Polarimetric synthetic aperture radar image processing for land cover classification

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**POLARIMETRIC SYNTHETIC APERTURE RADAR IMAGE
PROCESSING FOR LAND COVER CLASSIFICATION**

**LEE KEN YOONG
SCHOOL OF COMPUTER ENGINEERING
2009**

Polarimetric Synthetic Aperture Radar Image Processing for Land Cover Classification

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Abstract

This thesis presents the processing design and development towards an improved land cover classification of multi-look POLSAR data. In this context, three related processing aspects, namely edge detection, speckle suppression and region-based segmentation, were investigated. To detect edges in speckle-corrupted POLSAR data, two new edge detectors, which are based separately on the Roy's largest eigenvalue and trace ratio, were proposed. Their capabilities were compared with three other edge detectors, which use the likelihood ratio, Dowson-Landau metric and Euclidean distance, respectively. Applied to nine-look NASA/JPL POLSAR C- and L-band data, both the proposed edge detectors exhibited their satisfactory performance in detecting edges while coping with speckle noise disturbance. For the speckle suppression, a novel spatially adaptive speckle filter was developed, which aims at preserving image features during filtering process. In the experiments, the proposed filter showed its good performance in speckle removal, image feature retention and radiometric preservation. Comparisons with the boxcar, Lee-refined and annealing filters were carried out. In the area of region-based segmentation, an existing hybrid segmentation algorithm was extended for multi-look POLSAR data. The capabilities of the extended algorithm were examined and benchmarked against the HSWO algorithm. From the results, it was noticed that the segmentation outputs from both the algorithms relied strongly on the user-defined region number, which is employed as the termination rule. Finally, the classification of NASA/JPL POLSAR data over a selected area of Kuala Muda in Peninsular Malaysia was carried out based separately on scattering mechanisms and statistical distribution. For the scattering property-based unsupervised classification, three different schemes were examined, namely van Zyl's scattering classification, Freeman-Durden scattering model and Cloude-Pottier target decomposition. The derived scattering mechanisms of different land cover classes were studied. In the supervised complex Wishart classification, the obtained overall accuracies were 63% and 67% for both the C- and L-band, respectively. An improved accuracy of 75% was attained by using the dual-frequency input. Furthermore, comparison between per-pixel and per-segment classification approaches was conducted, where the per-segment approach was expectedly found to improve the classification accuracy.

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List of Abbreviations

AIRSAR	Airborne Synthetic Aperture Radar
ALOS	Advanced Land Observing Satellite
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CCT	Computer Compatible Tape
E-SAR	Experimental Synthetic Aperture Radar
EMISAR	Electromagnetics Institute Synthetic Aperture Radar
ENVISAT	Environment Satellite
ERS	European Remote Sensing Satellite
HH	Horizontal Transmit Horizontal Receive
HSWO	Hierarchical Stepwise Optimisation
HV	Horizontal Transmit Vertical Receive
IEEE	Institute of Electrical and Electronics Engineers
JERS	Japanese Earth Resources Satellite
JPL	Jet Propulsion Laboratory
Landsat	Land Observation Satellite
MASTER	MODIS/ASTER
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
Pi-SAR	Polarimetric and Interferometric Airborne Synthetic Aperture Radar
POLSAR	Polarimetric Synthetic Aperture Radar
PWF	Polarimetric Whitening Filter
RAR	Real Aperture Radar
RGB	Red, Green and Blue
SAR	Synthetic Aperture Radar
SIR-C	Shuttle Imaging Radar-C
SPOT	Satellite Probatoire d'Observation de la Terre
TM	Thematic Mapper
VV	Vertical Transmit Vertical Receive

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Chapter 1

Research Background

1.1 Introduction

“Satellite remote sensing is an appropriate and effective data source for national land cover mapping” (Haack and English, 1996)

According to Burley (1961), land cover refers to vegetation and artificial constructions covering the land surface. With the advent of Landsat-1¹ in 1972 and rapidly growing utilisation of other remote sensing satellites over the past three decades, the information-rich remotely sensed data have long been championed for land cover mapping due to the following reasons (Raghunathan, 1991; Schulman, 1999; Cihlar, 2000): Firstly, a relative wide spatial coverage is provided by remotely sensed data. For example, the image swath of the ERS-1 satellite is about 100 km. Secondly, remote sensing satellites can perform repetitive observations. The members of the NOAA and SPOT satellite families take only 12 hours and 26 days, respectively, to revisit the same location on Earth. Thirdly, remotely sensed data are nowadays cost-effective. The price for ASTER imagery is less than \$100 per scene. Furthermore, some remotely sensed data, namely AIRSAR, Landsat, MODIS, MASTER as well as SIR-C, are currently obtainable free of charge on web.

In general, there are two major types of most widely utilised remotely sensed data: optical data and synthetic aperture radar data. Optical data are collected in visible and in infrared regions of the electromagnetic spectrum by satellites, such as Landsat, SPOT, NOAA and so forth. The data have been widely utilised and well recognised for both

¹ Previously called the first Earth Resources Technology Satellite (ERST-1)

local- and global-scale land cover mapping (Anderson *et al.*, 1976; May *et al.*, 1986; Haack *et al.*, 1987; Townshend *et al.*, 1991; Tateishi *et al.*, 1997). On the other hand, the developments and launches of microwave remote sensing satellites (e.g. Seasat, Almaz-1, ERS-1, JERS-1, ERS-2 and RADARSAT-1) have enabled collection of remotely sensed data in the microwave portion of the electromagnetic spectrum. In particular, microwave satellites not only can work day and night, but also can provide cloud-free imagery. Owing to the cloud-penetrability, SAR data have gained acceptance to be included in land cover mapping, especially in tropical regions. This trend tallies with a remark by Forster (1993):

“Radar or microwave remote sensing is becoming an increasingly tool for monitoring earth resources, particularly in tropical zone countries where clouds interfere with the reception of visible and near-infrared sensors”

Nevertheless, both optical and SAR data impose certain problems on land cover classification over tropical regions. The occurrence of extensive and persistent cloud coverage is the main problem for optical remotely sensed data. Since clouds interfere with the reception of optical sensors, their presence causes information loss of land cover in the captured data. On the contrary, for single-frequency single-polarisation SAR data, which is provided by ERS-1/2, JERS-1 and RADARSAT-1, previous experience has shown that land cover features cannot be distinguished easily based on their single-band backscattering signature alone (Michelson *et al.*, 2000; Lee *et al.*, 2002). Hence, land cover classification using single-frequency single-polarisation SAR data is not very successful. Moreover, due to random interference of backscattered radar waves from elementary scatterers, SAR data are inherently corrupted by speckle noise which makes land cover interpretation difficult. Figure 1.1 illustrates the limitations of both optical and SAR satellite data.

With the realisation of multi-frequency fully polarimetric SAR imaging systems, such as SIR-C, AIRSAR, E-SAR, EMISAR and Pi-SAR, it is now possible to capture complete polarimetric signatures of the Earth's surface. To date, there is a growing interest within the remote sensing community to utilise the acquired data for various applications (Boerner *et al.*, 1998). One of the key applications is land cover

(a)

(b)

Figure 1.1: Limitations of optical and single-frequency single-polarisation SAR remotely sensed data in land cover mapping. (a) and (b) are Landsat-5 TM and JERS-1 data, respectively, which cover the same area of Sungai Pulai in Johor state, Malaysia. In (a), the boundaries of mangrove forest and other land cover features in its surrounding can be clearly observed. However, partial land cover information is lost due to the cloud coverage (in white colour). Although the spatial resolution of JERS-1 data (i.e. 18 meters) is better than Landsat-5 TM data (i.e. 30 meters), it gives a salt-and-pepper view of Sungai Pulai as a result of the presence of speckle noise. The fine and detailed land cover features cannot be seen clearly in (b).

classification (Lim *et al.*, 1989; Nagai *et al.*, 1997; Lee *et al.*, 2001; van den Broek *et al.*, 2004). This is because POLSAR data can, through different frequency and polarisation combinations, provide abundant and valuable information (e.g. intensity, total power, polarisation ratio, phase difference and correlation coefficient), which help in understanding and quantifying physical interaction behaviours between radar waves and illuminated land cover features.

1.2 Problem Statement and Motivation

So far only limited research work has been published on the application of POLSAR data for classifying land cover in tropical regions, especially in Southeast Asia. One of the main reasons for this is due to the complexity of POLSAR data format. In order to reduce the data storage, POLSAR data are always prepared in a compressed format. For instance, the NASA/JPL AIRSAR data are distributed in the so-called compressed Stokes matrix format. Except for the released PolSARpro software (Pottier *et al.*, 2005), there was previously no free or commercial remote sensing software, which can be used to retrieve the complete polarimetric information from the compressed POLSAR data. Consequently, the understanding and utilisation of the available POLSAR data have remained limited within the geoscience community since the majority of its members are unfamiliar with computer programming and depend strongly on existing remote sensing software packages.

In addition, POLSAR data suffer inherently from speckle noise disturbance, which can degrade the application for land cover classification (Lee and Grunes, 1999; Chen *et al.*, 2003; Rodionova, 2005). Being a critical pre-processing task, speckle suppression of POLSAR data remains challenging. This is because the perfectness of a speckle filter in removing noise disturbance while preserving meaningful image features, such as edges, lines, point targets and etc., is often difficult to be accomplished. Moreover, this presence of speckle noise has restricted the applicability of conventional image processing techniques. The conventional algorithms, such as edge detectors, region-based segmentation algorithms, pattern recognition classifiers and others, are needed to be refined by taking both speckle noise characteristics and POLSAR data contents into account.

Apart from these issues, most of the proposed classifiers for POLSAR data operate on a per-pixel basis. The classification outputs of POLSAR images based on individual pixels, however, can be unsatisfactory due to the presence of inherent speckle noise and the exclusion of intrinsic spatial neighbourhood information. Hence, a per-segment approach is more preferable for POLSAR image classification (Burl and Novak, 1991; van den Broek *et al.*, 2004).

1.3 Objectives

The main objective of this study is to assess possible impacting factors on the potential use and improvement of POLSAR data for classifying land covers in a tropical region. Along with the main objective, the following sub-objectives are identified:

- (i) to investigate image feature detection in speckle-corrupted POLSAR data,
- (ii) to develop an improved speckle filter for speckle suppression of POLSAR data,
- (iii) to extend a selected hybrid segmentation algorithm for POLSAR data,
- (iv) to evaluate quantitatively and qualitatively per-segment approach for improving land cover classification.

1.4 Methodology

The methodology of this study is outlined in Figure 1.2. It consists of five modules: (i) data acquisition, (ii) image feature detection, (iii) speckle suppression, (iv) segmentation and (v) classification. To achieve the objectives of this study, a set of airborne POLSAR data, which covers an area in Southeast Asia, is selected properly by considering the variety of land cover features. In the image feature detection, focus is placed mainly on edge detection in speckle-corrupted POLSAR data. The edge information extracted is further employed in the subsequent processing, i.e. speckle suppression and segmentation. For the speckle suppression, an improved speckle filter is developed in order to retain the meaningful image features, such as edges, lines, textures, during the filtering process. In the fourth module, an existing hybrid segmentation algorithm is extended for POLSAR data. The hybrid algorithm makes use of both edge and region information during the segmentation process. Finally, land cover classification of pre-processed POLSAR data is performed on per-pixel and per-segment bases. In addition, unsupervised classification of POLSAR data, which is based on scattering mechanisms,

is also conducted and analysed. Further detailed discussion about each module is given in Chapters 3–7.

Figure 1.2: Outline of methodology

1.5 Thesis Organisation

This thesis comprises eight chapters. The remaining part of this thesis is structured as follows:

Chapter 2 provides fundamental concepts of microwave remote sensing and radar polarimetry.

The geographical test site identified for this study is presented in Chapter 3. Furthermore, this chapter also gives the details of experimental data, namely NASA/JPL POLSAR data and simulated POLSAR data.

Chapter 4 describes edge detection in POLSAR data. Two new edge detectors, which are based separately on the Roy's largest eigenvalue and the trace ratio, are introduced

and benchmarked against the existing likelihood ratio edge detector. Moreover, edge detection based on the Dowson-Landau metric and the Euclidean distance is also discussed for comparisons.

In Chapter 5, focus is placed on speckle suppression in POLSAR data. A novel spatially adaptive speckle filter is introduced, which aims at preserving point-like textural features as well as structural features, i.e. edges and lines, during the filtering process. Comparisons of the proposed speckle filter with the existing boxcar, Lee-refined and annealing filters are also included in this chapter.

Chapter 6 presents region-based segmentation carried out in this study, in particular on the extension of an existing hybrid segmentation algorithm for POLSAR data. Besides the extended algorithm, the application and performance evaluation of another segmentation algorithm, i.e. the hierarchical stepwise optimisation algorithm, are also provided.

In Chapter 7, POLSAR image classification based separately on scattering mechanisms and statistical distribution is presented. For the scattering property-based unsupervised classification, the results from three different schemes are given, namely van Zyl's scattering classification, Freeman-Durden scattering model as well as Cloude-Pottier target decomposition. In the supervised classification based on complex Wishart distribution, the outputs generated using the following three different inputs are shown, namely (i) unfiltered data, (ii) filtered data, and (iii) segmented data.

Conclusions, contributions and recommendations are placed in the final Chapter 8.

Chapter 2

Basics of Radar Polarimetry

2.1 Introduction

This chapter presents fundamental concepts of microwave remote sensing and radar polarimetry, which are essential for the analysis of dual-frequency polarimetric SAR data in the following chapters. For an in-depth study on microwave remote sensing, the reader may refer to Ulaby *et al.* (1981, 1982, 1986), Oliver and Quegan (1998) as well as Henderson and Lewis (1998). A throughout discussion on radar polarimetry can be found in Ulaby and Elachi (1990), Kong (1990) as well as Mott (1992).

2.2 Microwave Remote Sensing

2.2.1 Electromagnetic Waves and Microwaves

The existence of electromagnetic waves was first mathematically formulated by James Clerk Maxwell in 1865. They were then proven experimentally by Heinrich Rudolf Hertz in 1886. As shown in Figure 2.1, the electromagnetic waves are the energy transports through free space in the form of periodic disturbances of both electric and magnetic fields propagating at the constant speed of light c . The distance from one wave crest to the next is the wavelength λ and the number of peaks passing in space per unit time is the wave frequency f . The relationship between these two quantities and the speed of light is

$$c = \lambda f = 2.99792458 \times 10^8 \text{ m/s.} \quad (2.1)$$

Figure 2.1: Electromagnetic wave. The electric field is perpendicular to the magnetic field along the propagating direction.

In the electromagnetic spectrum (Figure 2.2), radio waves are the electromagnetic waves having wavelengths greater than 1 mm. As a subset of the radio waves, microwaves are subdivided into bands and each band is designated by a letter. Table 2.1 tabulates the frequency and wavelength ranges of each microwave band. Both clouds and haze have no effect on microwaves at the wavelengths above 2 cm, while rain is transparent at wavelengths above 4 cm.

Figure 2.2: Electromagnetic spectrum (After Rees, 2001).

Table 2.1: Microwave band designations

Band	Frequency range (GHz)	Wavelength range (cm)
P	0.3 – 1	30 – 100
L	1 – 2	15 – 30
S	2 – 4	7.5 – 15
C	4 – 8	3.8 – 7.5
X	8 – 12.5	2.4 – 3.8
K _u	12.5 – 18	1.7 – 2.4
K	18 – 26.5	1.1 – 1.7
K _a	26.5 – 40	0.75 – 1.1

2.2.2 Imaging Radar

Imaging radar is an active remote sensing technique, which provides its own energy source of microwave radiation to illuminate targets (hereafter called scatterers). The word “radar” is the acronym for *radio detection and ranging*. Being an active remote sensing system, the imaging radar is independent of sun light and can work day and night equally well.

As shown in Figure 2.3, the side-looking imaging radar antenna first transmits a pulse of microwave energy in a direction perpendicular to the flight direction, which is known as range or across-track direction. It then records the microwave echoes, which are backscattered by the illuminated scatterers at different ranges from the radar antenna. The transmitting and receiving operations are continued along the flight direction (also called azimuth or along-track direction). A radar image is then produced in the final process where each image pixel exhibits two different resolutions, namely range resolution and azimuth resolution corresponding to the range and flight directions, respectively.

Figure 2.3: Operating principle of imaging radar. (a) Propagation of one radar pulse and (b) resulting antenna return (After Lillesand and Kiefer, 1994).

In microwave remote sensing, there are two common imaging radar systems: Real Aperture Radar (RAR) and Synthetic Aperture Radar (SAR). The main difference between both systems is the capability to generate a fine azimuth resolution. The azimuth resolution of a RAR system is defined by $r_a = R(\lambda/d_a)$, where R is the slant range between radar antenna and the illuminated scatters, λ refers to the wavelength and d_a is the antenna length in the azimuth direction. For a SAR system, the azimuth resolution is $r_a = d_a/2$. In spaceborne applications, RAR systems are found to be impractical. For example, if the slant range is in hundreds of kilometres, a very long antenna (in kilometres) is thus needed to obtain a fine azimuth resolution. Since the azimuth resolution of SAR system depends solely on d_a , it has been greatly accepted in the design of microwave satellites.

Table 2.2 lists all the past and currently available SAR satellites. The single-frequency single-polarisation SAR satellites include Seasat, ALMAZ-1, ERS-1, JERS-1 and ERS-2. Both ENVISAT and TerraSAR-X provide three different alternating polarisations, namely (i) HH and VV, (ii) HH and HV as well as (iii) HV and VV. To date, there are two fully polarimetric SAR satellites in space, i.e. ALOS and RADARSAT-2. Fully polarimetric SAR satellites can operate on full polarisations, i.e. HH, HV, VH and VV, during data acquisition.

Table 2.2: Past and currently available SAR satellites

Satellite	Owner	Launch date	Band	Wavelength	Polarisation
Seasat	USA	26 June 1978	L	23.5 cm	HH
ALMAZ-1	USSR	31 March 1991	S	9.6 cm	HH
ERS-1	Europe	17 July 1991	C	5.7 cm	VV
JERS-1	Japan	11 February 1992	L	23.5 cm	HH
ERS-2	Europe	21 April 1995	C	5.7 cm	VV
RADARSAT-1	Canada	4 November 1995	C	5.7 cm	HH
ENVISAT	Europe	1 March 2002	C	5.6 cm	HH/HV HH/VV HV/VV
TerraSAR-X	Germany	15 June 2007	X	3.1 cm	HH/HV HH/VV HV/VV
ALOS	Japan	24 January 2006	L	23.5 cm	HH, VV, HV, VH
RADARSAT-2	Canada	18 December 2007	C	5.7 cm	HH, VV, HV, VH

2.2.3 Scattering Mechanisms of Radar Waves

As explained in the previous section, the imaging radar measures the radar energy backscattered by illuminated scatterers. The degree of radar backscattering is characterised by the physical interactions between the incident radar waves and the scatterers. These interactions are known as scattering mechanisms, which can take the form of specular reflection, rough surface scattering, corner reflection and volume scattering. Figure 2.4 shows the scattering mechanisms of radar waves.

Figure 2.4: Scattering mechanisms of radar waves. (a) Specular reflection, (b) rough surface scattering, (c) corner reflection, and (d) volume scattering (After Richards and Jia, 1999).

The specular reflection occurs on smooth surfaces, which behave like mirrors. In Figure 2.4(a), the incident wave is completely reflected by the smooth surface in the forward direction and away from the radar antenna. Hence, the smooth surface appears very dark in the radar image. For example, roads and runways exhibit such a scattering behaviour.

If the smooth surface is tilted towards the radar antenna and perpendicular to the radar look direction, the incident wave is entirely reflected back towards the radar antenna causing a very strong radar backscattering [Figure 2.5(a)]. Thus, smooth surface appears very bright in radar imagery.

Figure 2.5: Backscattering mechanisms in urban areas. (a) Specular reflection by tilted building rooftop and (b) double-bounce reflection by wall-ground structures (After Dong *et al.*, 1997).

For a rough surface, the incident wave is scattered in all directions including back towards the radar antenna [Figure 2.4(b)]. In this mechanism, the strength of radar backscattering depends mainly on the surface roughness. The rougher the surface, the stronger the radar backscattering is. The rough surface scattering is often shown by rough bare soil surfaces and wind-blown ocean surfaces.

The corner reflection, also called double-bounce reflection, results from two perpendicularly intersecting surfaces as presented in Figure 2.4(c). In total, the radar wave is reflected twice in the forward direction and the forward-forward reflected wave then propagates back towards the radar antenna (in the backscatter direction) giving a strong radar backscattering. The double-bounce reflection occurs commonly in urban areas due to the wall-ground structure, which acts as a dihedral corner reflector [Figure 2.5(b)].

The volume scattering arises from the penetration of radar waves into a layer of randomly oriented scatterers, for example, a vegetation canopy layer containing leaves, twigs and branches. In Figure 2.4(d), the radar wave penetrates the canopy layer and is then scattered in all directions by the randomly oriented components in the canopy. The radar backscattering from the vegetation layer varies in degree depending on the radar

wavelength and the canopy structure. The volume scattering can be easily observed in both thick shrubs and forests.

2.3 Radar Polarimetry

2.3.1 Polarisation and Depolarisation

According to the IEEE (1997), polarisation refers to the locus of the electric field vector tip of an electromagnetic wave, which is observed in a plane orthogonal to the wave normal. A wave is elliptically polarised, where its electric field vector follows an elliptical path. However, there exist two special cases: linear and circular polarisations. The wave is linearly polarised if the electric vector lies on a fixed straight line. If the locus of the electric vector is a circle, the wave is said to be circularly polarised.

The polarisation of an electromagnetic wave can be altered. The change in polarisation occurs as a consequence of the propagation, reflection, scattering and/or diffraction. This process is known as depolarisation (Long, 2001).

2.3.2 Polarisation State and Polarisation Ellipse

Polarisation state refers to the condition of the polarisation of a plane wave, at a given point in space, as described by axial ratio, orientation angle and polarisation sense (IEEE, 1993). Based on the polarisation ellipse given in Figure 2.6, the axial ratio is defined as $r = b/a$, where a and b correspond to the major and minor axes of the ellipse, respectively. The ellipticity angle is obtained from the axial ratio as $\chi = \tan^{-1}(r)$. It ranges from -45° to 45° . For the orientation angle ψ , it is the angle between major axis and horizontal reference axis (i.e. x -axis). The range of the orientation angle is between 0° and 180° . Figure 2.7 presents the different ellipticity and orientation angles for different polarisation states.

The polarisation sense can only be defined in both circularly and elliptically polarised waves. It refers to the direction of rotation of the electric field vector of an electromagnetic wave. If the sense of rotation is defined as clockwise viewing along the propagation direction, then the polarisation sense is called right-handed. It is left-handed if anticlockwise viewing is considered (Figure 2.8).

Figure 2.6: Polarisation ellipse. a and b are the major and minor axes, respectively. $|E|$ refers to the amplitude of the electric field.

Figure 2.7: Different ellipticity and orientation angles for different polarisation states. (a) Linear horizontal polarisation where $b = 0$, $\chi = 0^\circ$ and $\psi = 0^\circ$, (b) linear vertical polarisation where $b = 0$, $\chi = 0^\circ$ and $\psi = 90^\circ$, (c) circular polarisation where $a = b$, $\chi = -45^\circ$ or 45° and $0^\circ \leq \psi \leq 180^\circ$.

Figure 2.8: Polarisation sense. (a) Right-handedness where $\chi < 0$ and (b) left-handedness where $\chi > 0$.

2.3.3 Stokes Vector and Poincaré Sphere

As shown in Equation (2.2), the Stokes vector $\mathbf{g}$ is composed of four quantities, which were introduced by Stokes (1852) for characterising the amplitude and polarisation of light:

$$\mathbf{g} = \begin{bmatrix} I \\ Q \\ U \\ V \end{bmatrix} = \begin{bmatrix} |E_x|^2 + |E_y|^2 \\ |E_x|^2 - |E_y|^2 \\ 2\Re(E_x E_y^*) \\ 2\Im(E_x E_y^*) \end{bmatrix}. \quad (2.2)$$

Only three of the four quantities are independent since $I^2 = Q^2 + U^2 + V^2$. The parameters I and Q are the summation and difference of the intensities of both orthogonal x - and y -axis components in electric field, respectively. The parameter U can be interpreted as the intensity difference of the 45° -rotated two orthogonal components, while V is the intensity difference of the right-hand and the left-hand circularly polarised components (Barakat, 1987; Touzi and Lopes, 1996).

An electromagnetic wave is said to be completely polarised if $I^2 = Q^2 + U^2 + V^2$ whereas it is unpolarised (or randomly polarised) if $Q = U = V = 0$. For the electromagnetic waves that consist of both completely polarised and unpolarised waves, the waves are known as partially polarised where $I^2 > Q^2 + U^2 + V^2$.

Alternatively, the Stokes vector can also be written in terms of the ellipticity angle χ and the orientation angle ψ as

$$\mathbf{g} = \begin{bmatrix} I \\ Q \\ U \\ V \end{bmatrix} = \begin{bmatrix} g_0 \\ g_1 \\ g_2 \\ g_3 \end{bmatrix} = \begin{bmatrix} g_0 \\ g_0 \cos 2\chi \cos 2\psi \\ g_0 \cos 2\chi \sin 2\psi \\ g_0 \sin 2\chi \end{bmatrix}. \quad (2.3)$$

Table 2.3 gives the Stokes vectors of different polarisation states, which are computed using Equation (2.3) with a normalisation by g_0 .

Table 2.3: Normalised Stokes vectors of different polarisation states

Polarisation state	Ellipticity angle χ	Orientation angle ψ	Normalised Stokes vector
Linear horizontal	0°	0°	$[1 \ 1 \ 0 \ 0]^T$
Linear vertical	0°	90°	$[1 \ -1 \ 0 \ 0]^T$
Linear 45°	0°	45°	$[1 \ 0 \ 1 \ 0]^T$
Linear 135°	0°	135°	$[1 \ 0 \ -1 \ 0]^T$
Left-handed circular	45°	$0^\circ-180^\circ$	$[1 \ 0 \ 0 \ 1]^T$
Right-handed circular	-45°	$0^\circ-180^\circ$	$[1 \ 0 \ 0 \ -1]^T$

Based on the above mentioned Stokes vector, any polarisation state can thus be represented on the well-known Poincaré sphere. The Poincaré sphere is centred at origin with the Stokes vector elements g_1 , g_2 and g_3 as the rectangular coordinates (Figure 2.9). It is a unit sphere with radius of g_0 . The equator represents all states of linear polarisation. Both north and south poles correspond to the left-handed and right-handed circular polarisations, respectively. All left-handed elliptical polarisations lie on the upper hemisphere while all right-handed elliptical polarisations are located on the lower hemisphere.

Figure 2.9: Poincaré sphere. The longitude and latitude for any points on Poincaré sphere are 2ψ and 2χ , respectively (Tsang *et al.*, 2000).

2.3.4 Scattering Matrix and Scattering Vector

The scattering matrix $\mathbf{S}$, which is also known as Sinclair matrix in the radar backscattering case, is a 2×2 complex matrix. It relates the received electric field $\mathbf{E}^{\text{rec}}$ to the transmitted electric field $\mathbf{E}^{\text{trans}}$ by

$$\mathbf{E}^{\text{rec}} = \frac{e^{jkr}}{r} \mathbf{S} \mathbf{E}^{\text{trans}}, \quad (2.4)$$

where $j = \sqrt{-1}$ (Boerner *et al.*, 1998). The parameter k is the radar wavenumber ($k = 2\pi / \lambda$ with λ being the radar wavelength), while r refers to the distance between the scatterer and the radar antenna.

Decomposing the electric field $\mathbf{E}$ into the horizontal and vertical components gives

$$\begin{bmatrix} E_H \\ E_V \end{bmatrix}^{\text{rec}} = \frac{e^{jkr}}{r} \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \begin{bmatrix} E_H \\ E_V \end{bmatrix}^{\text{trans}}, \quad (2.5)$$

where S_{pq} refers to the scattering matrix element of the received polarisation p and transmitted polarisation q . The subscripts H and V represent horizontal and vertical linear polarisation, respectively. S_{HH} and S_{VV} are known as the co-polarised scattering matrix elements, while S_{HV} and S_{VH} are the cross-polarised (or depolarised) scattering matrix elements. In the reciprocal backscattering case, the scattering matrix becomes a symmetric matrix with $S_{HV} = S_{VH}$. Each scattering matrix element has both amplitude A and phase ϕ as follows:

$$\mathbf{S} = \begin{bmatrix} A_{HH} \exp(j\phi_{HH}) & A_{HV} \exp(j\phi_{HV}) \\ A_{VH} \exp(j\phi_{VH}) & A_{VV} \exp(j\phi_{VV}) \end{bmatrix}. \quad (2.6)$$

Alternatively, the scattering matrix for the reciprocal backscattering case can also be expressed by a complex scattering vector $\mathbf{s}$:

$$\mathbf{s} = \begin{bmatrix} S_{HH} \\ \sqrt{2} S_{HV} \\ S_{VV} \end{bmatrix}. \quad (2.7)$$

The complex scattering vector was assumed by Kong *et al.* (1987), in a single-look POLSAR image classification, to follow a zero-mean three-variate complex Gaussian distribution (Wooding, 1953):

$$P(\mathbf{s}) = \frac{1}{\pi^3 |\mathbf{C}|} \exp(-\mathbf{s}^{*T} \mathbf{C}^{-1} \mathbf{s}), \quad (2.8)$$

where the superscript $*$ and T denote separately the complex conjugate and the transpose of a vector. The matrix $\mathbf{C}$ is the Hermitian covariance matrix.

