based segmentation to be very efficient through the use of evolving nonlinear partial differential equations (Aherrahrou and Tairi, 2015; Özdemir and Dizdaroğlu, 2016; Karasev et al., 2013). GAC model is one of the most-popular PDE-based tools for computer vision and is a powerful tool for edge detection. Nonlinear PDEs are now generally used for edge segmentation, edge detection, and image denoising. However, the GAC model also has its drawbacks, as nonlinearity will cause bad implementation. To linearize GAC model, Additive Operator Splitting (AOS) scheme is incorporated into the model (Li et al., 2016; Yu et al., 2014). Thus, the AOS numerical scheme is unconditionally stable for image processing problems.

Many authors have recently proposed fourth-order PDE analogues for edge detection and image detection. There are several reasons to consider fourth-order PDEs. First, they are much faster than second-order PDE when working with parallel executions. Second, it is possible to have schemes that include curvature effects in their dynamics, making them more efficient than second-order PDE (Barbu, 2015; 2016; Tan et al., 2013). Only a few segmentation techniques researchers have solved the segmentation model using numerical methods. Finite Element (FEM), Finite Volume (FVM), and Finite Difference Methods (FDM) are some alternative methods for PDE linearization (Meister, 2016; Liu et al., 2015; Chernogorova and Valkov, 2011). PDE can be solved using finite difference approaches that approximate solutions at a finite number of points that are usually arranged in a regular grid. Due to this, the mathematical model in this research is solved using FDM. Further details on FDM are discussed in Chapter 2.

Large sparse data for a linear system of equations (LSE) is obtained from FDM for simulation and visualization. In the existing image segmentation work on high-resolution satellite images, little attention has been paid to computational costs. Huge digital images may require a large amount of calculation. However, using only one CPU will take too much execution time to compute a solution. Therefore, to speed up computation, parallelization is implemented to solve large sparse data in large digital images. The parallel algorithm is implemented on a parallel computing toolbox. The sequential and parallel algorithms are developed using Matlab R2015a software in Windows 7 Ultimate on Intel (R) Core (TM) i5-3230M @ 2.60GHz CPU with 8 GB RAM. A detailed description on the parallel algorithm design methodology is included and discussed in Chapter 2.

1.3 Problem Statement

Existing mathematical models for image segmentation that use GAC model with classical edge stopping function gives very poor results for images with extensive noise and weak edges. The C-V model with local region-based information also produces unsatisfactory result for images with intensity inhomogeneity. The second problem is that some researchers only solved the image segmentation model statistically and analytically. The third problem is the challenge in acquiring a good balance between efficiency and accuracy for large-scale high-resolution satellite images. Despite achieving good performance in many scenarios, the second-order GAC model still faces many problems in maintaining its efficiency and accuracy in large-scale cases. The fourth problem is that large sparse digital data images are almost impossible to solve and are highly time-consuming. Execution time increases dramatically due to the high computation of intensities both inside and outside the contour.

Based on these limitations, the aim of this research is to enhance the GAC model with a modification on the Signed Pressure Force (SPF) function obtained from Zhang et al., (2011) and Reddy and Zaheeruddin, (2016). Enhancement of the GAC model will improve image quality in terms of resolution and desired detection efficiency. The proposed model is therefore capable of segmenting images with intense noise, weak edges, and inhomogeneity. Thereafter, the mathematical model is discretized using central FDM to obtain the results. This thesis developed algorithms for higher-order model, whose accuracies are improved based on higher-order FDM. The Jacobi (JB), Red Black Gauss-Seidel (RBGS), and Alternating Group Explicit (AGE) methods are used to solve LSE. Since this thesis deals with large digital data images, computational costs can be high, which renders its utilization for time-critical applications problematic despite the advantages of the GAC model. Therefore, parallelization is used to reduce computational time and improve performance.

1.4 Research Objective

The research objectives are as follows:

a) To enhance the GAC model with a modification of the Signed Pressure Force (SPF) function obtained from Zhang et al., (2011) and Reddy and Zaheeruddin, (2016).
b) To formulate the second-order modified GAC model in (a) for an extension to a fourth-order modified GAC model, which is discretized using FDM to approximate mathematical model solutions.
c) To solve the LSE in (b) using AGE, RBGS, and JB methods.
d) To develop sequential and parallel algorithms from (c) using Matlab R2015a software and MatlabMPI based on shared memory architecture.
e) To analyze the results in (d) based on the numerical results for sequential algorithms and PPE for the parallel algorithm.