2.3.5 Kennaugh Matrix

Using the aforementioned scattering matrix, a 4×4 real symmetric matrix, called Kennaugh matrix (Mott, 1992; Guissard, 1994), can be derived based on $\mathbf{K} = \frac{1}{2} \mathbf{Q}^* \mathbf{S} \otimes \mathbf{S}^* \mathbf{Q}^{*T}$ (see equation below) in which the symbol $\otimes$ denotes the Kronecker product:

$$\begin{bmatrix} k_{11} & k_{12} & k_{13} & k_{14} \\ k_{21} & k_{22} & k_{23} & k_{24} \\ k_{31} & k_{32} & k_{33} & k_{34} \\ k_{41} & k_{42} & k_{43} & k_{44} \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & -1 \\ 0 & 1 & 1 & 0 \\ 0 & j & -j & 0 \end{bmatrix}^* \begin{bmatrix} S_{HH} S_{HH}^* & S_{HH} S_{HV}^* & S_{HV} S_{HH}^* & S_{HV} S_{HV}^* \\ S_{HH} S_{VH}^* & S_{HH} S_{VV}^* & S_{HV} S_{VH}^* & S_{HV} S_{VV}^* \\ S_{VH} S_{HH}^* & S_{VH} S_{HV}^* & S_{VV} S_{HH}^* & S_{VV} S_{HV}^* \\ S_{VH} S_{VH}^* & S_{VH} S_{VV}^* & S_{VV} S_{VH}^* & S_{VV} S_{VV}^* \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & -1 \\ 0 & 1 & 1 & 0 \\ 0 & j & -j & 0 \end{bmatrix}^{T*}, \quad (2.9)$$

where

$$\begin{aligned} k_{11} &= \frac{S_{HH} S_{HH}^*}{2} + \frac{S_{VV} S_{VV}^*}{2} + S_{HV} S_{HV}^*, \\ k_{12} &= \frac{S_{HH} S_{HH}^*}{2} - \frac{S_{VV} S_{VV}^*}{2}, \\ k_{13} &= \Re(S_{HH} S_{HV}^*) + \Re(S_{HV} S_{VV}^*), \\ k_{14} &= \Im(S_{HH} S_{HV}^*) + \Im(S_{HV} S_{VV}^*), \\ k_{22} &= \frac{S_{HH} S_{HH}^*}{2} + \frac{S_{VV} S_{VV}^*}{2} - S_{HV} S_{HV}^*, \\ k_{23} &= \Re(S_{HH} S_{HV}^*) - \Re(S_{HV} S_{VV}^*), \\ k_{24} &= \Im(S_{HH} S_{HV}^*) - \Im(S_{HV} S_{VV}^*), \\ k_{33} &= S_{HV} S_{HV}^* + \Re(S_{HH} S_{VV}^*), \\ k_{34} &= \Im(S_{HH} S_{VV}^*), \\ k_{44} &= S_{HV} S_{HV}^* - \Re(S_{HH} S_{VV}^*). \end{aligned} \quad (2.10)$$

The Kennaugh matrix $\mathbf{K}$ relates the Stokes vector of the transmitted wave $\mathbf{g}^t$ to the Stokes vector of the backscattered wave $\mathbf{g}^s$ in the following manner: $\mathbf{g}^s = \mathbf{K} \mathbf{g}^t$. It is used together with the normalised Stokes vector in polarisation synthesis, which is discussed

in Section 2.3.10. Equation (2.11) shows the relationship and derivation of the Kennaugh matrix from the Stokes matrix provided in NASA/JPL POLSAR data (hereafter called NASA/JPL Stokes matrix):

$$\mathbf{K} = 2 \begin{bmatrix} m_{11} & m_{12} & m_{13} & -m_{14} \\ m_{21} & m_{22} & m_{23} & -m_{24} \\ m_{31} & m_{32} & m_{33} & -m_{34} \\ -m_{41} & -m_{42} & -m_{43} & m_{44} \end{bmatrix}, \quad (2.11)$$

where m_{ij} is the Stokes matrix element given in Appendix A.

2.3.6 Covariance Matrix

Another important matrix representation in radar polarimetry is the covariance matrix representation. It is defined by

$$\mathbf{C} = \langle \mathbf{s} \mathbf{s}^{*T} \rangle = \left\langle \begin{bmatrix} S_{HH} S_{HH}^* & \sqrt{2} S_{HH} S_{HV}^* & S_{HH} S_{VV}^* \\ \sqrt{2} S_{HV} S_{HH}^* & 2 S_{HV} S_{HV}^* & \sqrt{2} S_{HV} S_{VV}^* \\ S_{VV} S_{HH}^* & \sqrt{2} S_{VV} S_{HV}^* & S_{VV} S_{VV}^* \end{bmatrix} \right\rangle, \quad (2.12)$$

where $\mathbf{s}$ is the zero-mean complex scattering vector given in Section 2.3.4. In NASA/JPL POLSAR data, each element in the covariance matrix can be computed from the Stokes matrix using the following relations (Lee *et al.*, 1994):

$$\begin{aligned} S_{HH} S_{HH}^* &= m_{11} + m_{22} + 2m_{12}, \\ S_{HV} S_{HV}^* &= m_{11} - m_{22}, \\ S_{VV} S_{VV}^* &= m_{11} + m_{22} - 2m_{12}, \\ S_{HH} S_{VV}^* &= (m_{33} - m_{44}) + j(-2m_{34}), \\ S_{HH} S_{HV}^* &= (m_{13} + m_{23}) + j(-m_{14} - m_{24}), \\ S_{HV} S_{VV}^* &= (m_{13} - m_{23}) + j(-m_{14} + m_{24}). \end{aligned} \quad (2.13)$$

The covariance matrix $\mathbf{C}$ is a Hermitian positive semi-definite matrix, where $\mathbf{C} = \mathbf{C}^H$ with $\mathbf{C}^H$ being the complex conjugate transpose of $\mathbf{C}$. Multiplying the covariance matrix with the number of looks n , the matrix $\mathbf{Z} = n\mathbf{C}$ can be assumed to follow a central complex Wishart distribution $CW(n, q, \Sigma)$ with a population covariance matrix Σ (Goodman, 1963):

$$P(\mathbf{C}) = \frac{n^{qn} |\mathbf{C}|^{n-q} e^{-n \text{tr}(\Sigma^{-1} \mathbf{C})}}{K(n, q) |\Sigma|^n}, \quad (2.14)$$

where the operator tr denotes the matrix trace. The variable q refers to the dimension of the covariance matrix. The function $K(n, q)$ is equal to $\pi^{0.5q(q-1)}\Gamma(n)\dots\Gamma(n-q+1)$, with $\Gamma(\cdot)$ being the Gamma function.

2.3.7 Coherency Matrix

The coherency matrix $\mathbf{T}$ is based on the Pauli matrix representation. As shown in Equation (2.15) for the reciprocal backscattering case, it is formed using the Pauli-based coherency vector $\mathbf{k}$:

$$\mathbf{T} = \langle \mathbf{k} \mathbf{k}^{*T} \rangle = \frac{1}{2} \left\langle \begin{bmatrix} (S_{HH} + S_{VV})(S_{HH} + S_{VV})^* & (S_{HH} + S_{VV})(S_{HH} - S_{VV})^* & 2(S_{HH} + S_{VV})S_{HV}^* \\ (S_{HH} - S_{VV})(S_{HH} + S_{VV})^* & (S_{HH} - S_{VV})(S_{HH} - S_{VV})^* & 2(S_{HH} - S_{VV})S_{HV}^* \\ 2S_{HV}(S_{HH} + S_{VV})^* & 2S_{HV}(S_{HH} - S_{VV})^* & 4S_{HV}S_{HV}^* \end{bmatrix} \right\rangle, \quad (2.15)$$

with

$$\mathbf{k} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ 2S_{HV} \end{bmatrix}. \quad (2.16)$$

Since both the coherency and covariance matrices are linearly related, the Hermitian coherency matrix can be obtained through a linear conversion from the covariance matrix $\mathbf{C}$ (Lee *et al.*, 1999a), i.e.

$$\mathbf{T} = \mathbf{N} \mathbf{C} \mathbf{N}^T, \quad (2.17)$$

with

$$\mathbf{N} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 & 1 \\ 1 & 0 & -1 \\ 0 & \sqrt{2} & 0 \end{bmatrix}. \quad (2.18)$$

2.3.8 Incoherence Components

There are three incoherence components, namely intensity, total power and polarisation ratio. For HH, HV and VV polarisations, the intensities can be computed directly from the NASA/JPL Stokes matrix as follows:

$$|S_{HH}|^2 = m_{11} + m_{22} + 2m_{12}, \quad (2.19)$$

$$|S_{HV}|^2 = m_{11} - m_{22},$$

$$|S_{VV}|^2 = m_{11} + m_{22} - 2m_{12}.$$

The intensity is related to the radar cross section σ by $\sigma_r = 4\pi|S_r|^2$, where r and t refer to the received and transmitted polarisations, respectively. The summation of HH, HV and VV intensities is called total power or span:

$$\text{span} = |S_{HH}|^2 + 2|S_{HV}|^2 + |S_{VV}|^2. \quad (2.20)$$

The polarisation ratio is the ratio of two different polarisation intensities. Equations (2.21) and (2.22) define the co-polarisation ratio r_{co} and the cross-polarisation ratio r_{cross} , respectively. Also, their relationship with the NASA/JPL Stokes matrix elements is given:

$$r_{\text{co}} = \frac{|S_{VV}|^2}{|S_{HH}|^2} = \frac{m_{11} + m_{22} - 2m_{12}}{m_{11} + m_{22} + 2m_{12}}, \quad (2.21)$$

$$r_{\text{cross}} = \frac{|S_{HV}|^2}{|S_{HH}|^2} = \frac{m_{11} - m_{22}}{m_{11} + m_{22} + 2m_{12}}. \quad (2.22)$$

2.3.9 Coherence Components

One of the distinctive features of polarimetric radar is its ability to measure phase differences between different polarisations. The phase difference provides the information about the travelling delay in the electric path causing by the illuminated scatterers with respect to different polarisations. The expressions for both co-polarised phase difference $\phi_{\text{HH-VV}}$ and cross-polarised phase difference $\phi_{\text{HH-HV}}$ are

$$\begin{aligned} \phi_{\text{HH-VV}} &= \tan^{-1} \frac{\Im(S_{\text{HH}} S_{\text{VV}}^*)}{\Re(S_{\text{HH}} S_{\text{VV}}^*)} = \tan^{-1} \frac{-2m_{34}}{m_{33} - m_{44}}, \\ \phi_{\text{HH-HV}} &= \tan^{-1} \frac{\Im(S_{\text{HH}} S_{\text{HV}}^*)}{\Re(S_{\text{HH}} S_{\text{HV}}^*)} = \tan^{-1} \frac{-(m_{14} + m_{24})}{m_{13} - m_{23}}. \end{aligned} \quad (2.23)$$

Apart from the phase difference, there is another coherence component which has been of considerable interest in radar polarimetry, i.e. the co-polarised correlation coefficient. The complex correlation coefficient in co-polarisation takes the following form:

$$\rho_{HH-VV} = \frac{\langle S_{HH} S_{VV}^* \rangle}{\sqrt{\langle |S_{HH}|^2 \rangle \langle |S_{VV}|^2 \rangle}}, \quad (2.24)$$

where $\langle \cdot \rangle$ is the ensemble average. The correlation magnitude $|\rho_{HH-VV}|$, ranging from zero to one, can be computed from Equation (2.24). The correlation magnitude indicates the degree to which S_{HH} and S_{VV} are correlated. If $|\rho_{HH-VV}| = 1$, it implies that S_{HH} and S_{VV} are perfectly correlated. Both S_{HH} and S_{VV} are completely uncorrelated if $|\rho_{HH-VV}| = 0$.

2.3.10 Polarisation Synthesis and Polarisation Signature

Polarisation synthesis is a process for determining the response of a scatterer to an arbitrary combination of transmitted and received polarisations through the scattering matrix or Kennaugh matrix, without actually transmitting and receiving these polarisation states (Zebker *et al.*, 1987; Zebker and van Zyl, 1991; Sletten and McLaughlin, 1999). Here, the response refers to the intensity I , which is related to the amplitude A by $I = A^2$.

Equation (2.25) shows the derivation of the intensity in either co- or cross-polarisation for different ellipticity and orientation angle combinations by using both normalised Stokes vector and Kennaugh matrix:

$$I(\chi_r, \psi_r; \chi_t, \psi_t) = \begin{bmatrix} 1 \\ \cos 2\chi_r \cos 2\psi_r \\ \cos 2\chi_r \sin 2\psi_r \\ \sin 2\chi_r \end{bmatrix}^T \begin{bmatrix} k_{11} & k_{12} & k_{13} & k_{14} \\ k_{21} & k_{22} & k_{23} & k_{24} \\ k_{31} & k_{32} & k_{33} & k_{34} \\ k_{41} & k_{42} & k_{43} & k_{44} \end{bmatrix} \begin{bmatrix} 1 \\ \cos 2\chi_t \cos 2\psi_t \\ \cos 2\chi_t \sin 2\psi_t \\ \sin 2\chi_t \end{bmatrix}, \quad (2.25)$$

where ψ_t and χ_t denote the orientation and ellipticity angles of the transmitted polarisations, while ψ_r and χ_r are the orientation and ellipticity angles of the received polarisations. For the co-polarisation, $\chi_r = \chi_t$ and $\psi_r = \psi_t$, while $\chi_r = -\chi_t$ and $\psi_r = \psi_t + 90^\circ$ in the case of cross-polarisation.

The polarisation signature is a three-dimensional plot of the synthesised intensity values as a function of the ellipticity angle χ ($-45^\circ \leq \chi \leq 45^\circ$) and the orientation angle ψ ($0^\circ \leq \psi \leq 180^\circ$). Figure 2.10 shows an example of both co- and cross-polarisation

signature plots, where the z -axis gives the intensity values corresponding to the different ellipticity and orientation angle combinations.

$$\mathbf{K} = \begin{bmatrix} 0.1426 & -0.0105 & -0.0010 & 0.0009 \\ -0.0105 & 0.1176 & -0.0028 & 0.0008 \\ -0.0010 & -0.0028 & 0.0903 & -0.0051 \\ 0.0009 & 0.0008 & -0.0051 & -0.0653 \end{bmatrix}$$

(c)

Figure 2.10: Polarisation signature plots. (a) and (b) are separately the co- and cross-polarisation signature plots, which are generated based on the Kennaugh matrix in (c).

Chapter 3

Data Acquisition

3.1 Introduction

This chapter presents the geographical test site selected for this study. Furthermore, the details of experimental data, namely NASA/JPL POLSAR data and simulated POLSAR data, are also discussed in this chapter.

3.2 Study Area

The test site identified for this study is a coastal plain in the north-west of Peninsular Malaysia. It is selected because of (i) the variety of land cover features and (ii) the availability of multi-frequency POLSAR data. The test site is situated at Kuala Muda of Kedah state, which is bounded between $5^{\circ} 36'$ and $5^{\circ} 44'$ N latitude as well as between $100^{\circ} 23'$ and $100^{\circ} 29'$ E longitude. Figure 3.1 shows the location of the test site.

Being an active agricultural zone, large portions of the area are irrigated land which is cultivated mainly with rice paddy crops. Both rubber and oil palm trees are planted on a moderate scale. In Figures 3.2 and 3.3, a river called Sungai Merbok is observable, which flows into the Strait of Malacca. Along both riversides, mangrove forests are clearly found and are part of Sungai Merbok Forest Reserve which is under the jurisdiction of Kedah Forest Department. The town of Sungai Petani is located at the bottom left corner of the scene. The captured photographs of selected land cover features during a field visit, which was carried out on the 5th of February 2005, are also provided in Figures 3.2 and 3.3.

Figure 3.1: Location map of study area. The study area, which is located at the north-west of Peninsular Malaysia, is depicted with a rectangle (Source: Collins *et al.*, 1991).

3.3 Experimental Data

In this study both NASA/JPL POLSAR data as well as simulated POLSAR data were used for experiments. They are explained in detail below.

3.3.1 NASA/JPL POLSAR Data

The dual-frequency NASA/JPL POLSAR data employed in this study were acquired on the 19th of September 2000 using the AIRSAR imaging system onboard a DC-8 research aircraft. The aircraft flew at approximately 8 km altitude during the data collection of the PACRIM-2 science mission. The look angles were 26° and 62.5° corresponding to the near and far ranges of 9 km and 17 km, respectively. The nine-look POLSAR data, with C-, L- and P-band in full polarisation (HH, HV and VV), were completely processed on the 12th of March 2002 and released for public access through the NASA/JPL AIRSAR website since 2004. The POLSAR data are distributed in compressed Stokes matrix format where ten bytes resemble one pixel. Appendix A provides the derivation of the Stokes matrix for each pixel from the ten bytes. In this study only the C- and L-band data were examined since the P-band suffers from undesirable radio frequency interference. The details of the POLSAR test data are summarised in Table 3.1.

Figures 3.2 and 3.3 present separately the POLSAR C- and L-band images with an image size of 2250 columns by 2831 rows. In both figures, the colour images show the intensities of HH, HV and VV polarisations in the RGB colour space, where different land cover features can be obviously distinguished. For visual comparisons, the intensity image of individual polarisation is displayed in Figures 3.4 and 3.5 for the C- and L-band, respectively. As can be seen in Figures 3.4 and 3.5, the HH polarisation is found to be particularly good in highlighting built-up areas, while different plantation stages over rice paddy fields are clearly noticeable in the VV polarisation. For the HV polarisation, built-up areas appear darker compared with both the HH and VV polarisations. Moreover, oil palm plantation areas are easily distinguished in the C-band HV intensity image.

To emphasise scattering mechanisms embedded in the POLSAR data, the C- and L-band image displays, which are based on the coherency matrix representation (Chen,

2002), are also provided separately in Figures 3.6 and 3.7. In both figures, the intensities $\langle |S_{HH} - S_{VV}|^2 \rangle$, $\langle |S_{HV}|^2 \rangle$ and $\langle |S_{HH} + S_{VV}|^2 \rangle$ are displayed in the RGB colour space. For surface scattering, the scattering elements S_{HH} and S_{VV} are in-phase, while both are out of phase in the case of double-bounce scattering. Consequently, the summation $\langle |S_{HH} + S_{VV}|^2 \rangle$ and subtraction $\langle |S_{HH} - S_{VV}|^2 \rangle$ favour in highlighting the surface and double-bounce scattering, respectively. For volume scatterers, the higher returns in $\langle |S_{HV}|^2 \rangle$ are normally observed. As can be seen in Figure 3.6, both rice paddy fields and built-up areas in the C-band are in red or magenta colour showing their dominant double-bounce scattering behaviour. In both the C- and L-band, marshland appears in purple-blue colour due to its dominant surface scattering characteristics. For mangrove forests and rubber plantation areas, volume scattering is predominantly observed with their appearance in green colour. Further detailed analysis and quantitative assessment on the scattering mechanisms of each land cover features are discussed in Chapter 7.

Table 3.1: Specifications of NASA/JPL POLSAR test data

Image title	MudaMerbok354-1
CCT ID	CM6419
Data format	Compressed Stokes matrix
Acquisition date	19 th September 2000
Processing date	12 th March 2002
Wavelength (cm)	C (5.6), L (24)
Polarisation	Full polarisation (HH, VV, HV)
Number of looks in azimuth	9
Number of looks in range	1
Pixel spacing (m)	3.33 (in range), 4.63 (in azimuth)
Near slant range (m)	9001.64
Far slant range (m)	17459.05
Near look angle (°)	26
Far look angle (°)	62.5

3.3.2 Simulated POLSAR Data

In order to evaluate effectively the performance of image processing algorithms, four multi-look simulated POLSAR datasets were generated following the procedure suggested by Lee *et al.* (1994). These datasets included four-look C-band, four-look L-band, nine-look C-band, and nine-look L-band. Each simulated data consists of 400 columns and 150 rows. Figure 3.8 presents the simulated POLSAR data containing four different land cover classes, namely rubber, oil palm, scrub-grassland, and rice paddy.

The covariance matrix parameters of the four land cover classes, which were used in the simulation, were extracted from the NASA/JPL POLSAR test data and are listed in Table 3.2. Figure 3.9 shows the training samples of the four land cover classes.

The procedure for simulating multi-look POLSAR data is as follows:

- Step 1: For each covariance matrix $\mathbf{C}_m$ belonging to land cover class m , compute $\mathbf{C}_m^{1/2}$.
- Step 2: Simulate a complex vector $\mathbf{v}$ which has the standard multivariate complex normal distribution. This is accomplished by independently generating the real and imaginary components of each complex element of $\mathbf{v}$ with a normal distribution having zero mean and half variance.
- Step 3: Compute $\mathbf{u} = \mathbf{C}_m^{1/2} \mathbf{v}$. The complex vector $\mathbf{u}$ is a single-look SAR pixel having a zero-mean multivariate complex normal distribution with its covariance matrix of $\mathbf{C}_m$.
- Step 4: Compute n -look polarimetric SAR pixel based on the following expression:

$$\mathbf{C} = \frac{1}{n} \sum_{k=1}^n \mathbf{u}(k) \mathbf{u}(k)^{*T}, \quad (3.1)$$

where $*$ denotes complex conjugate and T refers to the matrix transpose.

Table 3.2: Average covariance matrix elements of four land cover classes used in POLSAR data simulation

	$\langle S_{HH} ^2 \rangle$	$\langle S_{VV} ^2 \rangle$	$\langle S_{HV} ^2 \rangle$	$\langle \Re(S_{HH}S_{VV}^*) \rangle$	$\langle \Im(S_{HH}S_{VV}^*) \rangle$	$\langle \Re(S_{HH}S_{HV}^*) \rangle$	$\langle \Im(S_{HH}S_{HV}^*) \rangle$	$\langle \Re(S_{HV}S_{VV}^*) \rangle$	$\langle \Im(S_{HV}S_{VV}^*) \rangle$
<u>C-band</u>									
Oil palm	0.264207	0.279004	0.040803	0.165937	-0.022220	-0.002371	-0.000025	0.002897	0.001153
Rice paddy	0.025623	0.239487	0.003163	-0.035489	-0.027778	-0.002624	-0.000156	0.007022	0.004347
Rubber	0.330692	0.349460	0.069779	0.162641	-0.033113	-0.015131	0.004355	0.003390	-0.000286
Scrub-grassland	0.198137	0.145331	0.039112	0.058159	0.000543	-0.005821	0.001402	0.002761	-0.001709
<u>L-band</u>									
Oil palm	0.085866	0.047428	0.011574	0.016199	-0.007220	-0.000317	-0.000789	0.001686	0.000876
Rice paddy	0.001708	0.002961	0.000135	0.000431	0.000129	0.000079	-0.000004	0.000089	-0.000006
Rubber	0.169047	0.130151	0.035279	0.015564	-0.008120	-0.006517	0.001414	0.003260	0.003866
Scrub-grassland	0.019067	0.018642	0.001763	0.010207	0.001415	0.000437	0.000269	0.000312	0.000076

Figure 3.2: NASA/JPL POLSAR C-band three-intensity image with HH, HV and VV intensities displayed in the RGB colour space.

Figure 3.3: NASA/JPL POLSAR L-band three-intensity image with HH, VV and HV intensities displayed in the RGB colour space.

Figure 3.4: NASA/JPL POLSAR C-band intensity images of different polarisations, where HH, HV, VV and total power are given separately in (a)–(d).

Figure 3.5: NASA/JPL POLSAR L-band intensity images of different polarisations, where HH, HV, VV and total power are given in (a)–(d).

Figure 3.6: NASA/JPL POLSAR C-band image in coherency matrix representation, where $\langle |S_{HH} - S_{VV}|^2 \rangle$, $\langle |S_{HV}|^2 \rangle$ and $\langle |S_{HH} + S_{VV}|^2 \rangle$ are displayed in the RGB colour space.

Figure 3.7: NASA/JPL POLSAR L-band image in coherency matrix representation, where $\langle |S_{HH} - S_{VV}|^2 \rangle$, $\langle |S_{HV}|^2 \rangle$ and $\langle |S_{HH} + S_{VV}|^2 \rangle$ are displayed in the RGB colour space.

Figure 3.8: Simulated POLSAR data. (a) and (b) are the four- and nine-look C-band, while the four- and nine-look L-band are given in (c) and (d). For each image, the HH, HV and VV intensities are displayed in the RGB colour space. The areas of scrub, rice paddy, oil palm and rubber are labelled as A, B, C and D, respectively.

Figure 3.9: Training samples for POLSAR data simulation. The samples for scrub-grassland, rice paddy, oil palm and rubber are coloured in cyan, white, red and magenta, respectively. The sample sizes for scrub-grassland, rice paddy, oil palm and rubber are separately 1672, 924, 1350 and 1395 pixels.

Chapter 4

Edge Detection

4.1 Introduction

Edge detection is based on locating intensity discontinuities in an image. Due to the presence of inherent speckle noise in single-frequency single-polarisation SAR intensity data, the use of gradient-based edge detectors, which employ difference operation and are suitable for optical images, has been found to be inefficient for SAR images (Frost *et al.*, 1982; Touzi *et al.*, 1988; Fjørtoft *et al.*, 1998; Schou *et al.*, 2003). In particular, a tendency towards detection of false edges in brighter homogeneous areas, due to the multiplicative speckle noise characteristics, can be observed. More suitable are ratio and likelihood ratio edge detectors, which provide a constant false-alarm rate, i.e. the probability of false alarm (probability of detecting edges in a homogeneous area) is independent of the underlying mean intensities.

In this chapter, Section 4.2 reviews previous work on edge detection in POLSAR data. In Section 4.3 two new edge detectors for multi-look POLSAR data based on Roy's largest eigenvalue and trace ratio, respectively, are proposed. The results of all edge detectors are analysed and discussed in Section 4.4. Finally, Section 4.5 summarises this chapter.

4.2 Previous Work

From the literature review, it was found that so far only limited effort has been devoted to edge detection of fully polarimetric SAR images compared with those of single-frequency single-polarisation SAR intensity images.

To detect edges in single-look POLSAR data, Borghys (2001) proposed two multivariate edge detectors by examining separately the differences in variances and means using the Levene test and the Hotellings T^2 test, respectively. Both edge detectors were applied to E-SAR L-band data and the results of both detectors were found to be complementary. The Hotellings T^2 test was capable of detecting smaller roads while edges of large objects were better delimited through the Levene test.

For edge detection in multi-look POLSAR data, Schou *et al.* (2003) introduced a constant false-alarm rate polarimetric edge detector based on an equality test of two covariance matrices following a complex Wishart distribution. This edge detector is called likelihood ratio edge detector hereafter and is explained in more detail in Section 4.2.1. Applied to EMISAR C- and L-band polarimetric data, superior edge detection results were obtained using polarimetric and / or multi-frequency data compared with using only intensity data.

4.2.1 Likelihood Ratio Edge Detector

As discussed in Chapter 2, each pixel in multi-look POLSAR data can be represented by a $p \times p$ Hermitian covariance matrix $\mathbf{C}$. Multiplying the covariance matrix with the number of looks L , the matrix $\mathbf{Z} = L\mathbf{C}$ can be assumed to follow a central complex Wishart distribution $CW(p, L, \Sigma)$ with a population covariance matrix Σ . In order to detect edges in multi-look POLSAR imagery, the first polarimetric edge detector was introduced by Schou *et al.* (2003) based on a likelihood ratio equality test of two covariance matrices. Similar to Equation (5) in Fang *et al.* (1982, p. 609), the derived likelihood ratio test statistic is defined as

$$Q = \frac{(m+n)^{p(m+n)}}{m^{pm}n^{pn}} \frac{|\mathbf{Z}_{r1}|^m |\mathbf{Z}_{r2}|^n}{|\mathbf{Z}_{r1} + \mathbf{Z}_{r2}|^{m+n}}. \quad (4.1)$$

Figure 4.1 shows four basic edge templates of 3×3 pixels with different orientations. In each edge template, there are two equal sized contiguous test regions, namely $r1$ and $r2$, containing the same number of pixels, i.e. $k = 3$ for a 3×3 edge template. The variables m and n in Equation (4.1) refer to the number of looks in both the test regions.

Let the complex Wishart matrices $\mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_m$ in the test region $r1$ be mutually independent, then the summation of these matrices is also complex Wishart distributed as $CW(p, L_1 + L_2 + \dots + L_k, \Sigma_{r1})$ (Andersen *et al.*, 1995, p. 43) and the matrix

$$\mathbf{Z}_{r1} = \left(\sum_{i=1}^k L_i \mathbf{C}_i \right) / \sum_{i=1}^k L_i \quad (4.2)$$

is the maximum likelihood estimator for Σ_{r1} . The matrix $\mathbf{C}_i$ in the above equation refers to the Hermitian covariance matrix of a pixel i within the test region $r1$. The variable k denotes the total number of pixels within the test region $r1$. If $L_1, L_2, \dots, L_k$ are equal, then the matrix $\mathbf{Z}_{r1}$ reduces to the average covariance matrix, i.e.

$$\mathbf{Z}_{r1} = \frac{1}{k} \sum_{i=1}^k \mathbf{C}_i. \quad (4.3)$$

Figure 4.1: 3×3 edge templates with orientation (a) 0°, (b) 45°, (c) 90° and (d) 135°. The two test regions $r1$ and $r2$ are coloured in light and dark grey, respectively.

As shown by Schou *et al.* (2003), the asymptotic distribution of $-2\rho \ln Q$ is given as

$$P\{-2\rho \ln Q \leq z\} \cong P\{\chi^2(f) \leq z\} + \omega_2 P\{\chi^2(f+4) \leq z\} - \omega_2 P\{\chi^2(f) \leq z\}, \quad (4.4)$$

with the parameters f , ρ and ω_2 defined as

$$\begin{aligned} f &= p^2, \\ \rho &= 1 - \frac{2p^2 - 1}{6p} \left(\frac{1}{m} + \frac{1}{n} - \frac{1}{m+n} \right), \\ \omega_2 &= -\frac{f}{4} \left(1 - \frac{1}{\rho} \right)^2 + \frac{f(f-1)}{24} \left(\frac{1}{m^2} + \frac{1}{n^2} - \frac{1}{(m+n)^2} \right) \frac{1}{\rho^2}. \end{aligned} \quad (4.5)$$

The term $-2\rho \ln Q$ is limited by $[0, \infty)$. Its value becomes zero if $\mathbf{Z}_{r1} = \mathbf{Z}_{r2}$ and $m = n$, i.e. in the absence of an edge. From Equation (4.4), it is apparent that the distribution is independent of the content of the complex Wishart matrices. It depends only on both the matrix dimension and number of looks.

4.3 Proposed Edge Detectors

4.3.1 Roy's Largest Eigenvalue-based Edge Detector

In this study, the well-known ratio edge detector (Bovik, 1988; Touzi *et al.*, 1988) was extended for multi-look POLSAR data. The extension was carried out based on Roy's largest eigenvalue. Roy (1953, 1957) initiated an equality test of two real symmetric covariance matrices following the union-intersection principle. This test was then studied by Chu and Pillai (1980) for the equality of two Hermitian covariance matrices. The equality test is explained first below, followed by its application for detecting edges in multi-look POLSAR imagery.

Let $\mathbf{Z}_x$ and $\mathbf{Z}_y$ be two independent complex Wishart matrices distributed as $CW(n_x, p, \Sigma_x)$ and $CW(n_y, p, \Sigma_y)$, respectively. Both matrices Σ_x and Σ_y are positive definite Hermitian population covariance matrices. Let $c_1, c_2, \dots, c_p$ be the eigenvalues of $\mathbf{Z}_x \mathbf{Z}_y^{-1}$ in decreasing order and similarly $\lambda_1, \lambda_2, \dots, \lambda_p$ be the eigenvalues of $\Sigma_x \Sigma_y^{-1}$, the matrix $\mathbf{Z}_x \mathbf{Z}_y^{-1}$ or $\Sigma_x \Sigma_y^{-1}$ is known as complex multivariate F matrix (Krishnaiah, 1976, p. 7). Finding the eigenvalues of $\Sigma_x \Sigma_y^{-1}$ is identical to solving the following determinantal equation for a Hermitian pencil (Lewis, 1991; Rao and Rao, 1998; Hartfiel, 2001):

$$|\Sigma_x - \lambda \Sigma_y| = 0. \quad (4.6)$$

Since both matrices Σ_x and Σ_y are positive definite, the eigenvalues of $\Sigma_x \Sigma_y^{-1}$ are real and positive. This can be verified through simultaneous diagonalisation of a pair of Hermitian forms.

To test the null hypothesis $H_0 : \Sigma_x = \Sigma_y$ against the alternative hypothesis $H_a : \Sigma_x \neq \Sigma_y$, the largest eigenvalue c_1 can be used as test statistic (Chu and Pillai, 1980). The cumulative distribution function of the largest eigenvalue under the alternative hypothesis was derived by Sugiyama (1972, p. 91) and given in terms of zonal polynomials as follows:

$$\Pr(c_1 < c) = \left(\tilde{\Gamma}_p(n_x + n_y) \tilde{\Gamma}_p(p) / \tilde{\Gamma}_p(n_x + p) \tilde{\Gamma}_p(n_y) \right) |c \Omega^{-1}|^{n_x} {}_2\tilde{F}_1(n_x + n_y, n_x; n_y + p; -c \Omega^{-1}), \quad (4.7)$$

where the variable c represents an upper limit. The matrix Ω is a diagonal matrix containing the largest eigenvalue λ_1 of $\Sigma_x \Sigma_y^{-1}$ on the diagonal. For explanations of the further notations in Equation (4.7) the reader is referred to Sugiyama (1972). As it can

be seen in Equation (4.7), the cumulative distribution function depends on Σ_x and Σ_y only through the largest eigenvalue λ_1 . Under the null hypothesis, the matrices $\Sigma_x \Sigma_y^{-1}$ and Ω become, respectively, identity matrices. Consequently, the null cumulative distribution function is independent of Σ_x and Σ_y . Hence, an edge detector based on the Roy's largest eigenvalue belongs to the group of constant false-alarm rate detectors (Touzi *et al.*, 1988; Schou *et al.*, 2003).

For the purpose of edge detection in multi-look POLSAR imagery, the Roy's largest eigenvalue test statistic is expressed as

$$\lambda_{\text{Roy}} = \max\{ch_1(\mathbf{Z}_{r1}\mathbf{Z}_{r2}^{-1}), ch_1(\mathbf{Z}_{r2}\mathbf{Z}_{r1}^{-1})\}, \quad (4.8)$$

where $ch_1(\mathbf{Z}_{r1}\mathbf{Z}_{r2}^{-1})$ is the largest eigenvalue of $\mathbf{Z}_{r1}\mathbf{Z}_{r2}^{-1}$ and max denotes the maximum operator. Using Equation (4.2) equivalently for the test region $r2$, the Roy's largest eigenvalue in Equation (4.8) can be solved. It is noticed that in Equation (4.8) the formulated Roy's largest eigenvalue-based edge detector is a symmetrical detector, which is independent of the scanning direction (Touzi *et al.*, 1988, p. 766). Because of the maximum operator in Equation (4.8), the computed value of λ_{Roy} belongs to the interval of $[1, \infty)$. If $\mathbf{Z}_{r1}$ and $\mathbf{Z}_{r2}$ are equal, then the matrix $\mathbf{Z}_{r1}\mathbf{Z}_{r2}^{-1}$ is an identity matrix with unit eigenvalues. Thus, the eigenvalue λ_{Roy} is unity for a perfectly homogeneous area. On the contrary, it differs from unity if a discontinuity exists within the tested edge template.

For detecting edges in multi-look POLSAR imagery, the processing steps are outlined below:

- Step 1: Place all edge templates over a pixel i .
- Step 2: Estimate $\mathbf{Z}_{r1}$ and $\mathbf{Z}_{r2}$ for each edge template based on Equation (4.2).
- Step 3: Compute the Roy's largest eigenvalue for each edge template using Equation (4.8).
- Step 4: Record the maximum of the computed Roy's largest eigenvalues in Step 3.
- Step 5: Move the edge templates to the next pixel and repeat Steps 1–4. Terminate the execution if there are no more pixels to be processed.

Afterward, a threshold can be roughly estimated from the obtained maximum Roy's largest eigenvalue output in order to determine a pixel as either an edge or non-edge pixel. The threshold selection procedures are explained as follows:

- Step 1: Select a speckle-corrupted homogeneous area from multi-look POLSAR image.
- Step 2: Construct the cumulative relative frequency plot for the maximum Roy's largest eigenvalues of the pixels within the selected homogeneous area. Figure

4.2 presents an example of the constructed cumulative frequency plot of a homogeneous.

Step 3: Determine the class interval which the cumulative relative frequency value of 0.995 falls into. Other cumulative relative frequency value can be specified by the user.

Step 4: Compute the class midpoint and use it as a threshold.

In practice, it is preferable to choose as many speckle-corrupted homogeneous areas as possible with the largest possible size. Note that both class limit and class width used in constructing the cumulative relative frequency plot for each selected homogeneous area have to be standardised. The threshold is then defined by the average of the obtained class midpoints. If the maximum Roy's largest eigenvalue of a pixel is greater than the estimated threshold value, the pixel is considered to be an edge pixel.

For edge detection in L -look single-frequency single-polarisation SAR intensity data, the Roy's largest eigenvalue-based edge detector turns into the well-known ratio edge detector (Bovik, 1988; Touzi *et al.*, 1988). If the matrices $\mathbf{Z}_{r1}$ and $\mathbf{Z}_{r2}$ are one-dimensional, Equation (4.8) simplifies to

$$\lambda_{\text{Roy}} = \max \left\{ \frac{z_{r1}}{z_{r2}}, \frac{z_{r2}}{z_{r1}} \right\} \quad (4.9)$$

with

$$z = \left(\sum_{i=1}^k L_i s_i^2 \right) / \sum_{i=1}^k L_i. \quad (4.10)$$

The variable s_i^2 is the variance (or intensity) of a pixel i within the test region which contains m pixels. If $L_1, L_2, \dots, L_k$ are equal, then the ratio z_{r1}/z_{r2} (or z_{r2}/z_{r1}) becomes the ratio of average intensities.

Figure 4.2: Edge threshold selection. (a) is an unfiltered POLSAR C-band data. (b) is the maximum Roy's largest eigenvalue output of (b) with a selected homogeneous area, which is indicated by a red coloured polygon. (c) shows the histogram of the maximum Roy's largest eigenvalue of the selected area in (b). (d) is the cumulative relative frequency plot of (c).

4.3.2 Trace Ratio Edge Detector

The trace ratio edge detector is formulated based on a metric, which was derived by Dowson and Landau (1982, p. 453). Consider two p -variate probability distributions X and Y with zero means as well as positive definite covariance matrices Σ_x and Σ_y , then

$$d_0^2(\Sigma_x, \Sigma_y) = \text{tr}(\Sigma_x + \Sigma_y) - \text{tr}\left(2(\Sigma_x \Sigma_y)^{1/2}\right) \quad (4.11)$$

defines a metric on the space of covariance matrices. The operator tr refers to the trace of a matrix. As it can be clearly seen in Equation (4.11), the right side of the equation consists of two terms and d_0^2 is computed based on their difference. For $\Sigma_x = \Sigma_y$, d_0^2 is equal to zero.

The direct application of Equation (4.11) for detecting edges in multi-look POLSAR data is not advisable, especially if small sized edge templates are utilised. This is due to the difference operation and the direct dependence of the Dowson-Landau metric on the covariance matrices. Moreover, it is well known that the intensities in multi-look POLSAR data suffer from multiplicative noise (Touzi and Lopes, 1994; Lee *et al.*, 1999b). As a consequence, the Dowson-Landau metric varies with the underlying covariance matrices, in particular for bright homogeneous areas due to the multiplicative nature of speckle noise. This inappropriateness is addressed in Section 4.4.1.

Since d_0^2 is non-negative, it is obvious that $\text{tr}(2\Sigma_x \Sigma_y)^{1/2} \leq \text{tr}(\Sigma_x + \Sigma_y)$ in Equation (4.11). This matrix trace inequality is also given in Bernstein (2005, p. 307). Keeping this in mind, the following trace ratio

$$t = \text{tr}\left(2(\Sigma_x \Sigma_y)^{1/2}\right) / \text{tr}(\Sigma_x + \Sigma_y) \quad (4.12)$$

is considered for edge detection in multi-look POLSAR data. Equation (4.12) can be rewritten as

$$t = \text{tr}(\Sigma_x \Sigma_y)^{1/2} / \text{tr}((\Sigma_x + \Sigma_y)/2). \quad (4.13)$$

The trace ratio depends on Σ_x and Σ_y only through the quotient of $\text{tr}(2\Sigma_x \Sigma_y)^{1/2}$ and $\text{tr}((\Sigma_x + \Sigma_y)/2)$. The use of the ratio in Equation (4.13) helps to reduce the scaling dependence of the diagonal element values of the covariance matrices, i.e. the POLSAR intensity values.

The trace ratio is always real and positive due to the positive definiteness of Σ_x and Σ_y as well as the use of the trace operator. Since $\text{tr}(\Sigma_x)$ and $\text{tr}(\Sigma_y)$ are real and

positive, the denominator $\text{tr}(\Sigma_x + \Sigma_y) = \text{tr}(\Sigma_x) + \text{tr}(\Sigma_y)$ is real and positive. For the numerator, only positive square root of matrix $(\Sigma_x \Sigma_y)^{1/2}$ is taken. Therefore, $\text{tr}(\Sigma_x \Sigma_y)^{1/2}$ is also real and positive. In addition, the values of the trace ratio are bounded between 0 and 1. This is a straightforward result from the above mentioned matrix trace inequality.

To detect edges in multi-look POLSAR imagery, the similar local edge detection approach as presented in the previous subsection is employed. Hence, Equation (4.12) becomes

$$t = \text{tr}\left(2(\Sigma_{r1} \Sigma_{r2})^{1/2}\right) / \text{tr}(\Sigma_{r1} + \Sigma_{r2}), \quad (4.14)$$

where Σ_{r1} and Σ_{r2} are estimated by $\mathbf{Z}_{r1}$ and $\mathbf{Z}_{r2}$, respectively. The trace ratio value is equal to unity if $\mathbf{Z}_{r1} = \mathbf{Z}_{r2}$, i.e. for a perfectly homogeneous area. It is less than unity if heterogeneity exists within the tested edge template. The steps contained in the edge detection process are as follows:

- Step 1: Place all edge templates over a pixel i .
- Step 2: Estimate $\mathbf{Z}_{r1}$ and $\mathbf{Z}_{r2}$ for each edge template based on Equation (4.2).
- Step 3: Compute the trace ratio for each edge template using Equation (4.14).
- Step 4: Record the minimum $t_{\min}$ of the computed trace ratio values in Step 3.
- Step 5: Reverse the obtained minimum trace ratio value by

$$t_{\text{reverse}} = 1 - t_{\min} \quad (4.15)$$

in order to result in low values for homogeneous areas.

- Step 6: Move the edge templates to the next pixel and repeat Steps 1–5. Terminate the execution if there are no more pixels to be processed.

After the above processing, a threshold can be determined from the reversed trace ratio output following the similar threshold selection procedure as discussed in the previous subsection. A pixel is declared as an edge pixel if its reversed trace ratio value is greater than the threshold.

The trace ratio edge detector can be applied to L -look single-frequency single-polarisation SAR intensity data. In this case, both matrices $\mathbf{Z}_{r1}$ and $\mathbf{Z}_{r2}$ are one-dimensional and Equation (4.12) takes the form of the geometric-arithmetic mean ratio with

$$t = 2\sqrt{\sigma_1^2 \sigma_2^2} / (\sigma_1^2 + \sigma_2^2), \quad (4.16)$$

where σ^2 represents the variance. Again, the value of t equals unity if $\sigma_1^2 = \sigma_2^2$.

4.4 Analysis and Discussion

The analysis and discussion of the edge detection outputs are organised in three parts: (i) the performance of the edge detectors, (ii) the effects of the presence of image textures, and (iii) the effects of different radar frequencies and polarisations.

4.4.1 Performance of Edge Detectors

In this study, the capabilities of the two proposed edge detectors as well as the likelihood ratio edge detector were examined using multi-look simulated POLSAR datasets. The simulated data included four-look C-band, four-look L-band, nine-look C-band, and nine-look L-band. The detailed descriptions of these data are given in Section 3.3.2. With the use of the simulated data, the performance evaluation can be carried out more practically since the locations of reference edges are known exactly.

For detecting the vertical edges in the simulated data, the edge template with edge orientation of 90° (i.e. vertical edge) was employed. Four different sizes, namely 3×3 , 5×5 , 7×7 as well as 9×9 pixels, were tested. Figure 4.3 shows the vertical edge templates of 5×5 , 7×7 and 9×9 pixels, which were used in the experiments. The two test regions $r1$ and $r2$ are coloured, respectively, in light and dark grey. The white coloured pixels in each template are excluded to ensure that both the test regions have the same number of pixels. Figures 4.4–4.6 show the C- and L-band edge maps of the likelihood ratio, trace ratio and Roy's largest eigenvalue-based edge detectors, respectively. In each edge map, the detected edges are represented by black coloured pixels against a white background (the non-edge pixels).

Figure 4.3: Vertical edge templates of (a) 5×5 , (b) 7×7 and (c) 9×9 pixels. The two test regions $r1$ and $r2$ are coloured in light and dark grey, respectively.

Figure 4.4: Edge maps of likelihood ratio edge detector.

Figure 4.5: Edge maps of trace ratio edge detector.

Figure 4.6: Edge maps of Roy's largest eigenvalue-based edge detector.

For quantitative performance evaluation, both identification rate and misidentification error were computed from edge maps. The identification rate is defined by the ratio of the number of correctly detected edge pixels to the total number of true edge pixels that are known precisely in the simulated data. In total, there were six edge segments in the simulated data, namely (i) edge between rubber region and scrub-grassland region, (ii) edge between oil palm region and rubber region, (iii) edge between oil palm region and scrub-grassland region, (iv) edge between rice paddy region and oil palm region, (v) edge between rice paddy region and rubber region, (vi) edge between rice paddy region and scrub-grassland region.

To assess false edge detection, the misidentification error is computed as the ratio of number of detected edge pixels in homogeneous area to total number of pixels in homogeneous area. The homogeneous areas under study included rubber, oil palm, rice paddy and scrub-grassland regions. Tables 4.1–4.3 tabulate both the identification rates and misidentification errors, which were computed from the C- and L-band outputs of different edge detectors and different template sizes. The higher the identification rate, the better is the edge detection. Also, the lower misidentification error indicates the better result.

Table 4.1: Identification rates and misidentification errors computed from likelihood ratio edge detection outputs

	Identification rate				Misidentification error		
	rubber – scrub	oil palm – rubber	oil palm – scrub	rice paddy – scrub	rice paddy – oil palm	rice paddy – rubber	rice paddy
<u>Four-look C-band</u>							
3×3	0.040	0.035	0.023	1.000	1.000	1.000	0.006
5×5	0.656	0.193	0.183	1.000	1.000	1.000	0.005
7×7	0.996	0.783	0.696	1.000	1.000	1.000	0.006
9×9	1.000	1.000	0.976	1.000	1.000	1.000	0.005
<u>Nine-look C-band</u>							
3×3	0.410	0.116	0.093	1.000	1.000	1.000	0.004
5×5	0.996	0.798	0.666	1.000	1.000	1.000	0.006
7×7	1.000	1.000	0.996	1.000	1.000	1.000	0.004
9×9	1.000	1.000	1.000	1.000	1.000	1.000	0.004
<u>Four-look L-band</u>							
3×3	1.000	0.323	0.993	1.000	1.000	1.000	0.006
5×5	1.000	0.998	1.000	1.000	1.000	1.000	0.005
7×7	1.000	1.000	1.000	1.000	1.000	1.000	0.005
9×9	1.000	1.000	1.000	1.000	1.000	1.000	0.005
<u>Nine-look L-band</u>							
3×3	1.000	0.928	1.000	1.000	1.000	1.000	0.005
5×5	1.000	1.000	1.000	1.000	1.000	1.000	0.007
7×7	1.000	1.000	1.000	1.000	1.000	1.000	0.007
9×9	1.000	1.000	1.000	1.000	1.000	1.000	0.005

Table 4.2: Identification rates and misidentification errors computed from Roy's largest eigenvalue-based edge detection outputs

	Identification rate						Misidentification error				
	rubber – scrub	oil palm – rubber	oil palm – scrub	rice paddy – scrub	rice paddy – oil palm	rice paddy – rubber	rice paddy – scrub	rubber	oil palm	scrub	rice paddy
<u>Four-look C-band</u>											
3×3	0.086	0.036	0.036	1.000	1.000	1.000	1.000	0.005	0.005	0.005	0.005
5×5	0.676	0.260	0.243	1.000	1.000	1.000	1.000	0.005	0.005	0.005	0.006
7×7	0.996	0.813	0.753	1.000	1.000	1.000	1.000	0.006	0.005	0.005	0.006
9×9	1.000	0.998	0.993	1.000	1.000	1.000	1.000	0.006	0.005	0.004	0.005
<u>Nine-look C-band</u>											
3×3	0.420	0.138	0.130	1.000	1.000	1.000	1.000	0.006	0.005	0.005	0.005
5×5	0.990	0.748	0.680	1.000	1.000	1.000	1.000	0.004	0.004	0.004	0.004
7×7	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.006	0.006	0.004	0.004
9×9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.005	0.004	0.003	0.002
<u>Four-look L-band</u>											
3×3	1.000	0.291	0.956	1.000	1.000	1.000	1.000	0.005	0.005	0.006	0.005
5×5	1.000	0.993	1.000	1.000	1.000	1.000	1.000	0.004	0.005	0.007	0.005
7×7	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.005	0.005	0.005	0.004
9×9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.007	0.007	0.005	0.004
<u>Nine-look L-band</u>											
3×3	1.000	0.911	1.000	1.000	1.000	1.000	1.000	0.005	0.005	0.005	0.005
5×5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.004	0.003	0.004	0.005
7×7	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.005	0.004	0.005	0.005
9×9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.004	0.004	0.003	0.003

Table 4.3: Identification rates and misidentification errors computed from trace ratio edge detection outputs

	Identification rate				Misidentification error			
	rubber – scrub	oil palm – rubber	oil palm – scrub	rice paddy – scrub	rice paddy – rubber	rice paddy – oil palm	rice paddy – scrub	rice paddy
<u>Four-look C-band</u>								
3×3	0.163	0.016	0.076	1.000	1.000	0.005	0.005	0.005
5×5	0.766	0.043	0.416	1.000	1.000	0.006	0.004	0.004
7×7	1.000	0.305	0.910	1.000	1.000	0.005	0.005	0.005
9×9	1.000	0.833	0.996	1.000	1.000	0.006	0.003	0.007
<u>Nine-look C-band</u>								
3×3	0.580	0.040	0.246	1.000	1.000	0.005	0.005	0.004
5×5	1.000	0.365	0.893	1.000	1.000	0.006	0.005	0.003
7×7	1.000	0.943	1.000	1.000	1.000	0.004	0.006	0.003
9×9	1.000	1.000	1.000	1.000	1.000	0.004	0.005	0.006
<u>Four-look L-band</u>								
3×3	1.000	0.336	0.966	1.000	1.000	0.005	0.005	0.005
5×5	1.000	0.995	1.000	1.000	1.000	0.005	0.007	0.006
7×7	1.000	1.000	1.000	1.000	1.000	0.005	0.006	0.005
9×9	1.000	1.000	1.000	1.000	1.000	0.007	0.007	0.003
<u>Nine-look L-band</u>								
3×3	1.000	0.911	1.000	1.000	1.000	0.006	0.004	0.004
5×5	1.000	1.000	1.000	1.000	1.000	0.005	0.005	0.005
7×7	1.000	1.000	1.000	1.000	1.000	0.004	0.005	0.004
9×9	1.000	1.000	1.000	1.000	1.000	0.006	0.004	0.004

As noted in Section 4.3.2, the direct use of the Dowson-Landau metric for edge detection is inappropriate due to the presence of multiplicative noise in the intensities. Figure 4.7 presents the edge maps of the simulated data, which were obtained based on the Dowson-Landau metric. The edge threshold for each edge map was chosen to maximise and minimise both the identification rate and misidentification error, respectively. Additionally, for further investigating the use of difference operations, edge detection based on the Euclidean distance was carried out. The Euclidean distance measure refers to the Euclidean distance between two matrices **A** and **B**, which is defined in Hartfiel (2001, p. 117) as

$$d^2(\mathbf{A}, \mathbf{B}) = \sum_i \sum_j |a_{ij} - b_{ij}|^2. \quad (4.17)$$

The variables a_{ij} and b_{ij} refer to the elements of the matrices **A** and **B**. For edge detection, both the matrices **A** and **B** were replaced by $\mathbf{Z}_{r1}$ and $\mathbf{Z}_{r2}$, respectively. The value of the Euclidean distance belongs to the interval of $[0, \infty)$. For a homogeneous area, the computed Euclidean distance is zero since $\mathbf{Z}_{r1} = \mathbf{Z}_{r2}$. It becomes non-zero if a discontinuity exists within the tested edge template. The resultant edge maps based on the Euclidean distance are given in Figure 4.8, where the edge threshold for each map was determined in the same way as for the edge detection using the Dowson-Landau metric.

By observing Figures 4.7 and 4.8, it was noticed that there were more wrongly detected edge pixels over the rubber and oil palm regions compared with the scrub and rice paddy regions. Tables 4.4 and 4.5 tabulate the corresponding identification rates and misidentification errors. Due to the multiplicative noise characteristics, the higher the intensity values of the homogeneous rubber and oil palm areas, the higher the misidentification errors over these areas. This property is indeed undesirable since both the Euclidean distance and Dowson-Landau metric may consequently cause the unwanted false edge detection over bright homogeneous areas.

To further validate the ineffectiveness of both measures, edge detection was performed on the NASA/JPL POLSAR C- and L-band data. The selected edge detection outputs are given separately in Figures 4.9 and 4.10, together with those resulting from the likelihood ratio, trace ratio and Roy's largest eigenvalue-based edge detectors. As indicated by the arrows, both the Dowson-Landau metric and Euclidean distance measures showed their weak immunity against the multiplicative noise. Unwanted

Figure 4.7: Edge maps based on the Dowson-Landau metric.

Figure 4.8: Edge maps based on the Euclidean distance.