1.5 Research Scope

This research focuses on detecting the land-use changes on high-resolution satellite images of Nusajaya using the modified GAC model. Based on the limitations of the existing edge stopping function, a modification of the SPF function is proposed for the GAC model that incorporates the advantages from both global region-based and local-region based models. The mathematical model is discretized using FDM based on a central difference formula. The numerical solution that supported discretization is focused on AGE, RBGS, and JB methods. The numerical solution is solved using both sequential and parallel algorithms. The sequential algorithm is implemented in Matlab software. Since high-resolution satellite images involve large sparse algorithms and large digital data, the parallel algorithm is applied on standard parallel processing techniques and Message Passing Interface (MPI) implementations in Matlab. The scope of this research is illustrated in Figure 1.1 where the highlighted component represents the area focused in this thesis.

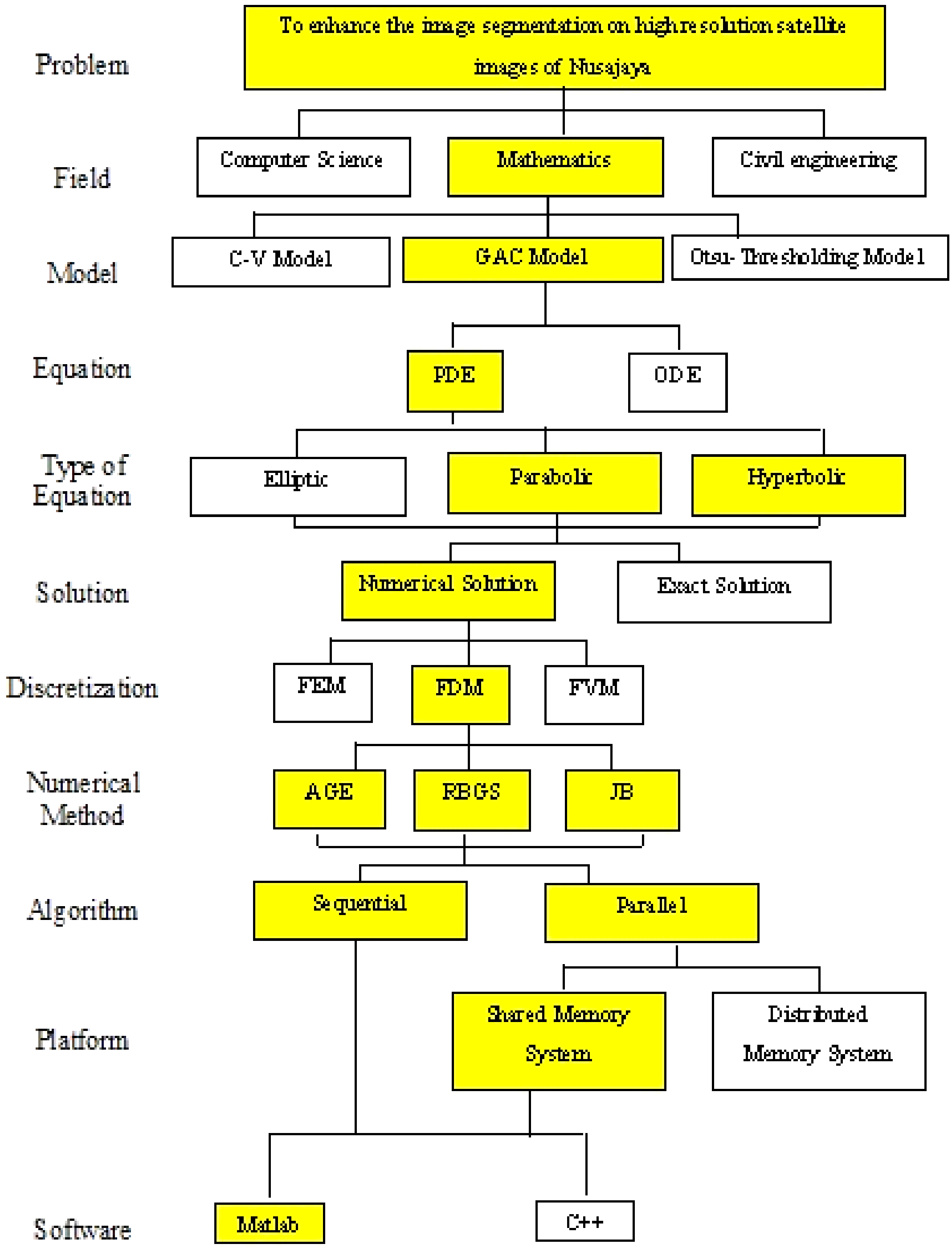

Figure 1.1 Scope of the research

1.6 Research Significance

The first significance of this research is the modification of the SPF function for the GAC model as an alternative method for simulating and visualizing the edge-region segmentation of high-resolution satellite images. The second significance of this thesis is the extension of the modified GAC model to a fourth-order PDE for high-resolution satellite image segmentation to improve partial differential equation accuracy. The third significance is the implementation of the AGE, RBGS and JB numerical methods to solve the modified GAC model. The fourth significance is the use of parallel implementation to solve large sparse data for the modified GAC model on a parallel computing system, reducing computational time and increasing performance. The numerical results are measured to prove that the AGE method is the best iterative method. It is also found that the fourth-order modified GAC model has better accuracy than the second-order modified GAC model. In addition, the parallel algorithm performed better than the sequential algorithm. Furthermore, this research is of great significance in ensuring sustainable land development.