Table 4.4: Identification rates and misidentification errors computed from edge detection outputs, which were based on the Dowson-Landau metric

	Identification rate				Misidentification error			
	rubber – scrub	oil palm – rubber	oil palm – scrub	rice paddy – scrub	rice paddy – rubber	rice paddy – scrub	rubber	oil palm
<u>Four-look C-band</u>								
3×3	0.623	0.350	0.327	1.000	1.000	0.977	0.322	0.106
5×5	0.980	0.676	0.840	1.000	1.000	1.000	0.330	0.113
7×7	1.000	0.858	0.933	1.000	1.000	1.000	0.131	0.034
9×9	1.000	0.975	0.993	1.000	1.000	1.000	0.046	0.011
<u>Nine-look C-band</u>								
3×3	0.923	0.517	0.527	1.000	1.000	1.000	0.274	0.089
5×5	1.000	0.852	0.950	1.000	1.000	1.000	0.121	0.032
7×7	1.000	0.978	1.000	1.000	1.000	1.000	0.018	0.004
9×9	1.000	0.995	1.000	1.000	1.000	1.000	0.001	0.000
<u>Four-look L-band</u>								
3×3	1.000	0.865	0.737	1.000	1.000	0.003	0.505	0.017
5×5	1.000	1.000	1.000	1.000	1.000	0.857	0.333	0.005
7×7	1.000	1.000	1.000	1.000	1.000	0.937	0.016	0.000
9×9	1.000	1.000	1.000	1.000	1.000	1.000	0.001	0.000
<u>Nine-look L-band</u>								
3×3	1.000	0.992	1.000	1.000	1.000	0.733	0.587	0.033
5×5	1.000	1.000	1.000	1.000	1.000	1.000	0.015	0.000
7×7	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.000
9×9	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.000

Table 4.5: Identification rates and misidentification errors computed from edge detection outputs, which were based on the Euclidean distance

	Identification rate				Misidentification error			
	rubber – scrub	oil palm – rubber	oil palm – scrub	rice paddy – scrub	rice paddy – rubber	rice paddy – scrub	oil palm	rice paddy
<u>Four-look C-band</u>								
3×3	0.860	0.758	0.633	0.973	0.997	0.780	0.493	0.031
5×5	0.950	0.417	0.783	1.000	1.000	0.973	0.122	0.001
7×7	1.000	0.625	0.960	1.000	1.000	1.000	0.099	0.000
9×9	1.000	0.825	1.000	1.000	1.000	1.000	0.061	0.000
<u>Nine-look C-band</u>								
3×3	0.923	0.590	0.650	1.000	1.000	0.950	0.230	0.004
5×5	1.000	0.465	0.910	1.000	1.000	1.000	0.050	0.000
7×7	1.000	0.818	1.000	1.000	1.000	1.000	0.037	0.000
9×9	1.000	0.955	1.000	1.000	1.000	1.000	0.015	0.000
<u>Four-look L-band</u>								
3×3	1.000	0.990	0.737	0.960	1.000	0.000	0.262	0.000
5×5	1.000	1.000	0.733	0.983	1.000	0.000	0.004	0.000
7×7	1.000	1.000	0.777	1.000	1.000	0.000	0.000	0.000
9×9	1.000	1.000	0.960	1.000	1.000	0.000	0.000	0.000
<u>Nine-look L-band</u>								
3×3	1.000	0.995	0.883	1.000	1.000	0.000	0.051	0.000
5×5	1.000	1.000	0.820	1.000	1.000	0.000	0.000	0.000
7×7	1.000	1.000	0.987	1.000	1.000	0.000	0.000	0.000
9×9	1.000	1.000	1.000	1.000	1.000	0.000	0.000	0.000

strong edge responses were found within speckle-corrupted homogeneous areas, especially in the case of the Euclidean distance. Conversely, the results confirmed the capability of the likelihood ratio, trace ratio and Roy's largest eigenvalue-based edge detectors in tackling the multiplicative noise disturbance.

4.4.2 Effects of the Presence of Image Textures

Figures 4.11 and 4.12 present the NASA/JPL POLSAR C- and L-band edge maps resulting from the likelihood ratio, trace ratio and Roy's largest eigenvalue-based edge detectors. Three different sizes of edge templates, namely 3×3 , 5×5 and 7×7 pixels, were employed for the edge detection. Figure 4.13 shows the edge templates of 5×5 and 7×7 pixels, which were used in the experiments. From Figures 4.11 and 4.12, a "noisy" appearance can be observed over the mangrove forests. However, it did not occur over the river and marshland. This noisy appearance was caused by the presence of textural features and the sensitivity of the edge detectors to these textural features.

Texture in a digital image can be regarded as the local pattern, which reveals the important information about spatial arrangements and interrelationships of image pixels. It is often characterised by roughness, smoothness, fineness, coarseness, regularity, contrary, likeness and so forth (Haralick *et al.*, 1973; Hsu, 1978). Since radar imaging is capable of detecting surface textures, the "rough" textural components can be therefore clearly found over the mangrove forests showing in both C- and L-band three-intensity images. The presence of these rough components may stem from the unevenness in mangrove canopies, the difference in proportion of mangrove trees and / or the existence of different mangrove species.

As discussed in Thompson (1977), Pietikäinen and Rosenfeld (1982), Haralick (1986) as well as Pratt (1991), an edge detector also serves as an effective textural operator in image processing. The rough components exhibited significant statistical variations. Hence, these variations were detected as the edges by all the three edge detectors. Since the river and marshland appeared homogeneous, the noisy appearance did not occur in these areas.

Figure 4.9. Edge detection in the unfiltered NASA/JPL POLSAR C-band data with the 5×5 edge templates. (a) is a three-intensity image with the HH, HV and VV intensities displayed in the RGB colour space, (b)–(d) are the outputs using the likelihood ratio, trace ratio and Roy's largest eigenvalue-based edge detectors, respectively, (e) and (f) are the results based separately on the Dowson-Landau metric and the Euclidean distance.

Figure 4.10. Edge detection in the unfiltered NASA/JPL POLSAR L-band data with the 5×5 edge templates. (a) is a three-intensity image with the HH, HV and VV intensities displayed in the RGB colour space, (b)–(d) are the outputs using the likelihood ratio, trace ratio and Roy's largest eigenvalue-based edge detectors, respectively, (e) and (f) are the results based separately on the Dowson-Landau metric and the Euclidean distance.

Figure 4.11: C-band edge maps of different edge detectors. The river of Sungai Merbok is located in the centre of the three-intensity image. Along the river sides, the mangrove forests in light green colour can be clearly observed, while the marshland in purple-blue colour is found in the upper right corner.

Figure 4.12: L-band edge maps of different edge detectors. The river of Sungai Merbok is located in the centre of the three-intensity image. Along the river sides, the mangrove forests in dark green colour can be clearly observed, while the marshland in purple-blue colour is found in the upper right corner.

Figure 4.13: Edge templates of (a) 5×5 and (b) 7×7 pixels.

4.4.3 Effects of Different Radar Frequencies and Polarisations

In this study it was found that both radar frequency and polarisation provided different edge information of land cover features. Figure 4.14 compares the C- and L-band detection outputs over rice paddy fields. As indicated by the arrows, more structural land cover features, i.e. walkways, were successfully detected in the L-band compared with the C-band. This can be ascribed to higher contrast between the walkways and their neighbouring rice paddy fields in the L-band.

To show the effects of different radar polarisations in edge detection, the Roy's largest eigenvalue-based edge detector was applied separately to the C- and L-band intensity images. Figures 4.15(a)–(c) present the edge detection results for the C-band HH, VV and HV intensities. Almost all desired edges are contained in the HH result, except for the mudflat boundary at the left centre. The mudflat boundary was well detected using the VV polarisation. However, the poor delineation of rice paddy field boundaries, as indicated by the green coloured arrow, is observed in the VV result compared with both HH and HV results. For the C-band HV result, the yellow coloured arrows indicate the two elongated fish farming structures, which remained undetected. In Figures 4.15(d)–(f), the edge detection results for the L-band HH, HV and VV intensities are presented. Again, a similar performance was observed in the L-band HH result which contains almost all desired edges. The VV polarisation provided a good degree of detection for the mudflat boundary, but a poor detection performance for the opposite riverbank boundary which is indicated by the cyan coloured arrows. The fish farming structures were well delineated in the L-band HV result.

C-band three-intensity image

L-band three-intensity image

C-band edge detection result

L-band edge detection result

Figure 4.14: Effects of different radar frequencies in edge detection. The rice paddy fields appear darker in colour. The displayed results were obtained using the trace ratio edge detector with the 5×5 edge templates.

Figure 4.15: Comparison of different radar frequencies and polarisations in edge detection. (a)–(c) are the C-band HH, VV and HV results produced using the 5×5 edge templates, (d)–(f) are the L-band HH, VV and HV results, respectively.

In this study, the advantage of using the complete covariance matrix for edge detection in the selected NASA/JPL POLSAR test data was observed, but it was not of major significance. The results generated using only the intensity components, i.e. the diagonal elements of the covariance matrix, did not differ much from those results using the complete covariance matrix. Figure 4.16(b) shows the Roy's largest eigenvalue-based edge detection result which was obtained using the complete C-band covariance matrix, while the combined edge detection result of the C-band HH, VV and HV intensities is given in Figure 4.16(c). The result in Figure 4.16(c) was produced by first applying the Roy's largest eigenvalue-based edge detector separately to the HH, VV and HV intensity images. Then, a maximum operator was employed to combine all edge detection results of the three intensity components. Comparison between Figures 4.16(b) and (c) shows that both the results were nearly alike, except for the boundaries of the highway. The similar findings in the L-band can be observed by comparing Figures 4.16(e) and (f).

Figure 4.16: Comparison between the use of the complete covariance matrix and only the intensity components in edge detection. (a) and (d) are, respectively the C- and L-band three-intensity image with the HH, HV and VV intensities displayed in the RGB colour space, where a highway crosses diagonally through the centre of the scene, (b) and (c) are the C-band results generated by using the complete covariance matrix and only the intensity components, respectively. (e) and (f) are the L-band results generated separately by using the complete covariance matrix and only the intensity components

4.5 Summary

In this chapter, two new edge detectors, which are based separately on the Roy's largest eigenvalue and trace ratio, were proposed and benchmarked against the existing likelihood ratio edge detector. Their performances were examined using both the simulated POLSAR data and NASA/JPL POLSAR data. From the results, all the three edge detectors exhibited satisfying and comparable performances in detecting edges while coping with speckle noise disturbance. Moreover, edge detection based on the Dowson-Landau metric and the Euclidean distance was carried out. Both measures showed their relative weak immunity against the multiplicative noise in the POLSAR data. In this study, the effects of the presence of image texture features in the edge detection were observed. Furthermore, different edge detection results were obtained from the use of different frequencies and polarisations. The advantage of including the off-diagonal elements of covariance matrix for a better detection was found in both the POLSAR C- and L-band edge detection outputs.

Chapter 5

Speckle Suppression

5.1 Introduction

“Speckle is the main problem of synthetic aperture radar (SAR) image interpretation and classification because a zone that is homogeneous on the ground still has a granular aspect and a statistical distribution with a large standard deviation...” (Durand *et al.*, 1987)

Polarimetric synthetic aperture radar images are inherently corrupted by speckle noise due to the constructive and destructive interference of backscattered radar waves from elementary scatterers within an illuminated resolution cell. This presence of speckle noise can significantly degrade the performance of post-processing applications, such as image segmentation and classification.

In this chapter, previous work on speckle suppression of POLSAR data is reviewed first in Section 5.2. Section 5.3 presents the selected existing speckle filters under study, which include boxcar, Lee-refined as well as annealing filters. Then, a spatially adaptive speckle filter is introduced in Section 5.4 for multi-look POLSAR data, which aims at preserving point-like textural features as well as structural features, i.e. edges and lines, during filtering process. The results of all filters are evaluated and discussed in Section 5.5. Finally, Section 5.6 summarises this chapter.

5.2 Previous Work

To date, numerous speckle filtering methods have been proposed for POLSAR data. Novak and Burl (1990) pioneered the area of speckle reduction in POLSAR data by introducing a so-called polarimetric whitening filter (PWF) for single-look POLSAR data. The PWF produces a speckle-reduced image through optimally combining the elements of the complex scattering matrix. Further studies on the PWF were carried out by Toma *et al.* (1991) and Fleischman *et al.* (1996), while an extension of the PWF for multi-look POLSAR data is given in Liu *et al.* (1998b). The disadvantage of the PWF-based approaches is that they do not preserve the polarimetric information (Liu *et al.*, 1998b).

Lee *et al.* (1991) proposed two filtering algorithms, namely (i) the optimal weighting method and (ii) the vector speckle filter, which produce speckle-reduced HH, HV and VV intensity images. The effectiveness of the two filters was demonstrated using NASA/JPL POLSAR C-, L- and P-band data. The phase or phase difference images, however, remained unfiltered.

A complex multiplicative speckle noise model was presented by Goze and Lopes (1993) for single-look POLSAR data, where both amplitude and phase are characterised by the multiplicative and additive noise, respectively. Based on the noise model, the first speckle filter which restores the full polarimetric information was proposed, but the suggested filter works only for single-look POLSAR data.

Touzi and Lopes (1994) drew out the principles of speckle filtering for POLSAR data. The filtering principles include: (i) speckle can be filtered if the covariance matrix is filtered, (ii) a multiplicative speckle model can only be applied to the four linear channel intensities, i.e. HH, HV, VH as well as VV, and (iii) speckle filtering can also be performed on the complex scattering vector where the correlation between scattering vector elements should be used and each vector element cannot be filtered independently.

Lopès and Séry (1997) developed several filters mainly to account for the texture variation in POLSAR data by using a product model. For a heterogeneous or textured surface, its covariance matrix is modelled as a product of a scalar textural random

variable and a covariance matrix of a homogeneous surface. In the product model, the texture variable is always positive and Gamma-distributed, while the covariance matrix of the homogeneous surface is complex Wishart-distributed.

In Lee *et al.* (1999b), three other filtering principles are reported: (i) each element of the covariance matrix has to be filtered independently in the spatial domain to avoid cross-talk between polarisation channels, (ii) all covariance matrix elements should be filtered by the same amount for preserving polarimetric properties, and (iii) the filtering has to be adaptive in order to retain the edge sharpness and point targets. Following these principles, a covariance matrix-based speckle filter (hereafter called Lee-refined filter) was developed. The Lee-refined filter is explained in more detail in Section 5.3.2.

Schou and Skriver (2001) extended the idea of the annealing filter, which was originally proposed for single-frequency single-polarisation SAR intensity data, in order to filter the complete covariance matrix of POLSAR data. In their work, the filtering algorithm is derived based on a complex Wishart distribution and maximum likelihood estimation. The annealing filter is an iterative approach and computationally expensive. Section 5.3.3 presents the details of the extended annealing filter.

All of the above-mentioned filters do not make use of the physical scattering properties embedded in POLSAR data during the filtering process. Yoon and Kim (2003) presented a classified pixel-based windowing technique as a replacement for the use of an edge-aligned window in the Lee-refined filter, where the classification involves the use of the underlying scattering information. In a further paper to preserve the scattering properties, Lee *et al.* (2006) proposed a speckle filter which includes only those pixels of same scattering characteristics in the average computation. The employed classification method is a combination of the Freeman-Durden three-component scattering model and the complex Wishart classifier.

5.3 Selected Speckle Filters

Three existing covariance matrix-based polarimetric filters, namely boxcar, Lee-refined and annealing filters, were implemented and compared in terms of their speckle suppression performance in NASA/JPL POLSAR C- and L-band data. In the following the detailed descriptions of all the three speckle filters are given, while a complete assessment of these filters can be found in Section 5.5.

5.3.1 Boxcar Filter

The boxcar filter is also known as mean or averaging filter. It is simple in concept and in implementation. The filtered output $\mathbf{C}_{\text{out}}$ is the average covariance matrix $\mathbf{C}_{\text{average}}$ computed within a local window:

$$\mathbf{C}_{\text{out}} = \mathbf{C}_{\text{average}}. \quad (5.1)$$

5.3.2 Lee-refined Filter

Lee *et al.* (1999b) proposed a covariance matrix-based speckle filtering by making use of a multiplicative noise model and linear minimum mean square error estimation. The filtered covariance matrix $\mathbf{C}_{\text{out}}$ is defined as

$$\mathbf{C}_{\text{out}} = \mathbf{C}_{\text{average}} + w(\mathbf{C}_{\text{current}} - \mathbf{C}_{\text{average}}). \quad (5.2)$$

The matrix $\mathbf{C}_{\text{average}}$ is the average covariance matrix computed using an edge-aligned window, while the matrix $\mathbf{C}_{\text{current}}$ refers to the covariance matrix of the currently processed pixel, which is located at the window's centre. The parameter w represents the weight computed within the edge aligned window from the total power image y . It is defined by

$$w = \frac{\sigma_y^2 - \mu_y^2 \sigma_v^2}{\sigma_y^2 + \sigma_y^2 \sigma_v^2}, \quad (5.3)$$

where the variables μ_y and σ_y^2 are the mean and variance computed within the edge aligned window, respectively. The variable σ_v^2 denotes the user-specified noise variance.

To preserve the edge sharpness, Lee *et al.* (1999b) introduced the use of edge-aligned windows. Figure 5.1 shows the eight edge-aligned variations for a window size of 7×7 pixels, whereby only one of the eight windows is selected for a specific pixel. In the window selection, the 7×7 window is first divided into nine 3×3 sub-windows

(Figure 5.2) and the mean value μ is then computed from the total power image for each 3×3 sub-window. Using these computed mean values, the 3×3 Prewitt edge detector is employed to find the corresponding edge orientation with the maximum absolute gradient value. Figure 5.3 presents the Prewitt edge detectors. Once the edge orientation is determined, for example, the vertical edge is detected, the edge-aligned window in Figure 5.1(a) is selected if $|\mu_{22} - \mu_{23}| < |\mu_{21} - \mu_{22}|$; otherwise the edge-aligned window in Figure 5.1(e) is used. Only those gray coloured pixels in the selected window are included in the filtering computation.

Figure 5.1: Edge-aligned windows used in Lee-refined filter.

Figure 5.2: Partitioning a 7×7 window into nine 3×3 sub-windows.

1	1	1	1	0	-1	1	1	0	0	1	1
0	0	0	1	0	-1	1	0	-1	-1	0	1
-1	-1	-1	1	0	-1	0	-1	-1	-1	-1	0

Figure 5.3: Prewitt edge detectors.

5.3.3 Annealing Filter

The annealing filter was developed by White (1994a, 1994b) for single-frequency single-polarisation SAR intensity data, and later modified by McConnell *et al.* (1995), McConnell and Oliver (1996) as well as Oliver and Quegan (1998). In the annealing filter, the estimation of the filtered or true covariance matrix is treated as an energy minimisation problem. To optimise the energy minimisation, the annealing filter is designed in an iterative form with the use of a simulated annealing algorithm.

Instead of using all pixels in the neighbourhood for estimating the filtered covariance matrix, a set of twelve filter configurations is employed, where each configuration contains the central pixel and two neighbouring pixels. Figure 5.4 shows the twelve filter configurations. The use of these filter configurations can assist in preserving structural features, such as edges and lines, in the filtered output.

Figure 5.4: Filter configurations used in annealing filter.

Based on the complex Wishart distribution and maximum likelihood estimation, Schou and Skriver (2001) extended the annealing filter for multi-look POLSAR data. The filtered covariance matrix $\mathbf{C}_{\text{out}}$ is given by

$$\mathbf{C}_{\text{out}} = \frac{\mathbf{C}_{\text{current}} + \frac{\kappa}{L}(\mathbf{C}_{k1} + \mathbf{C}_{k2})}{1 + 2\frac{\kappa}{L}}, \quad (5.4)$$

where the matrix $\mathbf{C}_{\text{current}}$ is the unfiltered covariance matrix of the currently processed pixel. The matrices $\mathbf{C}_{k1}$ and $\mathbf{C}_{k2}$ refer to the covariance matrices of the two neighbouring pixels according to the filter configuration k (Figure 5.4). The parameter κ is an estimated number of looks, while L denotes the original number of looks of POLSAR data. It is clearly noticed from Equation (5.4) that the annealing filter is actually an adaptive weighted averaging filter.

5.4 Proposed Speckle Filter

As mentioned in Section 5.2, all speckle filters, except for those proposed by Yoon and Kim (2003) as well as by Lee *et al.* (2006), do not make use of the physical scattering properties embedded in POLSAR data during the filtering process. However, the proposed filters by Yoon and Kim (2003) as well as Lee *et al.* (2006) do not take the information of structural features, i.e. edges and lines, into account. Moreover, the scattering property-based classification algorithms used in both filters are relatively complicated. Keeping these issues in mind, the concept of scattering property-based filtering is extended by incorporating the use of edge and line detectors. Furthermore, a relatively simple scattering property-based classification scheme is suggested and employed in the filtering process.

The proposed filter operates based on the aforementioned three filtering principles, which were suggested by Lee *et al.* (1999b). The central idea of the proposed filter is that the filtering operations are performed spatially variant for image features, i.e. edges, lines and point-like textural features, in order to preserve them. For homogeneous areas, the filtering is based on scattering properties. To achieve this, edge detection, line detection, texture analysis, and classification based on scattering mechanisms are carried out separately, followed by a final despeckling. Figure 5.5 shows the flow chart of the proposed filter. Each step is explained in more detail below.

Figure 5.5: Flow chart of the proposed speckle filter.

5.4.1 Edge Detection

In order to detect edges in multi-look POLSAR data, the Roy's largest eigenvalue-based edge detector is employed. The processing steps of the edge detection are given in Chapter 4 under Section 4.3.1.

From the maximum Roy's largest eigenvalue output, two edge thresholds e_{lower} and e_{upper} are determined and employed for computing the edge strength of each pixel. The threshold procedures are explained as follows:

- Step 1: Select a speckle-corrupted homogeneous area from the multi-look POLSAR image.
- Step 2: Compute the average of the maximum Roy's largest eigenvalues of the pixels within the selected homogeneous area. Use it as the lower threshold, i.e. e_{lower} .
- Step 3: Construct the cumulative relative frequency plot for the maximum Roy's largest eigenvalues of the pixels within the selected homogeneous area.
- Step 4: Determine the class interval which the cumulative relative frequency value of 0.990 falls into. Other cumulative frequency value can be specified by the user.
- Step 5: Compute the class midpoint and use it as the upper threshold, i.e. e_{upper} .

Using the two thresholds, the edge strength s_{edge} for each pixel is then computed as

$$s_{\text{edge}} = \begin{cases} 0 & \lambda_{\text{Roy}} \leq e_{\text{lower}} \\ (\lambda_{\text{Roy}} - e_{\text{lower}}) / (e_{\text{upper}} - e_{\text{lower}}) & e_{\text{lower}} < \lambda_{\text{Roy}} < e_{\text{upper}} \\ 1 & \lambda_{\text{Roy}} \geq e_{\text{upper}} \end{cases} \quad (5.5)$$

For a homogeneous area, the value of s_{edge} is zero, while it is equal to unity for a perfectly confirmed edge. The edge strength is used in Section 5.4.5 for defining the filtering weight. In fact, Equation (5.5) shows the fuzzy mapping of the edge strength transition, which resembles the fuzzy edge detection presented by Jeansoulin *et al.* (1981, p. 337).

5.4.2 Line Detection

The Roy's largest eigenvalue-based edge detector can be applied for line detection by using line templates in Equation (4.8). Figure 5.6 shows line templates with different orientations for different template sizes. The examples of line detection outputs are

given in Figure 5.7. Likewise, two line thresholds l_{lower} and l_{upper} are set in the same way as discussed in the subsection above. The line strength s_{line} is subsequently computed for each pixel as

$$s_{\text{line}} = \begin{cases} 0 & \lambda_{\text{Roy}} \leq l_{\text{lower}} \\ (\lambda_{\text{Roy}} - l_{\text{lower}}) / (l_{\text{upper}} - l_{\text{lower}}) & l_{\text{lower}} < \lambda_{\text{Roy}} < l_{\text{upper}} \\ 1 & \lambda_{\text{Roy}} \geq l_{\text{upper}} \end{cases} \quad (5.6)$$

For a homogeneous area, the value of s_{line} is zero, while it equals unity for a confirmed line.

Figure 5.6: Line templates of (a) 3×3, (b) 5×5, (c) 7×7 and (d) 9×9 pixels. The two test regions r_1 and r_2 are coloured in magenta and yellow, respectively.

Figure 5.7: Line detection applied to unfiltered NASA/JPL POLSAR C-band data. (a) Three-intensity image with the HH, HV and VV intensities displayed in the RGB colour space. The resultant maximum Roy's largest eigenvalue outputs using line templates of (b) 5×5 and (c) 9×9 pixels.

5.4.3 Texture Analysis

For characterising the intrinsic texture or spatial heterogeneity in POLSAR data, a relative dispersion measure is proposed and defined by the ratio of the root mean square deviation to the average overall variability, i.e.

$$D = \sqrt{\left\langle d^2(\mathbf{C}_k, \mathbf{C}_{\text{average}}) \right\rangle} / \text{tr}(\mathbf{C}_{\text{average}}) \quad (5.7)$$

with

$$d^2(\mathbf{C}_k, \mathbf{C}_{\text{average}}) = \sum_i \sum_j |a_{ij} - b_{ij}|^2. \quad (5.8)$$

The deviation $d(\mathbf{C}_k, \mathbf{C}_{\text{average}})$ is the Euclidean distance between the two matrices $\mathbf{C}_k$ and $\mathbf{C}_{\text{average}}$, which is defined in (Hartfiel, 2001, p. 117). The matrices $\mathbf{C}_k$ and $\mathbf{C}_{\text{average}}$ are the covariance matrix of pixel p_k and average covariance matrix within a local window, respectively. Both a_{ij} and b_{ij} refer to elements of the matrices $\mathbf{C}_k$ and $\mathbf{C}_{\text{average}}$. It is important to note that the Euclidean distance has no immunity against the multiplicative noise in POLSAR intensities. However, as it can be seen in Equation (5.7), the ratio operation is employed in the dispersion measurement, which can help to cope with the multiplicative noise disturbance by removing the scaling dependence in POLSAR intensities. Figure 5.8 compares the root mean square deviation and relative dispersion outputs, which were obtained using a 5×5 window. As indicated by the red-coloured arrow, unlike in the root mean square deviation result, the speckle-corrupted homogeneous area was mapped with much lower values in the relative dispersion result.

Figure 5.8: Texture analysis applied to unfiltered NASA/JPL POLSAR C-band data. (a) is three-intensity image with the HH, HV and VV intensities displayed in the RGB colour space. (b) and (c) are, respectively, the obtained root mean square deviation and relative dispersion outputs by using the 5×5 window.

For larger window sizes, the spatially weighted dispersion measure is used instead. The following spatially weighted versions of $\mathbf{C}_{\text{average}}$ as well as $\langle d^2(\mathbf{C}_k, \mathbf{C}_{\text{average}}) \rangle$ are computed and substituted into Equation (5.7):

$$\mathbf{C}_{\text{average}} = \frac{\sum_{k=1}^N w_k \mathbf{C}_k}{\sum_{k=1}^N w_k} \quad (5.9)$$

and

$$\langle d^2(\mathbf{C}_k, \mathbf{C}_{\text{average}}) \rangle = \frac{\sum_{k=1}^N w_k d^2(\mathbf{C}_k, \mathbf{C}_{\text{average}})}{\sum_{k=1}^N w_k}, \quad (5.10)$$

where the weight has the following form

$$w_k = \exp\left(-\sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}\right). \quad (5.11)$$

The variable N denotes the total number of pixels within the test window. The variables x_k and y_k are the x - and y -axis coordinates for a pixel p_k within the window, while x_0 and y_0 are the coordinates of the central pixel. The notation $\exp$ refers to the exponential function.

With the relative dispersion output, the spatial heterogeneity s_{texture} is computed for each pixel as

$$s_{\text{texture}} = \begin{cases} 0 & D \leq D_{\text{lower}} \\ (D - D_{\text{lower}})/(D_{\text{upper}} - D_{\text{lower}}) & D_{\text{lower}} < D < D_{\text{upper}} \\ 1 & D \geq D_{\text{upper}} \end{cases}, \quad (5.12)$$

where the thresholds D_{lower} and D_{upper} are determined by compiling the corresponding statistics as discussed in Section 5.4.1 from a selected speckle-corrupted homogeneous area.

5.4.4 Classification Based on Scattering Mechanisms

The three-component scattering model, which was proposed by Freeman and Durden (1998), is employed to retrieve the scattering properties in POLSAR data. The contributions of surface scattering P_s , double-bounce scattering P_d as well as volume scattering P_v in each pixel are computed. Each pixel is then classified into a scattering class S_c by comparing these three contributions:

$$S_c = \begin{cases} c = 1 & \text{if } P_d > P_s > P_v \\ c = 2 & \text{if } P_d > P_v > P_s \\ c = 3 & \text{if } P_s > P_d > P_v \\ c = 4 & \text{if } P_s > P_v > P_d \\ c = 5 & \text{if } P_v > P_d > P_s \\ c = 6 & \text{if } P_v > P_s > P_d \\ c = 7 & \text{otherwise} \end{cases} \quad (5.13)$$

The detailed descriptions of the three-component scattering model and the classification results are presented in Chapter 7 under Section 7.3.2. The classification result is used in the following section for estimating the filtered covariance matrix.

5.4.5 Despeckling

With the computed feature strengths s_{edge} , s_{line} as well as s_{texture} , the filtered covariance matrix for a given pixel is solved by

$$\mathbf{C}_{\text{out}} = w \mathbf{C}_{\text{spatial}} + (1 - w) \mathbf{C}_{\text{scatter}}, \quad (5.14)$$

where

$$w = \max\{s_{\text{edge}}, s_{\text{line}}, s_{\text{texture}}\}. \quad (5.15)$$

The matrices $\mathbf{C}_{\text{spatial}}$ and $\mathbf{C}_{\text{scatter}}$ are the filtered covariance matrices based separately on the spatial and scattering properties. The operator $\max$ denotes the maximum operation. From Equation (5.14), it is obvious that $\mathbf{C}_{\text{out}} = \mathbf{C}_{\text{scatter}}$ if the weight w is zero. This means that the currently processed pixel is part of a homogeneous area and, thus, the filtering is performed based on the scattering properties. If w equals unity, the currently processed pixel is found to be an edge pixel, a line pixel or part of a highly heterogeneous area. Hence, the filtered covariance matrix is computed based on the spatial properties.