1.7 Thesis Organization

This thesis presents two segmentation models for high-resolution satellite images using GAC model to address pertinent issues in satellite images such as weak edges and intensity inhomogeneity. Overall, this thesis contains six chapters. Chapter 1 describes the research problem of using image segmentation techniques on high-resolution satellite images. This chapter also discusses the research objectives, scope, and significance of the research.

Chapter 2 reviews past and current literature related to the GAC image segmentation tool. The review reveals the strengths and weaknesses found in each of the segmentation models. The chapter also provides intensive literature coverage on FDM and a basic scheme for solving PDE. JB, RBGS, and AGE numerical methods are also discussed in this chapter. The chapter then explains the numerical analysis based on convergence, consistency, stability, numerical error, and computational complexity. The parallel performance evaluation is based on speedup, efficiency, effectiveness, temporal performance, and granularity. This chapter also contains an overview of the parallel computing toolbox on Matlab. This chapter ends with summary on the GAC model in producing satisfactory segmentation result for satellite images.

Chapter 3 gives an overview of the methodology of the two proposed models that are able to improve the performance of the classical GAC model in segmenting more challenging satellite images. The chapter provides the formulation of the modified SPF function. Simulation of the segmentation models is analyzed and shown through graphical representations using Matlab R2015a software in Windows 7 Ultimate on Intel (R) Core (TM) i5-3230M @ 2.60GHz CPU with 8 GB RAM. Chapter 3 ends with a summary of each proposed method.

Chapter 4 introduces the first proposed second-order modified GAC model that improves the classical GAC model using modified SPF function. This chapter contains the governing process of the mathematical model, numerical results, and parallel performance evaluations of the sequential and parallel algorithms for the second-order modified GAC model. The LSE obtained from FDM is solved using the SAGE2, SRBGS2, and SJB2 numerical methods. Sequential performance is based on execution time, number of iterations, maximum error, and root mean square error (RMSE). These numerical methods are parallelized to improve the performance of the sequential algorithm. The parallel performance evaluations of the PAGE2, PRBGS2, and PJB2 methods are measured based on speedup, efficiency, effectiveness, temporal performance, and granularity.

Chapter 5 describes the governing process of the proposed fourth-order modified GAC model to enhance the capability and accuracy of the second-order modified GAC model for segmenting satellite images in the presence of high level of noise and high intensity inhomogeneity. The fourth-order modified GAC model is discretized using FDM with a fourth-order central difference formula to create a set of Penta-diagonal LSE. The LSE is solved using the SAGE4, SRBGS4, and SJB4 methods. The numerical results are compared based on execution time, number of iterations, maximum error, and RMSE. The parallel performance evaluations of the PAGE4, PRBGS4, and PJB4 methods are reported accordingly. To support the segmentation results, quantitative evaluation is conducted which is based on accuracy metric to measure the percentage of accuracy of the segmentation models.

Chapter 6 concludes the research and provides suggestions for future works. It mainly highlights the outcomes of the research in terms of its aim and objectives. The chapter also gives some recommendations for future research.

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LIST OF PUBLICATIONS

Index Journal

1. Alias, N., **Mustaffa, M. N**., Saipol, H. F. S., Ghani, A., & Che, A. (2014). The Chronology of Geographic Information System Image Processing: A Case Study for Land Changes at Nusajaya, Iskandar Malaysia. *Advanced Science Letters*, *20*(2), 435-438. (Indexed by Scopus, Web of Science) Q2

2. Alias, N., **Mustaffa, M. N**., Saipol, H. F. S., & Ghani, A. C. A. (2014). High Performance Large Sparse PDEs with Parabolic and Elliptic Types Using AGE Method on DPCS. *Advanced Science Letters*, *20*(10-12), 1956-1960. (Indexed by Scopus, Web of Science) Q2

3. Alias, N., Saipol, H. F. S., Ghani, A., Che, A., & **Mustaffa, M. N.** (2014). Parallel Performance Comparison of Alternating Group Explicit Method Between Parallel Virtual Machine and Matlab Distributed Computing for Solving Large Sparse Partial Differential Equations. *Advanced Science Letters*, *20*(2), 477-482. (Indexed by Scopus, Web of Science) Q2

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Non Index Journal

1. **Mustaffa, M. N**., Alias, N., & Mustapha, F. (2017). Some Numerical Methods for Solving Geodesic Active Contour Model on Image Segmentation Process. *Malaysian Journal of Fundamental and Applied Sciences*, *13*(4-1), 408-411. (Indexed by Clarivate Analytics (formerly Thomson Reuters) and Google Scholar)