To estimate $\mathbf{C}_{\text{scatter}}$, the scattering class contributing the majority within the test window is identified first. If the total number of pixels which belong to the dominant scattering class is greater than or equal to a heuristically chosen 70%, then the average covariance matrix is computed as $\mathbf{C}_{\text{scatter}}$ by using all pixels within the window that belong to this dominant class. For the case where the total number of pixels of the dominant class is less than 70%, the filtered covariance matrix is computed by taking both the spatial distances and the proportions of the different scattering classes into account:

$$\mathbf{C}_{\text{scatter}} = \left(\sum_{k=1}^N \text{dist}(p_k) \text{sum}(S_c) \mathbf{C}_{k,c} \right) / \left(\sum_{k=1}^N \text{dist}(p_k) \text{sum}(S_c) \right). \quad (5.16)$$

The matrix $\mathbf{C}_{k,c}$ is the covariance matrix of a pixel p_k belonging to scattering class S_c . The variable N denotes the total number of pixels within the test window, while $\text{sum}(S_c)$ represents the total number of pixels within the window that belong to scattering class S_c . The value of $\text{dist}(p_k)$ is equal to $1/(1 + d_k)$, where

$$d_k = \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}. \quad (5.17)$$

The same notations x_0 , y_0 , x_k and y_k as used in Equation (5.11) are applicable to above equation.

The matrix $\mathbf{C}_{\text{spatial}}$ is defined as

$$\mathbf{C}_{\text{spatial}} = \sum_{k=1}^N w_k \mathbf{C}_k / \sum_{k=1}^N w_k \quad (5.18)$$

with the weight of the form

$$w_k = \exp(-d_k h_k). \quad (5.19)$$

The weight w_k consists of two measures, namely spatial distance d_k and spatial heterogeneity h_k . The spatial distance measure refers to the Euclidean distance defined in Equation (5.17), while the spatial heterogeneity measure is given by

$$h_k = d(\mathbf{C}_k, \mathbf{C}) / \text{tr}(\mathbf{C}). \quad (5.20)$$

The matrix $\mathbf{C}$ denotes the covariance matrix of the currently processed pixel and $d(\mathbf{C}_k, \mathbf{C})$ is again the Euclidean distance between two matrices. The spatial heterogeneity is computed with respect to the currently processed pixel, i.e. the central pixel within the test window. From Equation (5.19), it is apparent that the weighting is decreased with an increase in both the spatial distance and spatial heterogeneity.

5.5 Evaluation and Discussion

A total of four odd window sizes ranging from 3×3 to 9×9 pixels were examined for speckle suppression using the boxcar and proposed filters. The Lee-refined filter was tested with the window sizes of 5×5, 7×7, 9×9 and 11×11 pixels. In despeckling with the annealing filter, the tested numbers of iterations were 1, 5, 10, 25 and 50. The processing was limited to 50 iterations since convergence of the solution was observed.

The performance of each filter was evaluated in terms of speckle suppression, radiometric preservation as well as image feature retention by using the nine-look NASA/JPL POLSAR C- and L-band data. Detailed performance assessments are given below. Moreover, the filtering impact on the Cloude-Pottier target decomposition parameters, namely alpha-angle, entropy and anisotropy, were investigated.

5.5.1 Speckle Removal

The selected C- and L-band filtering outputs are displayed in Figures 5.9 and 5.10. Visually, the speckle was effectively removed by the proposed filter. The remarkable smooth appearance can be distinctly observed over homogeneous areas for larger window sizes.

To evaluate quantitatively the effectiveness in speckle suppression, the total power surface plots and the corresponding standard deviation σ over a homogeneous rubber plantation area from both the C- and L-band are given in Figures 5.11 and 5.12, respectively. The lower standard deviation indicates a better speckle suppression for the homogeneous rubber plantation area. From the results, all filters reduced effectively the standard deviation, where the degree of reduction in standard deviation was directly proportional to the increased window sizes. Comparing the boxcar, Lee-refined and proposed filters, the boxcar filter gave the best speckle suppression, followed by the proposed filter.

The Lee-refined filter was found, in comparison with the same window size, to produce a relatively higher standard deviation than both the boxcar and proposed filters. This phenomenon was mainly due to the use of the edge-aligned windows, where only the pixels of the half-window size are included in estimating the filtered covariance matrix.

For the annealing filter, the standard deviation was reduced significantly, especially for an increased number of iterations. It is evident from Figures 5.11 and 5.12 that the annealing filtering converged after 50 iterations. The standard deviations obtained through 25 and 50 iterations were identical, i.e. 0.061 and 0.033, respectively, for both the C- and L-band.

Figure 5.9: NASA/JPL POLSAR C-band speckle filtering results, with the HH, HV and VV intensities displayed in the RGB colour space.

Figure 5.10: NASA/JPL POLSAR L-band speckle filtering results, with the HH, HV and VV intensities displayed in the RGB colour space.

Figure 5.11: NASA/JPL POLSAR C-band total power surface plots of a rubber plantation area.

Figure 5.12: NASA/JPL POLSAR L-band total power surface plots of a rubber plantation area.

Apart from the total power, the co-polarised correlation magnitude results were also analysed. Figures 5.13 and 5.14 present the selected C- and L-band correlation magnitude outputs. As shown in both figures, it is obvious that the correlation magnitude outputs derived from the unfiltered data were badly corrupted and better results were obtained after filtering. For quantitative assessment, the standard deviation of the correlation magnitude was computed from three homogeneous areas, namely oil palm plantation area, rubber plantation area as well as scrub-grassland. Tables 5.1 and 5.2 tabulate the corresponding standard deviation values for both the C- and L-band, respectively. Similar findings, which were discussed above in the speckle removal of the total power component, were observed for all filters.

5.5.2 Radiometric Preservation

In dealing with radiometric preservation, the C- and L-band co-polarisation signatures of a homogeneous marshland area are plotted separately in Figures 5.15 and 5.16. Additionally, the average covariance matrix elements of the marshland area were extracted and tabulated in Tables 5.3 and 5.4.

By looking closely at Figures 5.15 and 5.16, the shape of the polarisation signature was well preserved for each test window of the boxcar, Lee-refined and proposed filters. Moreover, it can be clearly recognised from Tables 5.3 and 5.4 that all the values extracted from the filtered outputs using the boxcar, Lee-refined and proposed filters were close to those extracted from the unfiltered data. This further confirmed that no undesirable radiometric distortion was introduced in the filtered outputs.

For the annealing filter, the resultant values of HH, HV and VV intensities dropped expectedly as can be seen in Figures 5.15 and 5.16 as well as Tables 5.3 and 5.4. This indicates that the annealing filter does not preserve the radiometric properties well. This inherent bias in the estimation was also observed and shown by Schou and Skriver (2001) as a result of the choice made by the annealing filter between the different filter configurations.

Figure 5.13: NASA/JPL POLSAR C-band co-polarised correlation magnitude results. (a) shows the total power image. (b) is the unfiltered correlation magnitude result of (a). (c)–(f) are separately the outputs from boxcar filter (7×7 window), Lee-refined filter (7×7 window), annealing filter (25 iterations) and proposed filter (7×7 window).

Figure 5.14: NASA/JPL POLSAR L-band co-polarised correlation magnitude results. (a) shows the total power image. (b) is the unfiltered correlation magnitude result of (a). (c)–(f) are separately the outputs from boxcar filter (7×7 window), Lee-refined filter (7×7 window), annealing filter (25 iterations) and proposed filter (7×7 window).

Table 5.1: Average and standard deviation of co-polarised correlation magnitude extracted from C-band outputs

	Oil palm plantation area		Rubber plantation area		Scrub-grassland	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Unfiltered	0.6429	0.1695	0.5423	0.1795	0.4560	0.1848
Boxcar filter						
3×3 window	0.6178	0.0827	0.4883	0.0931	0.3652	0.1093
5×5 window	0.6152	0.0533	0.4815	0.0608	0.3554	0.0737
7×7 window	0.6146	0.0390	0.4788	0.0443	0.3522	0.0586
9×9 window	0.6143	0.0312	0.4771	0.0337	0.3516	0.0495
Lee-refined filter						
5×5 window	0.6113	0.0732	0.4805	0.0776	0.3575	0.0892
7×7 window	0.6134	0.0587	0.4773	0.0590	0.3521	0.0708
9×9 window	0.6137	0.0514	0.4773	0.0470	0.3513	0.0590
11×11 window	0.6143	0.0452	0.4761	0.0386	0.3510	0.0531
Annealing filter						
1 iteration	0.6203	0.1306	0.5059	0.1445	0.4014	0.1507
5 iterations	0.5990	0.0789	0.4796	0.0937	0.3717	0.0991
10 iterations	0.5924	0.0661	0.4788	0.0820	0.3777	0.0906
25 iterations	0.5915	0.0637	0.4816	0.0795	0.3849	0.0929
50 iterations	0.5915	0.0636	0.4817	0.0796	0.3857	0.0934
Proposed filter						
3×3 window	0.6183	0.0879	0.4970	0.0958	0.3758	0.1197
5×5 window	0.6147	0.0631	0.4920	0.0649	0.3717	0.0830
7×7 window	0.6124	0.0518	0.4901	0.0493	0.3711	0.0647
9×9 window	0.6097	0.0480	0.4885	0.0404	0.3707	0.0546

Table 5.2: Average and standard deviation of co-polarised correlation magnitude extracted from L-band outputs

	Oil palm plantation area		Rubber plantation area		Scrub-grassland	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Unfiltered	0.5397	0.2095	0.4991	0.2068	0.6453	0.2087
Boxcar filter						
3×3 window	0.3412	0.1369	0.2653	0.1245	0.5507	0.1371
5×5 window	0.3088	0.0977	0.2075	0.0936	0.5437	0.0977
7×7 window	0.2996	0.0733	0.1864	0.0793	0.5420	0.0844
9×9 window	0.2951	0.0576	0.1781	0.0684	0.5418	0.0770
Lee-refined filter						
5×5 window	0.3198	0.1234	0.2315	0.1081	0.5393	0.1267
7×7 window	0.3067	0.1009	0.2045	0.0888	0.5383	0.1132
9×9 window	0.3017	0.0868	0.1891	0.0796	0.5353	0.1065
11×11 window	0.2975	0.0753	0.1806	0.0702	0.5392	0.1091
Annealing filter						
1 iteration	0.4488	0.1882	0.3902	0.1771	0.5919	0.1892
5 iterations	0.3629	0.1505	0.2834	0.1336	0.5573	0.1570
10 iterations	0.3338	0.1393	0.2537	0.1165	0.5523	0.1432
25 iterations	0.3224	0.1365	0.2426	0.1113	0.5543	0.1357
50 iterations	0.3218	0.1365	0.2431	0.1112	0.5545	0.1350
Proposed filter						
3×3 window	0.3636	0.1489	0.2783	0.1327	0.5755	0.1364
5×5 window	0.3360	0.1169	0.2130	0.1051	0.5707	0.0974
7×7 window	0.3300	0.0951	0.1854	0.0908	0.5630	0.0877
9×9 window	0.3271	0.0806	0.1717	0.0824	0.5549	0.0862

Figure 5.15: NASA/JPL POLSAR C-band co-polarisation signatures of a marshland area.

Figure 5.16: NASA/JPL POLSAR L-band co-polarisation signatures of a marshland area.

Table 5.3: Average of C-band covariance matrix elements extracted from a marshland area.

	$\langle S_{HH} ^2 \rangle$	$\langle S_{HV} ^2 \rangle$	$\langle S_{VV} ^2 \rangle$	$\langle \Re(S_{HH}S_{HV}^*) \rangle$	$\langle \Im(S_{HH}S_{HV}^*) \rangle$	$\langle \Re(S_{HV}S_{VV}^*) \rangle$	$\langle \Im(S_{HV}S_{VV}^*) \rangle$	$\langle \Re(S_{HH}S_{VV}^*) \rangle$	$\langle \Im(S_{HH}S_{VV}^*) \rangle$
Unfiltered	0.220	0.028	0.253	-0.004	0.002	0.002	0.001	0.128	-0.009
Boxcar filter									
3×3 window	0.220	0.028	0.254	-0.004	0.002	0.002	0.000	0.129	-0.010
5×5 window	0.220	0.028	0.254	-0.004	0.002	0.002	0.000	0.130	-0.010
7×7 window	0.219	0.028	0.255	-0.004	0.002	0.002	0.000	0.130	-0.010
9×9 window	0.218	0.028	0.255	-0.004	0.003	0.002	0.000	0.130	-0.009
Lee-refined filter									
5×5 window	0.215	0.028	0.251	-0.003	0.002	0.003	0.000	0.127	-0.010
7×7 window	0.219	0.028	0.254	-0.003	0.002	0.003	0.000	0.130	-0.010
9×9 window	0.221	0.028	0.258	-0.003	0.003	0.002	0.000	0.132	-0.010
11×11 window	0.218	0.027	0.257	-0.004	0.003	0.002	0.001	0.130	-0.009
Annealing filter									
1 iteration	0.187	0.024	0.217	-0.005	0.001	0.001	0.001	0.107	-0.011
5 iterations	0.154	0.020	0.180	-0.005	0.000	0.002	0.003	0.089	-0.011
10 iterations	0.139	0.019	0.171	-0.006	-0.001	0.002	0.004	0.084	-0.011
25 iterations	0.136	0.018	0.168	-0.006	-0.001	0.002	0.005	0.083	-0.011
50 iterations	0.136	0.018	0.168	-0.006	-0.001	0.002	0.005	0.083	-0.011
Proposed filter									
3×3 window	0.220	0.028	0.254	-0.004	0.002	0.001	0.000	0.131	-0.010
5×5 window	0.220	0.027	0.254	-0.004	0.002	0.002	0.000	0.132	-0.010
7×7 window	0.219	0.027	0.254	-0.004	0.002	0.002	0.000	0.133	-0.010
9×9 window	0.217	0.027	0.254	-0.004	0.002	0.002	0.000	0.133	-0.010

Table 5.4: Average of L-band covariance matrix elements extracted from a marshland area.

	$\langle S_{HH} ^2 \rangle$	$\langle S_{HV} ^2 \rangle$	$\langle S_{VV} ^2 \rangle$	$\langle \Re(S_{HH}S_{HV}^*) \rangle$	$\langle \Im(S_{HH}S_{HV}^*) \rangle$	$\langle \Re(S_{HV}S_{VV}^*) \rangle$	$\langle \Im(S_{HV}S_{VV}^*) \rangle$	$\langle \Re(S_{HH}S_{VV}^*) \rangle$	$\langle \Im(S_{HH}S_{VV}^*) \rangle$
Unfiltered	0.039	0.004	0.057	0.001	0.000	0.002	0.000	0.024	0.004
Boxcar filter									
3×3 window	0.039	0.004	0.057	0.001	0.000	0.002	0.000	0.024	0.004
5×5 window	0.038	0.004	0.057	0.001	0.000	0.002	0.000	0.025	0.004
7×7 window	0.038	0.004	0.057	0.001	0.000	0.002	0.000	0.025	0.005
9×9 window	0.037	0.004	0.058	0.001	0.000	0.002	0.000	0.024	0.005
Lee-refined filter									
5×5 window	0.038	0.004	0.056	0.001	0.000	0.002	0.000	0.024	0.004
7×7 window	0.038	0.004	0.057	0.001	0.000	0.002	0.000	0.025	0.004
9×9 window	0.038	0.004	0.058	0.001	0.000	0.002	0.000	0.025	0.005
11×11 window	0.038	0.004	0.058	0.001	0.000	0.002	0.000	0.025	0.004
Annealing filter									
1 iteration	0.034	0.004	0.051	0.001	0.000	0.001	0.000	0.022	0.004
5 iterations	0.028	0.003	0.045	0.000	0.000	0.001	0.001	0.019	0.005
10 iterations	0.026	0.003	0.043	0.000	0.000	0.001	0.000	0.018	0.006
25 iterations	0.024	0.002	0.042	0.000	0.000	0.001	0.000	0.018	0.006
50 iterations	0.024	0.002	0.042	0.000	0.000	0.001	0.000	0.018	0.006
Proposed filter									
3×3 window	0.038	0.004	0.058	0.001	0.000	0.002	0.000	0.025	0.005
5×5 window	0.037	0.004	0.057	0.001	0.000	0.002	0.000	0.025	0.005
7×7 window	0.036	0.004	0.056	0.001	0.000	0.001	0.000	0.025	0.005
9×9 window	0.035	0.004	0.056	0.001	0.000	0.001	0.000	0.024	0.005

5.5.3 Structural Feature Retention

For the assessment of structural feature retention, the contrast between a structural feature and its neighbouring background was studied. In this case, the contrast $|d|$ is defined by the absolute difference of the average total power between the selected structural feature and its neighbouring background. The higher the computed contrast, the better is the retention. The structural feature identified in this test was a road segment. Figures 5.17 and 5.18 present the C- and L-band selected retention results as well as the computed contrast over the tested road segment.

As discussed in Section 5.3.1, the boxcar filter does not take any strategy into account for image feature preservation. Hence, it was expected that the boxcar filter blurred the road segment, especially for the larger window sizes. The loss in contrast is clearly observable in Figures 5.17 and 5.18. The contrast for the boxcar filter was the lowest among all filters. Due to the use of the edge and line detectors in the filtering process, excellent retention results were shown by the proposed filter, where the resultant contrast remained high. For both the Lee-refined and annealing filters, the acceptable good retention results were obtained for both the C- and L-band.

5.5.4 Preservation of Point-Like Textural Features

In order to examine the preservation of point-like textural features, the coefficient of variation (CoV) of a heterogeneous area was computed from the total power output. The CoV is defined as the ratio of the standard deviation to the mean total power. Figures 5.19 and 5.20 present, respectively, the C- and L-band preservation results in which the selected heterogeneous area is depicted by the yellow coloured rectangle.

From Figures 5.19 and 5.20, it is clearly visible that the point-like textural features were almost smeared out by the boxcar filter. The CoV values for the boxcar filter were much lower, which revealed the failure of the boxcar filter in keeping the textural features. For the proposed filter, the heterogeneous area was still preserved after filtering; however, the proposed filter was outperformed by both the Lee-refined and annealing filters in this aspect. Noticeably, the proposed filter tended to retain darker pixels while fading brighter pixels in the heterogeneous area, whereas the Lee-refined filter yielded the opposite results. This tendency of the proposed filter was caused by the

relative dispersion measurement. As can be seen in Equation (5.7), the relative dispersion measure is proportional inversely to the average overall variability. Thus, the relative dispersion can be somewhat lower as a result of the higher overall variability for brighter pixels.

Figure 5.17: NASA/JPL POLSAR C-band results showing structural feature retention.

Figure 5.18: NASA/JPL POLSAR L-band results showing structural feature retention.

Figure 5.19: NASA/JPL POLSAR C-band results showing preservation of point-like textural features.

Figure 5.20: NASA/JPL POLSAR L-band results showing preservation of point-like textural features.

5.5.5 Filtering Impact on Cloude-Pottier Target Decomposition Parameters

The filtering impact on the Cloud-Pottier target decomposition parameters, namely entropy, anisotropy and average alpha-angle, was studied by Lee *et al.* (2006) and López-Martínez *et al.* (2006). It should be noted here that the detailed explanation of this target decomposition is given in Chapter 7 under Section 7.3.3. From their work, the speckle influence was found to be very significant in both the entropy and anisotropy. The entropy values increase while the anisotropy values decrease after filtering. For the average alpha-angle, it is less sensitive to the filtering process.

In order to gain insight into the filtering impact on these decomposition parameters in the POLSAR test data, the entropy, anisotropy and average alpha-angle outputs were derived from both the C- and L-band unfiltered and filtered data. Figures 5.21 and 5.22 present the selected entropy outputs from both the C and L bands, respectively. The C- and L-band anisotropy outputs are displayed separately in Figures 5.23 and 5.24. Figures 5.25 and 5.26 show the C- and L-band average alpha-angle outputs.

In Figures 5.21–5.24, a distinct difference can be visually observed between the outputs derived from the unfiltered and filtered data for both the entropy and anisotropy. The entropy and anisotropy outputs from the unfiltered data were rather noisy due to the speckle influence. Similar to the findings of Lee *et al.* (2006) and López-Martínez *et al.* (2006), the entropy values increase whereas the anisotropy values decrease after filtering. Conversely, there is no significant change in both the C- and L-band average alpha-angle outputs before and after filtering, except for the slightly noisy appearance in the unfiltered average alpha-angle outputs. From Figures 5.21–5.26, it is easily noticed that the outputs from the boxcar and Lee-refined filtered data were nearly alike as those results from the proposed filter.

Figure 5.21: NASA/JPL POLSAR C-band entropy results. (a) Unfiltered, (b) boxcar filter with the 7×7 window, (c) Lee-refined filter with the 7×7 window, (d) proposed filter with the 7×7 window, and (e) entropy scale bar.

Figure 5.22: NASA/JPL POLSAR L-band entropy results. (a) Unfiltered, (b) boxcar filter with the 7×7 window, (c) Lee-refined filter with the 7×7 window, (d) proposed filter with the 7×7 window, and (e) entropy scale bar.

Figure 5.23: NASA/JPL POLSAR C-band anisotropy results. (a) Unfiltered, (b) boxcar filter with the 7×7 window, (c) Lee-refined filter with the 7×7 window, (d) proposed filter with the 7×7 window, and (e) anisotropy scale bar.

Figure 5.24: NASA/JPL POLSAR L-band anisotropy results. (a) Unfiltered, (b) boxcar filter with the 7×7 window, (c) Lee-refined filter with the 7×7 window, (d) proposed filter with the 7×7 window, and (e) anisotropy scale bar.

Figure 5.25: NASA/JPL POLSAR C-band average alpha-angle results. (a) Unfiltered, (b) boxcar filter with the 7×7 window, (c) Lee-refined filter with the 7×7 window, (d) proposed filter with the 7×7 window, and (e) scale bar of average alpha-angle.

Figure 5.26: NASA/JPL POLSAR L-band average alpha-angle results. (a) Unfiltered, (b) boxcar filter with the 7×7 window, (c) Lee-refined filter with the 7×7 window, (d) proposed filter with the 7×7 window, and (e) scale bar of average alpha-angle.

5.6 Summary

In this chapter a novel spatially adaptive speckle filter was introduced for multi-look POLSAR data, which aims at preserving point-like textural features as well as structural features, i.e. edges and lines, during the filtering process. The central idea of the proposed filter is that the filtering operations are performed spatially variant for image features in order to preserve them. For homogeneous areas, the filtering is based on scattering properties. To achieve this, the proposed filter consists of five processing steps, namely edge detection, line detection, texture analysis, classification based on scattering mechanisms, and despeckling. Applied to the nine-look NASA/JPL POLSAR C- and L-band data, the proposed filter performed satisfactorily in the speckle removal, image feature retention as well as radiometric preservation. However, due to the involvement of up to five processing steps, the proposed filter is not necessarily suitable for real-time applications.

Comparisons with the boxcar, Lee-refined and annealing filters were carried out in this study. The Lee-refined filter exhibited its stable performance in the speckle removal, image feature retention as well as radiometric preservation. For the boxcar filter, a significant trade-off between the speckle removal and image feature retention was observed. The speckle was removed at the expense of destroying the image features for larger window sizes. The annealing filter was good in both speckle removal and image feature retention. It nevertheless suffered from the inherent defection in the radiometric preservation. In summary, no universally best speckle filter was found, where each filter possesses its own merits and limitations. Furthermore, different applications have different requirements on the speckle filter and its filtering outcomes. Identifying the best or most appropriate filter relies strongly on the subsequent applications of the filtered output.

Chapter 6

Segmentation

6.1 Introduction

Image segmentation is the process of partitioning an image into multiple meaningful segments. According to Haralick and Shapiro (1985), a good segmentation comprises the following criteria: (i) the resultant segments should be uniform and homogeneous, (ii) the segment interiors should be simple and without many small holes, (iii) the adjacent segments should have their distinct and different values with respect to the characteristics on which they are uniform as well as (iv) the boundaries of each segment should be simple, not ragged and spatially accurate. A good survey on image segmentation can be found in Fu and Mui (1981), Di Zenzo (1983), Pal and Pal (1993), Cheng *et al.* (2001) and others.

There are three common image segmentation approaches: (i) thresholding, (ii) edge detection and (iii) region-based segmentation. The edge detection in multi-look POLSAR data is discussed in Chapter 4, whereas this chapter focuses on the latter approach. A region in a digital image refers to an area in which there is a group of connected pixels sharing similar properties, such as grey level, colour, texture and so forth. The region-based segmentation involves finding these regions in an image based on spectral similarity and spatial proximity.

The remaining part of this chapter is structured as follows: Section 6.2 reviews previous work on region-based segmentation which was performed on POLSAR data. In this study an existing hybrid segmentation algorithm, which was proposed by Haris *et al.* (1998), was extended for segmenting multi-look POLSAR data and is explained in

Section 6.3. Section 6.4 analyses and discusses the segmentation outputs. Section 6.5 summarises this chapter.

6.2 Previous Work

From the literature review, it was found that only limited research work has been devoted to region-based segmentation of POLSAR images, while much more attention has been placed on POLSAR image classification. The classification of POLSAR images is discussed in Chapter 7.

In order to segment single-look POLSAR imagery into homogenous regions, Borghys (2001) extended the so-called merging using moments (MUM) algorithm, which was originally proposed by Cook *et al.* (1994) for single-frequency single-polarisation SAR image. The extension was based separately on the Hotelling T^2 test and the Mahalanobis distance. However, no detailed comparison between the use of the Hotelling T^2 test and the Mahalanobis distance was reported.

The MUM algorithm was also extended by Skriver *et al.* (2002) for multi-look POLSAR data. The likelihood ratio test statistic given in Equation (4.1) is employed as a region merging criterion. The algorithm was tested on EMISAR L-band data using (i) only all diagonal elements of the covariance matrix, i.e. HH, HV as well as VV intensities, and (ii) all diagonal elements plus the HH-VV off-diagonal elements. From the results, an advantage of including the HH-VV off-diagonal elements in the region-based segmentation was observed.

Beaulieu and Touzi (2004) presented a hierarchical stepwise optimisation (HSWO) algorithm for multi-look POLSAR images. The region merging criteria were derived from a complex Gaussian distribution, complex Wishart distribution and K -distribution. Applied to a Convair-580 POLSAR dataset, better segmentation results over textured forested areas were obtained with the K -distribution than with both the Gaussian and Wishart distributions.

6.2.1 Hierarchical Stepwise Optimisation Algorithm

The HSWO algorithm, which is inspired from the agglomerative hierarchical clustering and stepwise optimisation, was first proposed by Beaulieu and Goldberg (1989) for region-based segmentation. In order to segment POLSAR images, Beaulieu and Touzi (2004) redefined the region merging criteria based on the complex Gaussian distribution, complex Wishart distribution and K -distribution. The HSWO algorithm is an iterative bottom-up region-based segmentation approach. It consists of four steps:

Step 1: Define an initial image partition. Each pixel can be initially considered as an individual region.

Step 2: For each adjacent pair of regions i and j , compute the stepwise criterion SC :

$$SC = L(m_i + m_j) \ln |\mathbf{C}_{i \cup j}| - L m_i \ln |\mathbf{C}_i| - L m_j \ln |\mathbf{C}_j|, \quad (6.1)$$

where L denotes number of looks. The variable m_i and matrix $\mathbf{C}_i$ refer to the number of pixels and the average covariance matrix of region i , respectively. The symbol $|\cdot|$ represents the determinant of a matrix, while the symbol $\cup$ is the union of regions i and j . This stepwise criterion is derived from the complex Wishart distribution.

Step 3: Find and merge the region pair with the minimum stepwise criterion value.

Step 4: The process is terminated if no merging is needed; otherwise, go to Step 2. The termination depends on the desired number of regions.

6.3 Extended Hybrid Segmentation Algorithm

A hybrid segmentation algorithm was proposed by Haris *et al.* (1998) for segmenting optical pictures. Its advantage is that both edge and region information is considered during the segmentation process. There are four main modules in the segmentation algorithm: (i) noise reduction, (ii) gradient computation, (iii) initial segmentation by morphological watershed transform, and (iv) region merging. In this study, the hybrid segmentation algorithm was extended for segmenting multi-look POLSAR data. Figure 6.1 shows the flow chart of the extended hybrid segmentation algorithm, where the four modules become (i) speckle suppression, (ii) edge magnitude computation, (iii) initial segmentation by morphological watershed transform, and (iv) region merging. Each module is executed consecutively and discussed in more detail below.

6.3.1 Speckle Suppression

As mentioned in the previous chapter, POLSAR data are inherently corrupted by speckle noise. This presence of speckle noise can significantly degrade the performance of image segmentation. Thus, the proposed spatially adaptive speckle filter is employed for speckle suppression. The filtering output is then used as an input for computing the edge magnitudes.

Figure 6.1: Flow chart of the extended hybrid segmentation algorithm.

6.3.2 Edge Magnitude Computation

The purpose of this module is to generate an edge magnitude output, which is then used as an input into the subsequent watershed transformation. In this module, the proposed Roy's largest eigenvalue-based edge detector is employed to compute the edge magnitude from the filtered POLSAR data. The corresponding processing steps are outlined in Section 4.3.1. The edge magnitude of each pixel, i.e. the maximum Roy's largest eigenvalue, is computed by using the four basic edge templates of 3×3 pixels as shown in Figure 4.1.

6.3.3 Initial Segmentation by Watershed Transform

The concept of watershed was first applied by Beucher and Lantuejoul (1979) to image segmentation problems. To date, the use of the morphological watershed transform for segmenting single-frequency single-polarisation SAR data is well recognised and can be found in Fjørtoft *et al.* (1998), Lemarechal *et al.* (1998), Li *et al.* (1999) and others. Its advantages include that: (i) it is a natural segmentation approach, (ii) it is independent of any forms of probability density function in the segmentation process, and (iii) it does not need to state any controls. However, the drawback is that in most cases it produces an over-segmented result.

The watershed transform contains two steps: sorting and flooding. The input edge magnitude image is considered as a topographic surface. Each pixel value becomes the altitude of the surface. Firstly, all pixels are sorted in increasing order according to their edge magnitude value. The flooding is then carried out based on an immersion simulation. There are two rules in the flooding process: (i) random access to any pixels in the image and (ii) direct access to the neighbours of a given pixel. The water first rises from the minimum magnitude pixels, which are also known as local minima. The flooding process is continued for each magnitude k until the maximum. Each k -magnitude pixel, which is adjacent to an already labelled watershed region, is added into that region. A new region is constructed for the pixel which is not connected to any existing regions.

As mentioned before, the watershed transform always produces an over-segmented output. In order to remove spurious local minima, the following solution is thus adopted, where the edge magnitude image is thresholded prior to the watershed transform:

$$I(x, y) = \begin{cases} g(x, y) & \text{if } g(x, y) > T \\ T & \text{otherwise} \end{cases} \quad (6.2)$$

The variable $g(x, y)$ denotes the edge magnitude value of a pixel located at coordinate (x, y) and T is the user-defined threshold. The thresholding replaces all lower gradient values by the uniform threshold T and small regions can then be eliminated by removing insignificant local minima.

6.3.4 Region Merging

To further remedy the over-segmentation problem, a modified HSWO algorithm is proposed here. This modified version follows closely the original framework, except for the use of Roy's largest eigenvalue as the stepwise criterion. The modified HSWO algorithm involves four processing steps. It proceeds iteratively as follows:

Step 1: The segmented output resulting from the watershed transform is used as an initial image partition.

Step 2: For each adjacent pair of regions i and j , compute the stepwise criterion:

$$SC = \left(\frac{1}{N_i} + \frac{1}{N_j} \right) \times \frac{1}{\max\{ch_1(\mathbf{C}_i \mathbf{C}_j^{-1}), ch_1(\mathbf{C}_j \mathbf{C}_i^{-1})\}}. \quad (6.3)$$

As can be seen above, the stepwise criterion consists of two terms. The first term favours the merging of small regions, where N_i and N_j refer separately to the size of the two regions i and j . The larger the region sizes N_i and N_j , the smaller the value of $1/N_i + 1/N_j$. The second term measures the dissimilarity of the two regions. Both $\mathbf{C}_i$ and $\mathbf{C}_j$ are the average covariance matrix of the two regions i and j , respectively. The eigenvalue $ch_1(\mathbf{C}_i \mathbf{C}_j^{-1})$ refers to the largest eigenvalue of $\mathbf{C}_i \mathbf{C}_j^{-1}$ and $\max$ denotes the maximum operator. If both $\mathbf{C}_i$ and $\mathbf{C}_j$ are identical, the second term is equal to unity due to the fact that both $ch_1(\mathbf{C}_i \mathbf{C}_j^{-1})$ and $ch_1(\mathbf{C}_j \mathbf{C}_i^{-1})$ are unit eigenvalues. In contrast, the second term is less than unity for $\mathbf{C}_i \neq \mathbf{C}_j$.

Step 3: Perform the globally best merging. To achieve this, find and merge the spatially adjacent region pair with the maximum stepwise criterion value over the entire image.

Step 4: The process is terminated if no merging is needed; otherwise, go to Step 2. The termination depends on the preset desired number of regions.

6.4 Results and Discussion

In most of existing literature, the quality of a region-based segmentation technique is examined by applying the algorithm to a variety of test images, followed by a visual inspection of the obtained results or leaving the evaluation to the reader (Mueller *et al.*, 2003). Only few quantitative assessments were reported and found from the literature review. In this study the capabilities of the extended hybrid segmentation algorithm

were first examined using multi-look simulated POLSAR datasets and then with the NASA/JPL POLSAR data.

6.4.1 Simulated POLSAR Data

The simulated POLSAR datasets encompassed four-look C-band, four-look L-band, nine-look C-band and nine-look L-band. Each dataset is composed of eight regions belonging to four different land cover classes, namely oil palm, rice paddy, rubber and scrub-grassland. The use of these simulated data enabled the evaluation to be carried out more practically owing to the availability of reference regions. Prior to the segmentation, the simulated data were filtered using the proposed speckle filter with a window of 7×7 pixels. Figure 6.2 shows the simulated data after filtering, where the HH, HV and VV intensities are displayed in the RGB colour space.

Figure 6.2: Filtering results of POLSAR simulated data, with the HH, HV and VV intensities displayed in the RGB colour space.

In the initial segmentation of the filtered POLSAR data, the watershed transform yielded expectedly the over-segmented outputs. The outputs are given in Figure 6.3. There were 4039 and 3786 regions in the C-band four- and nine-look outputs, respectively. The L-band four- and nine-look outputs comprised separately 4052 and 4070 regions. To mitigate this over-segmentation effect, the previously explained thresholding was applied to the C- and L-band edge magnitude images. By using the thresholded edge magnitude images, the resultant number of regions was reduced to 85 and 33 for both the C-band four-look and nine-look. The top row of Figure 6.4 presents the corresponding C-band outputs. As can be seen in the figures, most of the small

regions are distributed especially along or near the boundaries between two different land cover regions. For both the L-band four- and nine-look, the thresholded edge magnitude images were successfully segmented into the desired eight regions. The resultant outputs are shown in the bottom row of Figure 6.4. Due to the remaining fragmentation in the C-band outputs, the subsequent region merging was performed. In the region merging, the termination is controlled by the desired number of regions. Hence, the number of regions was set to eight. Figure 6.5 presents the C-band four- and nine-look merging outputs, where the desired eight regions were contained in each output.

Figure 6.3: Over-segmented outputs resulting from the watershed transform.

Figure 6.4: Watershed transform outputs using the thresholded edge magnitude images.

Figure 6.5: Region merging outputs resulting from the modified HSWO algorithm.

In this study, the region-based segmentation of both the POLSAR C- and L-band filtered data, which was based on the HSWO algorithm, was also conducted. As shown in Figure 6.6, the HSWO algorithm produced satisfactory results, where all simulated datasets were successfully segmented into the desired eight regions. To assess quantitatively the performance of both the extended hybrid segmentation and HSWO algorithms, the following over- and under-merging errors were computed from the segmentation outputs:

$$\text{over-merging error} = \frac{\#A - \#(A \cap B)}{\#A} \times 100\% \quad (6.4)$$

and

$$\text{under-merging error} = \frac{\#B - \#(A \cap B)}{\#B} \times 100\%. \quad (6.5)$$

The notation $\#A$ represents the number of pixels of a segmented region A and $\#B$ denotes the number of pixels of a reference region B . Then, $\#(A \cap B)$ is the number of pixels of an area shared between A and B , which indicates the correct segmentation. An ideal segmentation should result in zero over- and under-merging errors. Table 6.1 tabulates both the over- and under-merging errors computed from the C- and L-band segmentation outputs. Both the extended hybrid segmentation and HSWO algorithms showed their promising performance, where the average segmentation errors were less than one percent. From Table 6.1, it was observed that the segmentation errors were higher for the C-band compared with the L-band. In addition, the increasing number of looks helped to improve the segmentation results.

Figure 6.6: Segmentation outputs resulting from the HSWO algorithm.

6.4.2 NASA/JPL POLSAR Data

In the experiments the C- and L-band NASA/JPL POLSAR filtering outputs, which were generated using the proposed speckle filter with a window of 7×7 pixels, were selected and tested. The watershed transform produced a total of 464484 and 457762 regions in the C- and L-band outputs, respectively. By using the thresholded edge magnitude images, the resultant number of regions was reduced separately to 410845 and 420055. The thresholds were set separately to 1.2 and 1.3 for the C- and L-band edge magnitude images. Figure 6.7 presents the distribution of all pixels in both bands, whose edge magnitude value was less than or equal to the threshold. The proportion of these pixels was about 9% and 6% in the C- and L-band, respectively. The majority of these pixels were from the homogenous river, rice paddy fields, oil palm as well as rubber plantation areas.

As previously stated in Section 6.3.4, the desired number of regions is employed as the termination rule in the subsequent region merging. In this study, the perfect setting of this parameter was found to be very difficult since the exact number of regions in the POLSAR test data is unknown. A similar situation was observed for the region-based segmentation using the HSWO algorithm. Thus, five different region numbers were heuristically chosen and examined, i.e. 10000, 25000, 50000, 100000 and 250000. Figures 6.8 and 6.9 show the subsets of the C- and L-band outputs, respectively. For comparison, the C- and L-band segmentation outputs resulting from the HSWO

Table 6.1: Over- and under-merging errors computed from C- and L-band segmentation outputs

	Percent of merging errors*								Total error	Average error
	Oil palm		Rubber		Rice paddy		Scrub-grassland			
	Over	Under	Over	Under	Over	Under	Over	Under		
<u>HSWO</u>										
C-band, four-look	0.68	1.20	0.78	0.73	0.00	0.05	0.80	0.28	4.52	0.57
C-band, nine-look	0.30	0.34	0.30	0.21	0.00	0.00	0.11	0.16	1.42	0.18
L-band, four-look	0.10	0.20	0.19	0.08	0.00	0.00	0.01	0.02	0.60	0.08
L-band, nine-look	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.05	0.01
<u>Extended hybrid segmentation</u>										
C-band, four-look	1.89	0.94	0.05	2.65	0.09	0.00	1.56	0.05	7.23	0.90
C-band, nine-look	0.80	0.34	0.03	1.02	0.00	0.00	0.58	0.05	2.82	0.35
L-band, four-look	0.70	0.23	0.00	0.78	0.13	0.00	0.31	0.13	2.28	0.28
L-band, nine-look	0.21	0.01	0.00	0.21	0.00	0.00	0.01	0.00	0.44	0.06

*Over = over-merging error; under = under-merging error.

algorithm are also given in Figures 6.10 and 6.11. From the results, it was found that the region merging as well as HSWO outputs relied strongly on the user-specified number of regions. As indicated by the yellow coloured arrows in Figures 6.8–6.11, the segmentation errors occurred in both the C- and L-band outputs when the desired number of regions was set to 10000. From the C- and L-band hybrid segmentation outputs, it was noticed that some pixels in the oil palm plantation area were wrongly merged into the same region from the neighbouring agricultural land. The oil palm plantation area is labelled with “A”, whereas the agricultural land is given the label “B” in the figures. For the HSWO segmentation outputs, a similar error was detected in the C-band, while part of the agricultural land was incorrectly merged into the same region from the oil plantation area in the L-band.

The retention of structural features, i.e. lines, was visually inspected for each region-based segmentation output. Figures 6.12 and 6.13 present separately the C- and L-band retention results, in which a road segment was selected for the inspection. From the results, it was found that the setting of the desired number of regions again played an important role in determining a good retention. Both the extended hybrid segmentation and HSWO algorithms exhibited their identical performance in this aspect. Only the segmentation outputs with the desired region number of 100000 and 250000 preserved the road segment well, while the road segment became fragmented for other tested region numbers for both the C and L bands.

In this study both the extended hybrid segmentation and HSWO algorithms were programmed using the C-language. They were executed on a single personal computer with Microsoft Windows as operating system. The computer processor was an Intel Core™ 2 at 2.66 GHz with 2 GB of memory. Table 6.2 gives the time expenses of the corresponding tasks in obtaining both the C- and L-band segmentation outputs. From the table, it can be clearly seen that the watershed transform required less computational time since there are only two simple operations, i.e. sorting and flooding. The use of edge magnitude inputs with or without thresholding occupied the same amount of computational time in the watershed transformation. On the other hand, the HSWO algorithm was found to be more time-consuming. This is because it involves the global search of a region pair, which minimises the stepwise criterion, for each merging. Moreover, the stepwise criterion between the newly merged region and its adjacent regions has to be computed after each merging. Comparing Equations (6.1) and (6.3), it

Figure 6.7: Thresholding applied to edge magnitude image. (a) and (b) are separately the C- and L-band edge magnitude image, while (c) and (d) are the C- and L-band thresholded images, respectively. In the thresholded images, the pixels whose edge magnitude value is less than or equal to the threshold are coloured in black.

Figure 6.8: C-band outputs resulting from the extended hybrid segmentation algorithm. Note that each display is only part of the entire processed output.

Figure 6.9: L-band outputs resulting from the extended hybrid segmentation algorithm. Note that each display is only part of the entire processed output.

Figure 6.10: C-band outputs resulting from the HSWO algorithm. Note that each display is only part of the entire processed output.

Figure 6.11: L-band outputs resulting from the HSWO algorithm. Note that each display is only part of the entire processed output.

is obvious that the region merging algorithm involves more complicated calculations than the HSWO algorithm due to the eigenvalue computation. However, the time consumption for the extended hybrid segmentation algorithm, i.e. watershed transform plus region merging, was lower than for the HSWO algorithm. This was mainly due to the initial segmentation by the watershed transform, which reduced greatly the number of regions before the region merging process. Conversely, each pixel in the filtered POLSAR data was initially considered as an individual region in the region-based segmentation by the HSWO algorithm.

In Chapter 7, the C- and L-band region-based segmentation outputs were used as inputs for supervised classification. The segmentation outputs, resulting from the extended hybrid segmentation and HSWO algorithms with the desired region number of 100000, were tested for each frequency band. In each segmented input, the covariance matrix of each pixel was replaced by the average covariance matrix of the region which the pixel belongs to. To examine radiometric preservation in the segmented inputs, the covariance matrix elements were extracted from six land cover categories. The land cover classes included mangrove forest, oil palm, rice paddy, river, rubber and scrub-grassland. Tables 6.3 and 6.4 present the average covariance matrix elements, which were extracted separately from both the C- and L-band. As it can be seen in both tables, all the extracted values from the segmented data were close to those extracted from the filtered data. This confirmed that there were no unwanted radiometric distortions, which were introduced in the segmented data.

Table 6.2: Computational time for the hybrid segmentation and HSWO algorithms

	Computational time (minutes)	
	C-band	L-band
<u>Watershed transform</u>		
edge magnitude image	6	6
thresholded edge magnitude image	6	6
<u>Watershed transform plus region merging</u>		
250000 regions	10	11
100000 regions	15	15
50000 regions	20	21
25000 regions	23	23
10000 regions	26	26
<u>HSWO</u>		
250000 regions	43	44
100000 regions	48	49
50000 regions	51	51
25000 regions	53	53
10000 regions	54	54

Figure 6.12: Structural feature retention in C-band segmentation outputs. The extended hybrid segmentation results are given in the left column, while the right column presents the segmentation outputs resulting from the HSWO algorithm. Note that each display is only part of the entire processed output.

Figure 6.13: Structural feature retention in L-band segmentation outputs. The extended hybrid segmentation results are given in the left column, while the right column presents the segmentation outputs resulting from the HSWO algorithm. Note that only subimages are displayed.

Table 6.3: Average of covariance matrix elements extracted from C-band filtered and segmented POLSAR data

	$\langle S_{HH} ^2 \rangle$	$\langle S_{HV} ^2 \rangle$	$\langle S_{VV} ^2 \rangle$	$\langle \Re(S_{HH}^* S_{HV}) \rangle$	$\langle \Im(S_{HH}^* S_{HV}) \rangle$	$\langle \Re(S_{HV}^* S_{VV}) \rangle$	$\langle \Im(S_{HV}^* S_{VV}) \rangle$	$\langle \Re(S_{HH}^* S_{VV}) \rangle$	$\langle \Im(S_{HH}^* S_{VV}) \rangle$
C-band filtered data using the proposed speckle filter with a window of 7x7 pixels									
Mangrove forest	0.219	0.054	0.259	-0.004	0.002	-0.001	-0.002	0.125	-0.026
Oil palm plantation area	0.256	0.040	0.272	-0.003	0.000	0.003	0.001	0.162	-0.021
Rice paddy field	0.024	0.003	0.219	-0.002	0.000	0.006	0.004	-0.033	-0.025
River	0.004	0.001	0.008	0.000	0.000	0.000	0.000	0.002	0.000
Rubber plantation area	0.329	0.070	0.345	-0.015	0.005	0.004	-0.001	0.162	-0.032
Scrub-grassland	0.195	0.039	0.147	-0.005	0.001	0.003	-0.001	0.061	0.001
C-band segmented data using the extended hybrid segmentation with the desired regions of 100000									
Mangrove forest	0.217	0.054	0.258	-0.004	0.002	-0.001	-0.002	0.123	-0.026
Oil palm plantation area	0.254	0.040	0.271	-0.003	0.000	0.003	0.001	0.161	-0.022
Rice paddy field	0.025	0.003	0.214	-0.002	0.000	0.006	0.004	-0.031	-0.024
River	0.004	0.001	0.008	0.000	0.000	0.000	0.000	0.002	0.000
Rubber plantation area	0.316	0.068	0.333	-0.013	0.004	0.004	-0.003	0.154	-0.031
Scrub-grassland	0.195	0.039	0.149	-0.006	0.001	0.003	-0.002	0.061	0.002
C-band segmented data using the HSWO algorithm with the desired regions of 100000									
Mangrove forest	0.219	0.054	0.259	-0.005	0.002	-0.002	-0.002	0.123	-0.026
Oil palm plantation area	0.254	0.040	0.273	-0.002	0.001	0.003	0.000	0.160	-0.023
Rice paddy field	0.024	0.003	0.214	-0.002	0.000	0.006	0.004	-0.032	-0.024
River	0.004	0.001	0.008	0.000	0.000	0.000	0.000	0.002	0.000
Rubber plantation area	0.324	0.070	0.343	-0.014	0.004	0.006	-0.002	0.162	-0.033
Scrub-grassland	0.194	0.039	0.149	-0.006	0.001	0.003	-0.002	0.061	0.001

Table 6.4: Average of covariance matrix elements extracted from L-band filtered and segmented POLSAR data

	$\langle S_{HH} ^2 \rangle$	$\langle S_{HV} ^2 \rangle$	$\langle S_{VV} ^2 \rangle$	$\langle \Re(S_{HH}^* S_{HV}) \rangle$	$\langle \Im(S_{HH}^* S_{HV}) \rangle$	$\langle \Re(S_{HV}^* S_{VV}) \rangle$	$\langle \Im(S_{HV}^* S_{VV}) \rangle$	$\langle \Re(S_{HH}^* S_{VV}) \rangle$	$\langle \Im(S_{HH}^* S_{VV}) \rangle$
L-band filtered data using the proposed speckle filter with a window of 7x7 pixels									
Mangrove forest	0.019	0.005	0.024	-0.001	0.000	0.000	0.001	0.009	0.019
Oil palm plantation area	0.084	0.011	0.046	0.000	-0.001	0.002	0.001	0.018	0.084
Rice paddy field	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.001
River	0.002	0.000	0.012	0.000	0.000	0.000	0.000	0.004	0.002
Rubber plantation area	0.158	0.037	0.123	-0.007	0.001	0.003	0.004	0.012	0.158
Scrub-grassland	0.019	0.002	0.018	0.000	0.000	0.000	0.000	0.010	0.019
L-band segmented data using the extended hybrid segmentation with the desired regions of 100000									
Mangrove forest	0.019	0.005	0.024	-0.001	0.000	0.000	0.001	0.009	0.019
Oil palm plantation area	0.085	0.012	0.046	-0.001	-0.001	0.002	0.001	0.018	0.085
Rice paddy field	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.001
River	0.002	0.000	0.012	0.000	0.000	0.000	0.000	0.004	0.002
Rubber plantation area	0.158	0.037	0.123	-0.007	0.001	0.003	0.004	0.013	0.158
Scrub-grassland	0.019	0.002	0.018	0.000	0.000	0.000	0.000	0.010	0.019
L-band segmented data using the HSWO algorithm with the desired regions of 100000									
Mangrove forest	0.019	0.005	0.024	-0.001	0.000	0.000	0.001	0.008	0.019
Oil palm plantation area	0.084	0.012	0.046	0.000	-0.001	0.002	0.001	0.018	0.084
Rice paddy field	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.001
River	0.002	0.000	0.012	0.000	0.000	0.000	0.000	0.004	0.002
Rubber plantation area	0.155	0.038	0.122	-0.007	0.001	0.003	0.004	0.013	0.155
Scrub-grassland	0.019	0.002	0.018	0.000	0.000	0.000	0.000	0.010	0.019

6.5 Summary

In this chapter the hybrid segmentation algorithm, which was proposed by Haris *et. al* (1998), has been extended for segmenting multi-look POLSAR data. There are four modules in the segmentation algorithm, namely (i) speckle suppression, (ii) edge magnitude computation, (iii) initial segmentation by morphological watershed transform, and (iv) region merging. The capabilities of the extended hybrid segmentation algorithm were examined using both the simulated POLSAR data and NASA/JPL POLSAR data. Its performance was benchmarked against the HSWO algorithm, which was introduced by Beaulieu and Touzi (2004).

Applied to the C- and L-band NASA/JPL POLSAR data, the extended hybrid segmentation algorithm was found to be less time-consuming than the HSWO algorithm. The segmentation outputs resulting from both the algorithms rely strongly on the user-defined region number, which is employed as the termination rule. As a result, segmentation errors may occur for improper settings of this parameter. In this study, the retention of the structural features in the segmentation outputs was visually inspected. Both the algorithms showed their similar performance in this aspect. Again, their performance was controlled by the desired number of regions. In Chapter 7, the region-based segmentation outputs are used as the inputs for land cover classification. Thus, the radiometric preservation in the segmented data was validated in this chapter.

Chapter 7

Classification

7.1 Introduction

Previous experience has confirmed the capability of optical remotely sensed data for classifying land cover in the tropical regions, but the occurrence of extensive cloud coverage over these areas has restricted the utilisation of the data. Hence, the cloud-penetrating capability of SAR is particularly useful in tropical regions. However, based on the past experience, the application of single-frequency single-polarisation SAR data, which are provided by ERS-1/2, JERS-1 and RADARSAT-1, has proven to be difficult. Land cover features cannot be easily distinguished according to their single-band backscattering signature alone. With the advent of multi-frequency polarimetric SAR imaging systems, it is now possible to capture the complete polarimetric signatures of the Earth's surface. The POLSAR data have successfully attracted a great deal of attention in various applications (Boerner *et al.*, 1998). One of the key applications is land cover classification. More details on land cover classification using POLSAR data can be found in Nagai *et al.* (1997), Lee *et al.* (2001), van den Broek *et al.* (2004) and others.

This chapter reports the results of the previously pre-processed NASA/JPL POLSAR C- and L-band data in land cover classification over a selected tropical area, i.e. Kuala Muda in Peninsular Malaysia. It is organised as follows: Previous work on POLSAR image classification is reviewed in Section 7.2. Then, Sections 7.3 and 7.4 present the classification, which was carried out in this study, based on scattering mechanisms and statistical distribution. Also, the corresponding classification results are analysed in both sections. Section 7.5 summarises this chapter.

7.2 Previous Work

To date, numerous classification algorithms have been developed for POLSAR data. They are designed and work in either a supervised or an unsupervised mode. The supervised classifiers use a set of samples of known identity, i.e. training fields, to classify image pixels of unknown identity. In contrast, the unsupervised classifiers group pixels which have similar characteristics into a class without the need of any training samples.

Generally, the POLSAR image classification can be divided into five categories: (i) classification based on physical scattering mechanisms of electromagnetic waves, (ii) classification based on POLSAR data attributes, (iii) classification based on POLSAR image statistics, (iv) classification based on pattern recognition techniques, and (v) hybrid classification.

7.2.1 Classification Based on Physical Scattering Mechanisms

Van Zyl (1989) was the first who showed retrieval of scattering information from NASA/JPL POLSAR data and used it for POLSAR image classification. In his proposed approach the co-polarised phase difference and cross-polarised intensity are employed to define three different scattering classes, namely odd number of reflections, even number of reflections and diffuse scattering. Section 7.3.1 discusses the approach in more detail. Improved versions can be found in Qong *et al.* (2001), Yamada and Hoshi (2001) as well as Lee *et al.* (2002).

A three-component scattering model was proposed by Freeman and Durden (1992, 1998) for POLSAR data. Their model involves fitting of a combination of canopy/volume scattering, double-bounce scattering and surface scattering, which is further explained in Section 7.3.2. The use of their model for classifying POLSAR data is given in Borghys (2001).

In Cloude and Pottier (1997), an unsupervised classification scheme using target decomposition theorems is presented for POLSAR data. The decomposition is based on an eigenanalysis of the coherency matrix. From the eigenvalues and eigenvectors, two important parameters, namely entropy H and alpha angle $\bar{\alpha}$, are derived and used

together to form the so-called $H - \bar{\alpha}$ plane. Different scattering classes are then defined based on the partitioning given by the $H - \bar{\alpha}$ plane. Section 7.3.3 provides a detailed explanation of the classification scheme, while further improvements are shown in Pottier and Cloude (1997), Hellman (2000) as well as Kimura *et al.* (2004).

7.2.2 Classification Based on POLSAR Data Attributes

The main difference between the classification algorithms which operate separately based on scattering mechanisms and POLSAR data attributes is that the former generates a scattering classification output in the final process, while a land cover classification output is produced by the latter.

In Pierce *et al.* (1994) a knowledge-based classifier with the inputs from both POLSAR C- and L-band data was developed. The classifier uses knowledge of the nature of radar backscattering from surfaces and volumes to construct appropriate discriminators for land cover classification. The POLSAR image attributes, i.e. intensities, co-polarised phase difference and texture component are used to establish classification rules.

Two supervised hierarchical classification schemes were presented by Ferrazzoli *et al.* (1997, 1999). Together with *a priori* knowledge about scattering behaviours, both schemes use backscattering coefficients of different polarisations in C-, L- and P-band data for separating agricultural fields from other land cover classes and discriminating among classes of agricultural species.

Xu *et al.* (2002) showed the usefulness of the total power and four similarity parameters in a supervised POLSAR image classification. The similarity parameters included the similarity between a pixel and a plane, a dihedral, a helix and a wire. The classification was carried out based on principal component analysis.

Yamada and Hoshi (2004) introduced a knowledge-based hierarchical classifier for both Pi-SAR X- and L-band images. The hierarchical classification tree is constructed using four parameters: (i) total power, (ii) scattering types, (iii) pedestal height and (iv) linear polarisation state which has the peak value. Different land cover classes, such as water surface, bare soil, grass field, forest, artificial constructions as

well as paddy field, are then formed by merging the X- and L-band classification outputs accordingly.

7.2.3 Classification Based on POLSAR Image Statistics

As mentioned in Section 2.3.4, the complex scattering vector in a single-look POLSAR data was assumed by Kong *et al.* (1987) to have a zero-mean complex Gaussian distribution. Based on this assumption, a Bayesian maximum likelihood classifier was derived, which is also known as optimal polarimetric classifier. Yueh *et al.* (1988) introduced another classifier, called normalised polarimetric classifier, mainly for single-look normalised POLSAR data. In order to improve the classification accuracy of the normalised classifier, an iterative way was presented by van Zyl and Burnette (1992) to change the *a priori* probabilities adaptively. Following the works done by Kong *et al.* (1987) and Yueh *et al.* (1988), Burl and Novak (1991) proposed a so-called polarimetric whitening filter classifier and found that their classifier performed almost as good as the optimal polarimetric classifier.

For multi-look single-frequency POLSAR data, Lee *et al.* (1994) proposed a supervised classifier where the distance measure was derived based on a complex Wishart distribution. Meanwhile, they also generalised their classifier for multi-frequency POLSAR data. The complex Wishart classifier is further discussed in Section 7.4. Instead of using the conventional distance measure in a fuzzy *c*-means clustering algorithm, Du and Lee (1996) replaced it with the derived complex Wishart distance measure and applied the fuzzy classifier for unsupervised classification of multi-look POLSAR imagery. The utilisation of a generalised multiplicative speckle model and adaptive *a priori* probabilities in the complex Wishart classifier was discussed by Liu *et al.* (1998a). Lately, Chen *et al.* (2003) incorporated the complex Wishart distance measure into a supervised fuzzy dynamic learning neural network classifier.

7.2.4 Classification Based on Pattern Recognition Techniques

From the literature review, it was found that some existing pattern recognition techniques were also applied directly to POLSAR imagery without taking valuable scattering mechanisms and statistical distributions into consideration. Among all, the neural network classifiers were frequently used, which can be found in Hara *et al.*

(1994), Chen *et al.* (1996), Ito and Omatu (1998), Tzeng and Chen (1998) as well as Gamba and Dell'Acqua (2003). For other techniques, a so-called scale-space clustering algorithm was proposed by Wong and Posner (1993) based on the concept of scale-space and cluster independence. The use of support vector machines for POLSAR image classification is shown in Fukuda and Hirose (2001).

7.2.5 Hybrid Classification

In Ito and Omatu (1997) POLSAR data were first classified using van Zyl's classification scheme into three scattering categories, i.e. odd, even and unknown number of reflections. Then, a neural network classifier was used to reclassify each scattering class into different land cover classes. Following the same idea of Ito and Omatu (1997) but using different classification algorithms, Lee *et al.* (2001) employed a multi-pixel-based unsupervised classification scheme which was proposed by Qong *et al.* (2001) to group POLSAR image pixels into scattering categories of odd number of reflections, even number of reflections and diffuse scattering. The supervised complex Wishart classifier was then used to reclassify the pixels of different scattering classes.

Lee *et al.* (1999a) presented an unsupervised hybrid classifier which combines Cloude-Pottier target decomposition and complex Wishart classification. The target decomposition is initially applied to classify POLSAR imagery. The classification map is then used to define training sets for a subsequent iterative complex Wishart classification. Ferro-Famil *et al.* (2001) further extended the hybrid classifier for dual-frequency single-look POLSAR data. In a recent paper by Lee *et al.* (2004), the Cloude-Pottier target decomposition was replaced with the Freeman-Durden scattering model.

In summary, the classification algorithms based on the scattering mechanisms or POLSAR image statistics are the most frequently used among all categories. In the following sections of this chapter, the classification algorithms based separately on the scattering mechanisms and complex Wishart distribution are assessed for the nine-look NASA/JPL POLSAR C- and L-band data.

7.3 Classification Based on Scattering Mechanisms

Three scattering property-based unsupervised classification approaches were examined in this study based on van Zyl's scattering classification, Freeman-Durden scattering model as well as Cloude-Pottier target decomposition. Each classification scheme is explained in this section. Also, the implementation and results of each classification scheme are presented.

7.3.1 van Zyl's Scattering Classification

Van Zyl (1989) proposed an unsupervised classification algorithm based on scattering behaviours of POLSAR data. Each pixel in the POLSAR imagery is classified accordingly into three different scattering classes, namely odd number of reflections, even number of reflections and diffuse scattering. Figure 7.1 illustrates the three scattering classes.

Figure 7.1: Scattering behaviour of different scattering mediums in van Zyl's scattering classification. (a) and (b) show an odd number of reflections from a slightly rough surface and even number of reflections from a dihedral corner reflector, respectively. In (c), diffuse scattering from a forested area is presented. The arrows represent the propagation of backscattered radar waves (Source: van Zyl, 1989).

To define the scattering behaviour of each pixel, the co-polarised phase difference ϕ_{HHVV} and HV intensity $|S_{HV}|^2$ are compared. For a scattering event giving an odd number of reflections, the phase difference angle of $S_{HH}^* S_{VV}$ is very small or nearly zero, i.e. $\phi_{HHVV} \approx 0$. Consequently, $\Re(S_{HH}^* S_{VV}) = \cos(\phi_{HHVV}) \approx 1$. Then, a pixel is classified as having an odd number of reflections if its $\Re(S_{HH}^* S_{VV})$ value is greater than $|S_{HV}|^2$. Conversely, the phase difference angle of $S_{HH}^* S_{VV}$ is nearly 180° and $\Re(S_{HH}^* S_{VV}) \approx -1$ for an even number of scattering events. If a pixel whose $|\Re(S_{HH}^* S_{VV})|$ value is greater than $|S_{HV}|^2$, it is considered to have an even number of reflections. In diffuse scattering, both HH and VV returns are almost completely uncorrelated. Hence, a pixel with this

scattering behaviour exhibits $|\Re(S_{HH}^* S_{VV})| < |S_{HV}|^2$. Table 7.1 summarises the scattering classification results observed by van Zyl (1989) for different scattering mediums.

Table 7.1: Scattering classification of different scattering mediums

Scattering medium	Scattering mechanism
Specular reflection	Odd number of reflections
Slightly rough surface	Odd number of reflections
Dihedral corner reflector	Even number of reflections
Very sparse forest	Odd number of reflections
Sparse forest	Even number of reflections
Moderately thick forest	Diffuse scattering
Very thick forest	Odd number of reflections

In this study, the filtered C- and L-band data resulting from the proposed spatially adaptive filter with a 7×7 window were selected as the inputs for van Zyl's scattering classification. The classification results are given in Figure 7.2 where the scattering classes of odd number of reflections, even number of reflections as well as diffuse scattering are coloured separately in red, green and blue. Tables 7.2 and 7.3 present the scattering mechanisms of land cover classes for both C- and L-band data, which were extracted from Figures 7.2 (a) and (b), respectively.

In the first built-up area (i.e. built-up area 1), the buildings were aligned in parallel with the flight direction while this is not the case for the second built-up area (i.e. built-up area 2). The buildings in the first built-up area showed the expected double-bounce scattering characteristic in both C- and L-band. The double-bounce reflection was generated by wall-ground structures as illustrated in Figure 2.5(b). For the second built-up area, the dominant scattering class in the C-band was the odd-bounce (61.1%), while diffuse scattering (59.1%) was predominantly observed in the L-band.

As can be seen in Tables 7.2 and 7.3, the bridge produced a double-bounce scattering. The double-bounce scattering mechanism was contributed by the radar wave interactions (i) between the bridge supporting pillars and the river surface as well as (ii) between the vehicles and the bridge deck. For the bareland and scrub-grassland, the dominant scattering class was the odd-bounce scattering for both C- and L-band. As expected, the marshland, mudflat areas and roads were characterised as having an odd-bounce scattering behaviour.

Due to the short wavelength of the C-band (i.e. 5.7 cm), the dryland forest, mangrove forests, oil palm and rubber plantation areas exhibited the behaviour of very thick forest (Table 7.1) with an odd-bounce scattering mechanism. In the L-band, most of the mangrove forests and oil palm plantation areas were majorly categorised into the odd-bounce class, while the diffuse scattering dominates over the dryland forest and rubber plantation area. The resultant diffuse scattering in the rubber plantation area was mainly due to the less dense rubber tree canopies, which was also observed by Lee *et al.* (2001).

In the C-band classification output in Figure 7.2(a), the green-coloured portion as indicated by the arrow was made up from rice paddy fields exhibiting double-bounce characteristics. The double-bounce scattering was caused by the radar wave interactions between the rice crops and the water surface. However, the odd-bounce was observed instead of the double-bounce in the L-band result as can be seen in Figure 7.2(b). This may be because the crop height of the planted rice paddies was shorter than the L-band wavelength (i.e. 24 cm). Consequently, the rice crop became transparent in the L-band imaging. Other scattering mechanisms can be found over other rice paddy fields in both the C- and L-band classification results representing different farming stages.

Table 7.2: C-band scattering mechanisms (in percent) of land cover classes based on van Zyl's scattering classification

Land cover class	Odd number of reflections	Even number of reflections	Diffuse scattering
Bareland	99.1	0.2	0.7
Bridge	3.5	95.3	1.2
Built-up area 1	30.0	57.8	12.2
Built-up area 2	61.1	4.4	34.5
Dryland forest	98.7	0.0	1.3
Mangrove forest	95.3	0.0	4.7
Marshland	100.0	0.0	0.0
Mudflat	98.8	0.0	1.2
Oil palm	99.9	0.0	0.1
Rice paddy	36.8	23.7	39.5
Road	83.9	0.0	16.1
Rubber	98.8	0.0	1.2
Scrub-grassland	94.1	0.0	5.9

Note that buildings in the built-up area 1 aligned in parallel with the flight direction, while this is not the case for built-up area 2.

Figure 7.2: Van Zyl's classification results obtained from NASA/JPL POLSAR (a) C- and (b) L-band data. The scattering classes of odd number of reflections, even number of reflections as well as diffuse scattering are coloured separately in red, green and blue.

Table 7.3: L-band scattering mechanisms (in percent) of land cover classes based on van Zyl's scattering classification

Land cover class	Odd number of reflections	Even number of reflections	Diffuse scattering
Bareland	98.5	1.3	0.2
Bridge	40.8	58.6	0.6
Built-up area 1	22.8	71.9	5.3
Built-up area 2	15.2	25.7	59.1
Dryland forest	15.5	0.5	84.0
Mangrove forest	75.4	0.1	24.5
Marshland	98.6	0.1	1.3
Mudflat	99.1	0.3	0.6
Oil palm	71.9	0.4	27.7
Rice paddy	67.8	15.9	16.3
Road	84.6	2.6	12.8
Rubber	9.1	1.2	89.7
Scrub-grassland	99.7	0.0	0.3

Note that buildings in the built-up area 1 aligned in parallel with the flight direction, while this is not the case for built-up area 2.

7.3.2 Freeman-Durden Scattering Model

Freeman and Durden (1992, 1998) presented a model-fitting approach for retrieving surface scattering, double-bounce scattering and canopy/volume scattering from each pixel in POLSAR data. Figure 7.3 depicts the three different scattering mechanisms. For the surface scattering, a first-order Bragg model is used for a moderately rough surface. The double-bounce scattering component is modelled by scattering from a dihedral corner reflector, where the two orthogonal reflector surfaces can be made of different dielectric materials. For the volume scattering, it is assumed that the radar return is from a cloud of randomly oriented, very thin, cylinder-like dipoles.

Figure 7.3: Scattering mechanisms used in Freeman-Durden three-component scattering model. (a), (b) and (c) show the surface scattering, double-bounce scattering and volume scattering, respectively (Source: Freeman and Durden, 1998).

In the scattering model, four equations with five unknowns are derived as follows:

$$\begin{aligned}
 \langle |S_{HH}|^2 \rangle &= f_s |\beta|^2 + f_d |\alpha|^2 + f_v, \\
 \langle |S_{VV}|^2 \rangle &= f_s + f_d + f_v, \\
 \langle S_{HH} S_{VV}^* \rangle &= f_s \beta + f_d \alpha + f_v / 3, \\
 \langle |S_{HV}|^2 \rangle &= f_v / 3,
 \end{aligned} \tag{7.1}$$

where f_s, f_d and f_v are the surface, double-bounce and volume scatter contributions to the backscatter at VV polarisation, respectively. The symbol β is a real number describing the first-order Bragg model for surface scatter, while α is a complex number related to the Fresnel reflection coefficient. Since neither the surface nor the double-bounce scattering contribute to $\langle |S_{HV}|^2 \rangle$, the volume scatter contribution can be estimated directly and subtracted from $\langle |S_{HH}|^2 \rangle$, $\langle |S_{VV}|^2 \rangle$ and $\langle S_{HH} S_{VV}^* \rangle$. To solve for the remaining unknowns, the parameter α is set to -1 if $\Re(S_{HH} S_{VV}^*)$ is positive, i.e. the surface scatter is dominant. If $\Re(S_{HH} S_{VV}^*)$ is negative, the double-bounce scatter is dominant and then the parameter β is fixed to 1.

After obtaining f_s, f_d, f_v , α and β , the contribution of each scattering mechanism to the total power P (also called span in Section 2.3.8) can be estimated:

$$P = |S_{HH}|^2 + 2|S_{HV}|^2 + |S_{VV}|^2 = P_s + P_d + P_v, \tag{7.2}$$

with

$$\begin{aligned}
 P_s &= f_s (1 + |\beta|^2), \\
 P_d &= f_d (1 + |\alpha|^2), \\
 P_v &= 8f_v / 3.
 \end{aligned} \tag{7.3}$$

The variables P_s , P_d and P_v denote separately the contributions of surface scattering, double-bounce scattering and volume scattering in each pixel of POLSAR data. By comparing the three contributions, each pixel is classified into a scattering class S_c where

$$S_c = \begin{cases} c = 1 & \text{if } P_d > P_s > P_v \\ c = 2 & \text{if } P_d > P_v > P_s \\ c = 3 & \text{if } P_s > P_d > P_v \\ c = 4 & \text{if } P_s > P_v > P_d \\ c = 5 & \text{if } P_v > P_d > P_s \\ c = 6 & \text{if } P_v > P_s > P_d \\ c = 7 & \text{otherwise} \end{cases} \quad (7.4)$$

Figures 7.4 (a) and (b) present separately the C- and L-band classification outputs resulting from the Freeman-Durden scattering model. The percentage of the three scattering mechanisms of each land cover class extracted from the classification outputs is given, respectively, in Tables 7.4 and 7.5.

Similar to van Zyl's classification results, the bridge and first built-up area showed predominantly double-bounce scattering. In the C-band, the second built-up area was classified as volume (80.8%) scattering, while it exhibited both double-bounce (31.4%) and volume (54.9%) scattering behaviours in the L-band.

The marshland was dominated by the surface (59.7%) and volume (40.3%) scattering classes in the C-band. In the L-band, the major scattering mechanism of the marshland belonged to the type of surface scattering. The mudflat and roads gave separately the dominant volume scattering in the C-band, but surface scattering in the L-band.

The dryland forests, mangrove forests, oil palm and rubber plantation areas were characterised by volume scattering in both C- and L-band. For the rice paddy fields, the volume scattering (69.9%) was largely detected in the C-band, while both the surface (54.8%) and volume (25.8%) scattering classes dominated in the L-band.

The scrub-grassland showed different scattering behaviours in both the C- and L-band. The volume scattering contributed the majority in the C-band while the surface scattering was found to be the dominant scattering class in the L-band. For the bareland, there were two major scattering classes in the C-band, namely the volume scattering (58.6%) and surface scattering (41.1%). In the L-band, the bareland was classified mostly into the surface scattering class.

Figure 7.4: Freeman-Durden scattering classification results obtained from NASA/JPL POLSAR (a) C- and (b) L-band data. The input into the Freeman-Durden scattering model were the filtered POLSAR data using the proposed spatially adaptive filter with a 7×7 window.

Table 7.4: C-band scattering mechanisms (in percent) of land cover classes based on Freeman-Durden scattering model

Land cover class	$P_d > P_s > P_v$	$P_d > P_v > P_s$	$P_s > P_d > P_v$	$P_s > P_v > P_d$	$P_v > P_d > P_s$	$P_v > P_s > P_d$
Bareland	0.0	0.3	0.0	41.1	0.3	58.3
Bridge	50.3	45.0	4.7	0.0	0.0	0.0
Built-up area 1	43.8	19.4	32.5	2.9	1.0	0.3
Built-up area 2	0.0	4.0	0.0	15.2	12.7	68.1
Dryland forest	0.0	0.0	0.0	0.1	0.8	99.1
Mangrove forest	0.0	0.2	0.0	0.3	3.1	96.4
Marshland	0.0	0.0	0.0	59.7	0.0	40.3
Mudflat	0.0	0.0	0.0	18.6	0.0	81.4
Oil palm	0.0	0.0	0.0	18.0	0.0	82.0
Rice paddy	0.6	24.9	0.1	4.5	20.8	49.1
Road	0.0	0.5	0.0	5.4	5.2	88.9
Rubber	0.0	0.0	0.0	0.0	0.6	99.4
Scrub-grassland	0.0	0.1	0.0	0.1	0.4	99.4

Note that buildings in the built-up area 1 aligned in parallel with the flight direction, while this is not the case for built-up area 2.

Table 7.5: L-band scattering mechanisms (in percent) of land cover classes based on Freeman-Durden scattering model

Land cover class	$P_d > P_s > P_v$	$P_d > P_v > P_s$	$P_s > P_d > P_v$	$P_s > P_v > P_d$	$P_v > P_d > P_s$	$P_v > P_s > P_d$
Bareland	1.3	0.1	9.3	89.1	0.0	0.2
Bridge	58.6	0.0	41.4	0.0	0.0	0.0
Built-up area 1	67.2	7.4	24.3	1.0	0.0	0.1
Built-up area 2	0.1	31.3	0.9	12.8	31.9	23.0
Dryland forest	0.0	1.2	0.0	1.1	50.6	47.1
Mangrove forest	0.0	0.7	0.0	1.4	15.6	82.3
Marshland	0.2	0.1	0.5	85.7	0.4	13.1
Mudflat	0.6	0.0	5.3	94.1	0.0	0.0
Oil palm	0.0	1.1	0.0	9.0	4.1	85.8
Rice paddy	3.6	15.8	10.2	44.6	4.4	21.4
Road	0.4	5.4	4.8	50.5	3.4	35.5
Rubber	0.0	1.4	0.0	1.2	69.3	28.1
Scrub-grassland	0.1	0.0	0.2	91.8	0.1	7.8

Note that buildings in the built-up area 1 aligned in parallel with the flight direction, while this is not the case for built-up area 2.

7.3.3 Cloude-Pottier Target Decomposition

Cloude and Pottier (1997) presented an unsupervised classification scheme for POLSAR data by using target decomposition theorems. The decomposition is based on an eigenanalysis of a coherency matrix $\mathbf{T}$, where the representation of the coherency matrix is given in Section 2.3.7:

$$\mathbf{T} = \mathbf{U}_3 \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \mathbf{U}_3^{*T}, \quad (7.5)$$

with

$$\mathbf{U}_3 = \begin{bmatrix} \cos\alpha_1 & \cos\alpha_2 & \cos\alpha_3 \\ \sin\alpha_1 \cos\beta_1 e^{i\delta_1} & \sin\alpha_2 \cos\beta_2 e^{i\delta_2} & \sin\alpha_3 \cos\beta_3 e^{i\delta_3} \\ \sin\alpha_1 \sin\beta_1 e^{i\gamma_1} & \sin\alpha_2 \sin\beta_2 e^{i\gamma_2} & \sin\alpha_3 \sin\beta_3 e^{i\gamma_3} \end{bmatrix}. \quad (7.6)$$

The matrix $\mathbf{U}_3$ is a 3×3 unitary matrix whose columns are the orthonormal eigenvectors of $\mathbf{T}$. The symbol λ denotes a real and non-negative eigenvalue where the eigenvalues are ordered such that $\lambda_1 \geq \lambda_2 \geq \lambda_3$. The operators $*$ and T refer to complex conjugate and matrix transpose, respectively. The α angle is an angle indicating the scattering types of a target, while the β angle gives the target orientation. Both δ and γ angles are the target phase angles.

From the eigenvalues, a measure of disorder of backscattered polarimetric radar signal, called entropy H , can be defined as

$$H = - \sum_{i=1}^3 P_i \log_3 P_i, \quad (7.7)$$

with

$$P_i = \lambda_i / \sum_{j=1}^3 \lambda_j. \quad (7.8)$$

The value of H ranges from zero to one, describing the randomness of a scattering process from isotropic scattering ($H = 0$) to totally random scattering ($H = 1$). To characterise the scattering mechanisms, the average of alpha angles is computed as follows:

$$\bar{\alpha} = P_1 \alpha_1 + P_2 \alpha_2 + P_3 \alpha_3. \quad (7.9)$$

The angle value depends on the dominant scattering mechanism ranging from 0° for surface scattering, through 45° for dipole scattering, to 90° for dihedral scattering

(Figure 7.5). With the derived H and $\bar{\alpha}$, a so-called $H - \bar{\alpha}$ plane is formed as shown in Figure 7.6, where it is partitioned into nine zones. The bounds in Figure 7.6 are chosen generically, i.e. based on the general properties of the scattering mechanisms and are independent of a particular dataset (Cloude and Pottier, 1997). The entropy axis is divided in low ($H \leq 0.5$), medium ($0.5 < H < 0.9$) and high ($H \geq 0.9$). Table 7.6 gives the physical scattering characteristics of each zone.

Figure 7.5: Interpretation of average alpha angle (Source: Hellman, 2001).

Figure 7.6: $H - \bar{\alpha}$ plane in Cloude-Pottier target decomposition.

Table 7.6: Descriptions of scattering characteristics for each zone in $H - \bar{\alpha}$ plane

Zone	Scattering mechanism	Examples
1	High entropy multiple scattering ($\alpha > 55^\circ$)	Double-bounce scattering event in forests and vegetations which have well developed branch and crown structures.
2	High entropy vegetation scattering ($40^\circ \leq \alpha \leq 55^\circ$)	Scattering from forest canopies or vegetation surfaces with random highly anisotropic scattering elements.
3	High entropy surface scattering ($\alpha < 40^\circ$)	This zone is not part of the feasible regions. The surface scattering cannot be distinguished with entropy $H \geq 0.9$.
4	Medium entropy multiple scattering ($\alpha > 50^\circ$)	Dihedral scattering with moderate entropy which occurs in forests and urban areas.
5	Medium entropy vegetation scattering ($40^\circ \leq \alpha \leq 50^\circ$)	Scattering from vegetated surface with anisotropic scatterers and moderate correlation of scatterers' orientations.
6	Medium entropy surface scattering ($\alpha < 40^\circ$)	Surface scattering with increasing entropy due to changes in surface roughness and canopy propagation effects.
7	Low entropy multiple scattering ($\alpha > 47.5^\circ$)	Low entropy double or even bounce scattering, such as provided by isolated dielectric and metallic dihedral scatterers.
8	Low entropy dipole scattering ($42.5^\circ \leq \alpha \leq 47.5^\circ$)	Isolated dipole scattering and scattering from vegetation with strongly correlated orientation of anisotropic scattering elements.
9	Low entropy surface scattering ($\alpha < 42.5^\circ$)	Geometrical / physical optics surface scattering, Bragg surface scattering as well as specular scattering.

In this study, the inputs for the Cloude-Pottier target decomposition were the filtered C- and L-band data resulting from the proposed spatially adaptive filter with a 7×7 window. The corresponding classification results are given in Figures 7.7 and 7.8, respectively. Tables 7.7 and 7.8 tabulate separately the scattering mechanisms of each land cover class which were extracted from Figures 7.7 and 7.8.

From both tables, it is clearly noticed that the bridge fell into the low entropy double-bounce class in both the C- and L-band. This finding was similar to van Zyl's and Freeman-Durden classification results in the previous two subsections. In both C- and L-band, the buildings in the first built-up area exhibited the expected low and medium entropy double-bounce scattering mechanisms, together with medium entropy

vegetation scattering. The second built-up area was characterised mainly by medium entropy vegetation scattering in the C-band, while in the L-band both the medium entropy multiple scattering (50.8%) and vegetation scattering (46.1%) dominated over the second built-up area

The dryland forests, mangrove forests, oil palm and rubber plantation areas showed the dominant medium entropy surface scattering in the C-band. For the mangrove forests, there were three main scattering classes in the L-band, namely the medium entropy vegetation scattering (37.6%), high entropy vegetation scattering (31.4%) and medium entropy surface scattering (30%). The oil palm plantation areas were dominated by the medium entropy vegetation scattering in the L-band. The dryland forest and rubber plantation areas gave the high entropy vegetation scattering in the L-band.

Due to the different farming stages, the rice paddy fields were classified in the C-band as having medium entropy vegetation scattering (33.3%), high entropy vegetation scattering (27%), low entropy multiple scattering (15.9%), medium entropy surface scattering (12%) and medium entropy multiple scattering (11.3%). In the L-band, the medium entropy vegetation scattering (38.9%) as well as medium entropy surface scattering (36.3%) were found to be the main scattering classes over the rice paddy fields.

As can be seen from Tables 7.7 and 7.8, the medium entropy surface scattering was the dominant scattering class for the marshland. In both the C- and L-band, the major scattering behaviours of the roads were the medium entropy surface scattering and vegetation scattering. The mudflat presented both the medium entropy and high entropy surface scattering behaviours, respectively, in the C- and L-band.

For the scrub-grassland, the medium entropy and high entropy volume scatterings were the two main scattering components in the C-band. The former contributed 51.5% while the latter was about 28.3%. In the L-band, the scrub-grassland showed a strong behaviour of the medium entropy surface scattering (96.9%). Both the medium surface and vegetation scattering mechanisms were found to dominate over the bareland in the C-band, while the low and medium entropy surface scattering was observed in the L-band.

Figure 7.7: NASA/JPL POLSAR C-band classification result based on Cloude-Pottier target decomposition in the $H - \bar{\alpha}$ plane.

Figure 7.8: NASA/JPL POLSAR L-band classification result based on Cloude-Pottier target decomposition in the $H - \bar{\alpha}$ plane.

Table 7.7: C-band scattering mechanisms (in percent) of land cover classes based on Cloude-Pottier target decomposition

Land cover class	Zone 1	Zone 2	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9
Bareland	0.0	2.7	0.4	32.9	57.2	0.0	0.0	6.8
Bridge	0.0	0.0	0.0	1.2	0.0	88.2	9.4	1.2
Built-up area 1	0.0	0.0	22.8	41.4	8.3	23.5	2.0	2.0
Built-up area 2	0.0	1.1	12.6	69.9	15.8	0.4	0.0	0.2
Dryland forest	0.0	8.8	0.0	20.2	71.0	0.0	0.0	0.0
Mangrove forest	0.0	14.0	0.0	26.9	59.1	0.0	0.0	0.0
Marshland	0.0	0.0	0.0	0.6	99.4	0.0	0.0	0.0
Mudflat	0.0	0.0	0.6	94.4	5.0	0.0	0.0	0.0
Oil palm	0.0	0.1	0.0	0.7	99.2	0.0	0.0	0.0
Rice paddy	0.3	27.0	11.3	33.3	12.0	15.9	0.2	0.0
Road	0.0	15.5	0.9	39.3	44.3	0.0	0.0	0.0
Rubber	0.0	7.9	0.0	20.7	71.4	0.0	0.0	0.0
Scrub-grassland	0.0	28.3	0.0	51.5	20.2	0.0	0.0	0.0

Note that buildings in the built-up area 1 aligned in parallel with the flight direction, while this is not the case for built-up area 2.

Table 7.8: L-band scattering mechanisms (in percent) of land cover classes based on Cloude-Pottier target decomposition

Land cover class	Zone 1	Zone 2	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9
Bareland	0.0	0.0	0.1	2.1	68.1	0.9	0.3	28.5
Bridge	0.0	0.0	3.0	4.1	5.9	52.7	4.1	30.2
Built-up area 1	0.0	0.0	28.3	26.3	6.2	30.4	4.3	4.5
Built-up area 2	0.1	0.6	50.8	46.1	1.7	0.3	0.2	0.2
Dryland forest	6.4	83.7	0.5	8.8	0.6	0.0	0.0	0.0
Mangrove forest	0.2	31.4	0.8	37.6	30.0	0.0	0.0	0.0
Marshland	0.0	0.0	0.2	10.9	83.8	0.0	0.0	5.1
Mudflat	0.0	0.0	0.0	6.8	2.2	0.0	0.3	90.7
Oil palm	0.0	6.9	3.3	76.9	12.9	0.0	0.0	0.0
Rice paddy	0.0	1.4	17.0	38.9	36.3	0.7	0.5	5.2
Road	0.0	0.9	4.9	34.7	59.5	0.0	0.0	0.0
Rubber	10.7	77.0	4.2	7.7	0.4	0.0	0.0	0.0
Scrub-grassland	0.0	0.1	0.0	2.6	96.9	0.0	0.0	0.4

Note that buildings in the built-up area 1 aligned in parallel with the flight direction, while this is not the case for built-up area 2.

7.4 Classification Based on Complex Wishart Distribution

In n -look POLSAR data, the covariance matrix $\mathbf{C}$ in Equation (2.12) can also be written as

$$\mathbf{C} = \frac{1}{n} \sum_{k=1}^n \mathbf{s}_k \mathbf{s}_k^{*T}. \quad (7.10)$$

Goodman (1963) showed that a matrix $\mathbf{A} = n\mathbf{C} = \sum_{k=1}^n \mathbf{s}_k \mathbf{s}_k^{*T}$ obeys a complex Wishart distribution with its probability density function given in Equation (2.14). Based on this result, Lee *et al.* (1994) derived a distance measure and introduced a supervised complex Wishart classifier for multi-look POLSAR data. The distance measure is defined by

$$d(\mathbf{C}, \mathbf{C}_m) = \ln|\mathbf{C}_m| + \text{tr}(\mathbf{C}_m^{-1}\mathbf{C}). \quad (7.11)$$

The matrix $\mathbf{C}$ is the covariance matrix for a candidate pixel p , while $\mathbf{C}_m$ is the average covariance matrix of a target class m . The operators $|\cdot|$ and tr denote the determinant and trace of a matrix, respectively. The pixel p is assigned to the nearest class.

By assuming that the POLSAR data of different frequencies are statistically independent, the distance measure in Equation (7.11) can be generalised for classifying multi-frequency POLSAR data (Lee *et al.*, 1994). The generalised distance measure is given as follows:

$$d(\mathbf{C}_n, \mathbf{C}_{m,n}) = \sum_{n=1}^N \ln|\mathbf{C}_{m,n}| + \text{tr}(\mathbf{C}_{m,n}^{-1} \mathbf{C}_n), \quad (7.12)$$

where $\mathbf{C}_n$ is the covariance matrix for a candidate pixel p in the n -th frequency band. The matrix $\mathbf{C}_{m,n}$ refers to the average covariance matrix of a target class m in the n -th frequency band. The variable N denotes the total number of frequency bands.

In this study the supervised classification was performed on per-pixel and per-segment bases. The inputs for the per-pixel classification were both the unfiltered and filtered C- and L-band data. The filtered C- and L-band data resulting from the proposed spatially adaptive filter with a 7×7 window were selected for the experiments. In the

per-segment classification, the segmented C- and L-band outputs obtained in Chapter 6 were used as inputs. The segmented outputs from the HSWO and hybrid segmentation algorithms with 100000 target regions were tested for each frequency band. Figures 7.9–7.13 show the per-pixel and per-segment classification outputs. In the following, the discussion on the classification results is divided into three parts: (i) assessment of classification accuracies, (ii) effect of radar frequencies as well as (iii) comparison between per-pixel and per-segment classification approaches.

7.4.1 Assessment of Classification Accuracies

To evaluate the classification outputs, the existing topographical and land use maps as well as optical remotely sensed images (i.e. Landsat-5 TM, MASTER and ASTER data) were used for locating the test samples. The test samples identified are hereafter called reference data. A field work was carried out on the 5th of February 2005 in order to validate the suitability of the reference data. For each classification output, a classification error matrix was constructed and the corresponding overall accuracy (Congalton and Green, 1999) was computed as

$$\frac{\text{Sum of diagonal elements in classification error matrix}}{\text{Total number of test points in classification error matrix}} \times 100\%. \quad (7.13)$$

Furthermore, the Kappa statistic (Congalton and Green, 1999) was also computed and included in the classification error matrix. Tables 7.9–7.10 present the error matrices from the per-pixel classification outputs of the unfiltered data. As expected, the classification results using the unfiltered data were relatively poor. The overall accuracies of both the C- and L-band were 35.09% and 42.16%, respectively. The improved results were obtained by using the filtered data, but the results were mildly satisfying. As shown in Tables 7.11 and 7.12, the overall accuracies were separately 62.78% and 66.95% for both C- and L-band. An improved accuracy of 74.82% was attained by using a dual-band input, i.e. the combination of both the C- and L-band. The increase in accuracy was due to the complementary of both the C- and L-band in improving the classification of mangrove forest and rice paddy classes. In the C-band alone, the mangrove forests were found to be largely misclassified into the rubber category, while the rice paddy fields were mistakenly classified as water bodies. Further discussion on this misclassification is given in next section.

Figure 7.9: Per-pixel complex Wishart classification outputs obtained from NASA/JPL POLSAR (a) C- and (b) L-band unfiltered data.

Figure 7.10: Per-pixel complex Wishart classification outputs obtained from NASA/JPL POLSAR (a) C- and (b) L-band filtered data.

Figure 7.11: Per-segment (HSWO algorithm) complex Wishart classification outputs obtained from NASA/JPL POLSAR (a) C- and (b) L-band segmented data. The segmented data were generated using the HSWO algorithm.

Figure 7.12: Per-segment (hybrid segmentation algorithm) complex Wishart classification outputs obtained from NASA/JPL POLSAR (a) C- and (b) L-band segmented data. The segmented data were generated using the hybrid segmentation algorithm.

Figure 7.13: Complex Wishart classification outputs obtained from NASA/JPL POLSAR dual-frequency data. (a) is the per-pixel classification output, (b) and (c) are the per-segmentation outputs, where the segmented data were generated separately using the HSWO and hybrid segmentation algorithm. Please refer to Figure 7.9 for the legend.

In the experiments, some difficulties were encountered in classifying the diversified cropland, dryland forest, fish farm, mudflat and road segments. The classification difficulties were mainly caused by the poor separation between these and other land cover classes. In the C-band, the diversified cropland was erroneously classified into the rubber category, while it was assigned into the mangrove forest and oil palm categories in the L- band. For the dryland forest, it was wrongly grouped into the mangrove forest and rubber categories in the C-band, whereas only into the rubber category in the L-band. The fish farms were improperly classified as the bareland and marshland in the C- and L-band, respectively. For the road segments, the misclassification into the bareland category was observed. The mudflat was misclassified as the rice paddy fields and water bodies separately in both the C- and L-band.

7.4.2 Effect of Radar Frequencies

From the results, it was found that the effectiveness of POLSAR data for land cover classification relies on the radar frequencies. For example, the rice paddy fields in the C-band were better classified than in the L-band. As mentioned in Subsection 7.3.1, the rice crops became transparent in the L-band imaging due to the shorter crop heights compared with the L-band wavelength (i.e. 24 cm). The scattering mechanisms over the rice paddy fields in the L-band were almost entirely contributed by the water surface. Hence, the rice paddy fields were partially misclassified as water bodies which can be seen in the L-band results.

For the mangrove forests, a better classification result was obtained using the L-band data. With the longer wavelength, the L-band showed a stronger radar penetration in both mangrove forests and rubber plantation areas. Subsequently, the L-band provided a more distinct discrimination between both mangrove forests and rubber plantation areas. As mentioned in Subsection 7.3.1, the mangrove forests gave an odd-bounce scattering in the L-band following their expected behaviour of very thick forest, while the diffuse scattering was detected over the rubber plantation areas owing to the more openness of rubber tree canopies.

7.4.3 Comparison between Per-pixel and Per-segment Classification Approaches

It is well-known that per-pixel classification approaches always produce classification outputs with salt-and-pepper effects over homogeneous areas. To mitigate these effects, per-segment classification approaches or post-classification operations are normally employed. In this study, the salt-and-pepper effects were observed in the C- and L-band per-pixel classification results (Figures 7.10). The per-segment classification approaches were found to improve the C-band classification accuracies. The overall accuracy of the C-band per-pixel output was 62.78%, while it increased to 69.19% and 68.01% for the per-segment classification of the segmented data from the HSWO and hybrid segmentation algorithms. For the L-band classification outputs, only a slightly increase in accuracy was observed. An overall accuracy of 66.95% was obtained from the per-pixel L-band result, while the computed overall accuracies were 70.81% and 68.47%, respectively, for the per-segment classification of the segmented data from the HSWO and hybrid segmentation algorithms. As expected, the use of the dual-band inputs in the per-segment classification produced the better accuracy, which resulted in an overall accuracy of about 76%.

7.5 Summary

In this chapter the classification of NASA/JPL POLSAR C- and L-band data based separately on scattering mechanisms and statistical distribution was presented. For the scattering property-based unsupervised classification, three different classification schemes were examined, namely van Zyl's scattering classification, Freeman-Durden scattering model as well as Cloude-Pottier target decomposition. The scattering mechanisms of different land cover classes were derived and can be explained, except for the river.

In the supervised classification based on complex Wishart distribution, the C- and L-band per-pixel land cover classification results were mildly satisfying. The overall accuracies were 62.78% and 66.95% for both C- and L-band, respectively. An improved accuracy of 74.82% was, however, attained by using the dual-frequency input. Furthermore, the comparison between per-pixel and per-segment classification approaches was carried out in this study, where the per-segment approach was found to

improve the classification accuracy. Nevertheless, there is still more work to be conducted before the POLSAR classification outputs can be used reliably. For example, other types of information can be included in the classification process, such as textural features, polarimetric discriminators, and so on.

Table 7.9: Error matrix for per-pixel classification output using NASA/JPL C-band unfiltered data

	Reference data	Classified image										Total	Producer's accuracy
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
	C1. Bareland	246				7		289		289	66	897	0.274
	C2. Bridge		90	69				10				169	0.533
	C3. Built-up		35	1358		20	8	232	6	18		1677	0.810
	C4. Mangrove forest	59		340	1647	996	1405	1615	2381	4430	32	12905	0.128
	C5. Marshland	2		33	34	526	175	189	44	440		1443	0.365
	C6. Oil palm	3		208	741	1323	2551	511	1039	2068	1	8445	0.302
	C7. Rice paddy	658		106	51	190	49	6806	163	689	461	9173	0.742
	C8. Rubber	1		374	1058	577	1207	1083	2455	2075		8830	0.278
	C9. Scrub-grassland			1	5	58	21	154	12	477		728	0.655
	C10. Water body	2						5			3103	3110	0.998
	C11. Diversified cropland	3		126	174	107	262	315	589	788	1	2365	0.000
	C12. Dryland forest	2		106	512	267	487	427	856	1244		3901	0.000
	C13. Fish farm	53		13				123	1	64	15	269	0.000
	C14. Mudflat	10						305		6	1	322	0.000
	C15. Road	291						165		14	181	651	0.000
	Total	1330	125	2734	4222	4071	6165	12229	7546	12602	3861	54885	
	User's accuracy	0.185	0.720	0.497	0.390	0.129	0.414	0.557	0.325	0.038	0.804		
Overall accuracy = 35.09%, Kappa statistic = 0.2742													

Table 7.10: Error matrix for per-pixel classification output using NASA/JPL L-band unfiltered data

Reference data														
	C1	C2	C3	C4	C5	Classified image			C7	C8	C9	C10	Total	Producer's accuracy
C1. Bareland	289				10	15	49		69	465	897	0.322		
C2. Bridge		122	25		1	11	8		2		169	0.722		
C3. Built-up	2	110	1121	5	71	73	207	33	53	2	1677	0.668		
C4. Mangrove forest	94		56	5891	1125	1518	1111	244	2857	9	12905	0.456		
C5. Marshland	1		10	192	522	153	355	3	207		1443	0.362		
C6. Oil palm		1	309	2129	538	3865	593	339	671		8445	0.458		
C7. Rice paddy	509		3	341	588	192	1758	13	958	4811	9173	0.192		
C8. Rubber			1239	532	13	759	149	6135	3		8830	0.695		
C9. Scrub-grassland	129		1	38	58	61	84		343	14	728	0.471		
C10. Water body	10				1		4			3095	3110	0.995		
C11. Diversified cropland			95	923	3	777	115	158	294		2365	0.000		
C12. Dryland forest			428	409	11	493	106	2438	16		3901	0.000		
C13. Fish farm	4	2	5	66	52	12	78	3	47		269	0.000		
C14. Mudflat	5				4		55		3	255	322	0.000		
C15. Road	370				4	5	50		81	141	651	0.000		
Total	1413	235	3292	10526	3001	7934	4722	9366	5604	8792	54885			
User's accuracy	0.205	0.519	0.341	0.560	0.174	0.487	0.372	0.655	0.061	0.352				
Overall accuracy = 42.16% , Kappa statistic = 0.3403														

Table 7.11: Error matrix for per-pixel classification output using NASA/JPL C-band filtered data

	Classified image										Total	Producer's accuracy
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
C1. Bareland	297						270		326	4	897	0.331
C2. Bridge		114	45				10				169	0.675
C3. Built-up		4	1431		8		231		3		1677	0.853
C4. Mangrove forest	61		22	5685	93	315	205	3486	3025	13	12905	0.441
C5. Marshland					1126	45	1	6	265		1443	0.780
C6. Oil palm	2			561	237	6931	2	344	368		8445	0.821
C7. Rice paddy	917		1	12	29	4	7839	128	117	126	9173	0.855
C8. Rubber				974		263	8	7199	386		8830	0.815
C9. Scrub-grassland							3		725		728	0.996
C10. Water body										3110	3110	1.000
C11. Diversified cropland	2			335		31	24	1619	354		2365	0.000
C12. Dryland forest				1275		168	20	1947	491		3901	0.000
C13. Fish farm	163		12				61		25	8	269	0.000
C14. Mudflat							322				322	0.000
C15. Road	426						83		54	88	651	0.000
Total	1868	118	1511	8842	1493	7757	9079	14729	6139	3349	54885	
User's accuracy	0.159	0.966	0.947	0.643	0.754	0.894	0.863	0.489	0.118	0.929		
Overall accuracy = 62.78%, Kappa statistic = 0.5685												

Table 7.12: Error matrix for per-pixel classification output using NASA/JPL L-band filtered data

	Reference data	Classified image										Total	Producer's accuracy
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
	C1. Bareland	359					1	13		86	438	897	0.400
	C2. Bridge		142	3			2	20		2		169	0.840
	C3. Built-up		2	1340	1	89	30	164	6	45		1677	0.799
	C4. Mangrove forest	38			10900	225	716	347	1	678		12905	0.845
	C5. Marshland				57	1070	70	230		16		1443	0.742
	C6. Oil palm			13	504		7915	4		9		8445	0.937
	C7. Rice paddy	290			150	624	86	2693		818	4512	9173	0.294
	C8. Rubber			13	4		10		8803			8830	0.997
	C9. Scrub-grassland	205			22	19	32	28		422		728	0.580
	C10. Water body	3						3			3104	3110	0.998
	C11. Diversified cropland				1158		1132	5		70		2365	0.000
	C12. Dryland forest			14	89		97		3701			3901	0.000
	C13. Fish farm	1		4	59	104	2	43	3	53		269	0.000
	C14. Mudflat	3						74			245	322	0.000
	C15. Road	486			1		3	31		105	25	651	0.000
	Total	1385	144	1387	12945	2131	10096	3655	12514	2304	8324	54885	
	User's accuracy	0.259	0.986	0.966	0.842	0.502	0.784	0.737	0.703	0.183	0.373		
Overall accuracy = 66.95% , Kappa statistic = 0.6144													

Table 7.13: Error matrix for NASA/JPL dual-band per-pixel classification output

	C1	Classified image									Total	Producer's accuracy
		C2	C3	C4	C5	C6	C7	C8	C9	C10		
Reference data												
C1. Bareland	509						319		17	52	897	0.567
C2. Bridge		154	4				11				169	0.911
C3. Built-up		45	1474		40	2	114		2		1677	0.879
C4. Mangrove forest	72			11499	196	87	128	21	902		12905	0.891
C5. Marshland				29	1333	47			34		1443	0.924
C6. Oil palm				350		8078		3	14		8445	0.957
C7. Rice paddy	910			116	285		5483		270	2109	9173	0.598
C8. Rubber				7		3		8820			8830	0.999
C9. Scrub-grassland					4	5	110		609		728	0.837
C10. Water body	2									3108	3110	0.999
C11. Diversified cropland	1			2234		92		2	36		2365	0.000
C12. Dryland forest				718	557	23	133	1621	576	273	3901	0.000
C13. Fish farm	153		11	9		44	39	10	1	2	269	0.000
C14. Mudflat	3						319				322	0.000
C15. Road	605					1			20	25	651	0.000
Total	2255	199	1489	14962	2415	8382	6656	10477	2481	5569	54885	
User's accuracy	0.226	0.774	0.990	0.769	0.552	0.964	0.824	0.842	0.245	0.558		
Overall accuracy = 74.82% , Kappa statistic = 0.7046												

Table 7.14: Error matrix for NASA/JPL C-band per-segment (HSWO algorithm) classification output

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Total	Producer's accuracy
Reference data	C1. Bareland	254					254		389		897	0.283
	C2. Bridge		111				12				169	0.657
	C3. Built-up	2			4		219				1677	0.866
	C4. Mangrove forest	43		6698	175		119	3293	2568	9	12905	0.519
	C5. Marshland				1149				294		1443	0.796
	C6. Oil palm			1		8402		14	28		8445	0.995
	C7. Rice paddy	930			3		7816	229	104	91	9173	0.852
	C8. Rubber			534			2	8265	29		8830	0.936
	C9. Scrub-grassland								720		728	0.989
	C10. Water body									3110	3110	1.000
	C11. Diversified cropland			422				1879	64		2365	0.000
	C12. Dryland forest				1641			1945	315		3901	0.000
	C13. Fish farm	178					22		43	14	269	0.000
	C14. Mudflat						322				322	0.000
	C15. Road	456					18		23	154	651	0.000
Total	1863	111	1510	7663	2972	8402	8784	15625	4577	3378	54885	
User's accuracy	0.136	1.000	0.962	0.874	0.387	1.000	0.890	0.529	0.157	0.921		
Overall accuracy = 69.19% , Kappa statistic = 0.6433												

Table 7.15: Error matrix for NASA/JPL C-band per-segment (hybrid segmentation algorithm) classification output

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Total	Producer's accuracy
Reference data	C1. Bareland	470					259		168		897	0.524
	C2. Bridge		120				3				169	0.710
	C3. Built-up	2			2		190		1		1677	0.884
	C4. Mangrove forest	81		6460	129		111	3298	2814	12	12905	0.501
	C5. Marshland				1124				319		1443	0.779
	C6. Oil palm			229	75	7969		72	100		8445	0.944
	C7. Rice paddy	793			6		7921	161	53	239	9173	0.864
	C8. Rubber			795			40	7943	52		8830	0.900
	C9. Scrub-grassland								728		728	1.000
	C10. Water body									3110	3110	1.000
	C11. Diversified cropland			320				1818	227		2365	0.000
	C12. Dryland forest			1291				2120	490		3901	0.000
	C13. Fish farm	193					27			37	269	0.000
	C14. Mudflat						322				322	0.000
	C15. Road	501					55		14	81	651	0.000
Total	2040	120	1540	9095	1336	7969	8928	15412	4966	3479	54885	
User's accuracy	0.230	1.000	0.962	0.710	0.841	1.000	0.887	0.515	0.147	0.894		
Overall accuracy = 68.01% , Kappa statistic = 0.6281												

Table 7.16: Error matrix for NASA/JPL L-band per-segment (HSWO algorithm) classification output

	C1	C2	C3	C4	Classified image					Total	Producer's accuracy
					C5	C6	C7	C8	C9	C10	
C1. Bareland	371						26		80	420	897
C2. Bridge		138	7			2	22				169
C3. Built-up			1391		127	17	138		4		1677
C4. Mangrove forest	37			11906	4	508	262		188		12905
C5. Marshland				68	1322		53				1443
C6. Oil palm						8445					8445
C7. Rice paddy	131			86	581	62	2887		774	4652	9173
C8. Rubber						10		8820			8830
C9. Scrub-grassland	221					2	26		479		728
C10. Water body							3			3107	3110
C11. Diversified cropland				1457		862			46		2365
C12. Dryland forest				4				3897			3901
C13. Fish farm			2	28	151		33	5	50		269
C14. Mudflat										322	322
C15. Road	542			8	2	6	1		92		651
Total	1302	138	1400	13557	2187	9914	3451	12722	1713	8501	54885
User's accuracy	0.285	1.000	0.994	0.878	0.604	0.852	0.837	0.693	0.280	0.365	
Overall accuracy = 70.81% , Kappa statistic = 0.6586											

Table 7.17: Error matrix for NASA/JPL L-band per-segment (hybrid segmentation algorithm) classification output

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Total	Producer's accuracy
Reference data	C1. Bareland	321							63	513	897	0.358
	C2. Bridge		139			3	24				169	0.822
	C3. Built-up				123	5	110	28	3		1677	0.840
	C4. Mangrove forest			11972	43	356	367		167		12905	0.928
	C5. Marshland			81	1269		93				1443	0.879
	C6. Oil palm			32		8413					8445	0.996
	C7. Rice paddy	381		84	687	70	1670		722	5559	9173	0.182
	C8. Rubber					6		8824			8830	0.999
	C9. Scrub-grassland	220		14		1	39		454		728	0.624
	C10. Water body									3110	3110	1.000
	C11. Diversified cropland			1104		1200			61		2365	0.000
	C12. Dryland forest			3		93		3805			3901	0.000
	C13. Fish farm		12	38	109		45		65		269	0.000
	C14. Mudflat									322	322	0.000
	C15. Road	529		10	3	3	4		96	6	651	0.000
Total	1451	139	1423	13338	2234	10150	2352	12657	1631	9510	54885	
User's accuracy	0.221	1.000	0.989	0.898	0.568	0.829	0.710	0.697	0.278	0.327		
Overall accuracy = 68.47% , Kappa statistic = 0.6323												

Table 7.18: Error matrix for NASA/JPL dual-band per-segment (HSWO algorithm) classification output

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Total	Producer's accuracy
Reference data	C1. Bareland	394					429		14	60	897	0.439
	C2. Bridge		154		1		14				169	0.911
	C3. Built-up			35	1571		70		1		1677	0.937
	C4. Mangrove forest	42		11878	117	160	228	11	469		12905	0.920
	C5. Marshland				1375	68					1443	0.953
	C6. Oil palm					8445					8445	1.000
	C7. Rice paddy	895		5	289		5589		161	2234	9173	0.609
	C8. Rubber							8830			8830	1.000
	C9. Scrub-grassland						70		658		728	0.904
	C10. Water body									3110	3110	1.000
	C11. Diversified cropland			2234		129			2		2365	0.000
	C12. Dryland forest			205				3696			3901	0.000
	C13. Fish farm	123	7				6	5	128		269	0.000
	C14. Mudflat						322				322	0.000
	C15. Road	613				5	5		28		651	0.000
Total	2067	161	1572	14357	1781	8807	6733	12542	1461	5404	54885	
User's accuracy	0.191	0.957	0.999	0.827	0.772	0.959	0.830	0.704	0.450	0.575		
Overall accuracy = 76.53% , Kappa statistic = 0.7233												

Table 7.19: Error matrix for NASA/JPL dual-band per-segment (hybrid segmentation algorithm) classification output

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Total	Producer's accuracy
C1. Bareland	748						84		6	59	897	0.834
C2. Bridge		146	14				9				169	0.864
C3. Built-up	1		1616		28	1	31				1677	0.964
C4. Mangrove forest	49			11811	223	132	212		478		12905	0.915
C5. Marshland					1362	81					1443	0.944
C6. Oil palm						8445					8445	1.000
C7. Rice paddy	1077			35	322		5353		98	2288	9173	0.584
C8. Rubber								8830			8830	1.000
C9. Scrub-grassland	4						105		619		728	0.850
C10. Water body										3110	3110	1.000
C11. Diversified cropland				2046						319	2365	0.000
C12. Dryland forest				116		5		3780			3901	0.000
C13. Fish farm	212		12				10		35		269	0.000
C14. Mudflat							322				322	0.000
C15. Road	627				2	1	5		16		651	0.000
Total	2718	146	1642	14008	1937	8665	6131	12610	1252	5776	54885	
User's accuracy	0.275	1.000	0.984	0.843	0.703	0.975	0.873	0.700	0.494	0.538		
Overall accuracy = 76.60% , Kappa statistic = 0.7251												

Chapter 8

Conclusions, Contributions and Recommendations

8.1 Conclusions

In this thesis, three pre-processing aspects, namely edge detection, speckle suppression as well as region-based segmentation, were investigated towards an improved land cover classification using nine-look NASA/JPL POLSAR C- and L-band data. To detect edges in speckle-corrupted POLSAR data, two new edge detectors, which are based separately on the Roy's largest eigenvalue and trace ratio, were proposed. The performance of both edge detectors was analysed using the simulated POLSAR data as well as NASA/JPL POLSAR data. Comparisons with three other edge detectors, which use separately on the likelihood ratio, the Dowson-Landau metric and the Euclidean distance, were conducted. From the obtained results, both the proposed edge detectors and the likelihood ratio edge detector exhibited their satisfactory performances in detecting edges as well as in coping with speckle noise disturbance. In contrast, the Dowson-Landau metric and the Euclidean distance showed their relative weak immunity against the multiplicative noise in the C- and L-band data. Both measures caused the unwanted false edge detection, especially over bright homogeneous areas. Although both the Roy's largest eigenvalue-based and trace ratio edge detectors showed their capabilities in detecting edges while tackling the multiplicative noise disturbance, both the edge detectors were computationally expensive. The Roy's largest eigenvalue-based edge detector involved solving a cubic equation for eigenvalue computation, while the trace ratio edge detector involved a computation for finding a square root of a matrix.

For the speckle suppression, a novel spatially adaptive speckle filter was introduced, which aims at preserving point-like textural features as well as structural

features, i.e. edges and lines, during the filtering process. The central idea of the proposed filter is that the filtering operations are performed spatially variant for image features in order to preserve them. For homogeneous areas, the filtering is based on scattering properties. To achieve this, the proposed filter consists of five processing steps, namely (i) edge detection, (ii) line detection, (iii) texture analysis, (iv) classification based on scattering mechanisms, and (v) despeckling. Applied to the NASA/JPL POLSAR C- and L-band data, the proposed filter performed satisfactorily in the speckle removal, image feature retention as well as radiometric preservation. Comparisons with the boxcar, Lee-refined and annealing filters were carried out. The Lee-refined filter exhibited its stable performance in the speckle removal, image feature retention as well as radiometric preservation. For the boxcar filter, a significant trade-off between the speckle removal and image feature retention was observed. The speckle noise was removed at the expense of destroying the image features for larger window sizes. The annealing filter was good in both speckle removal and image feature retention. It nevertheless suffered from the inherent defection in the radiometric preservation. No universally best speckle filter was found, where each filter possesses its own merits and limitations.

In the region-based segmentation, the hybrid algorithm, which was proposed by Haris *et al.* (1998), was selected and extended for multi-look POLSAR data. There are four modules in the segmentation algorithm, namely (i) speckle suppression, (ii) edge magnitude computation, (iii) initial segmentation by morphological watershed transform, and (iv) region merging. The capabilities of the extended hybrid segmentation algorithm were examined using both the simulated POLSAR data and NASA/JPL POLSAR data. Its performance was benchmarked against the existing HSWO algorithm, which was introduced by Beaulieu and Touzi (2004). Applied to the NASA/JPL POLSAR C- and L-band data, the extended hybrid segmentation algorithm was found to be less time-consuming than the HSWO algorithm. From the results, it was noticed that the segmentation outputs from both the algorithms rely strongly on the user-defined region number, which is employed as the termination rule.

The classification of NASA/JPL POLSAR C- and L-band data over a selected area of Kuala Muda in Peninsular Malaysia was carried out based separately on scattering mechanisms and statistical distribution. For the scattering property-based unsupervised classification, three different classification schemes were examined,

namely van Zyl's scattering classification, Freeman-Durden scattering model as well as Cloude-Pottier target decomposition. The scattering mechanisms of different land cover classes were derived and can be explained, except for the river. In the supervised classification based on complex Wishart distribution, the C- and L-band per-pixel land cover classification results were mildly satisfying. The overall accuracies were 63% and 67% for both the C- and L-band, respectively. An improved accuracy of 75% was, however, attained by using the dual-frequency input. Furthermore, the comparison between per-pixel and per-segment classification approaches was performed in this study, where the per-segment approach was expectedly found to improve the classification accuracy. The per-segment approach reduced significantly the salt-and-pepper effects in the classification outputs.

8.2 Contributions

The contributions of this research work are listed as follows:

- (i) Two new edge detectors, which are capable of detecting edges while coping with speckle noise disturbance, were introduced for speckle-corrupted POLSAR data.
- (ii) A novel spatially adaptive filter, which performs well in speckle removal, image feature retention and radiometric preservation, was developed for multi-look POLSAR data.
- (iii) An existing hybrid segmentation algorithm, which uses both the edge and region information, was extended for multi-look POLSAR data.
- (iv) The potential application and improvement of multi-look POLSAR C- and L-band data for classifying land covers over a selected tropical region in Southeast Asia was presented. Moreover, the use of dual-frequency input and per-segment approach in improving the land cover classification was showed.

8.3 Recommendations

Several recommendations for possible future work are given below:

- (i) To further improve the edge detection in POLSAR data, a multi-resolution approach, which involves multiple-sized edge templates, can be developed. The

use of small sized edge templates may help to detect micro edges, while larger template sizes may assist in removing speckle noise influence during edge detection. Moreover, the effects of using different radar frequencies and polarisations in the edge detection were noticed in this study. Thus, it is suggested to investigate detailed roles played by different frequencies and polarisations.

- (ii) For the speckle suppression, the speckle characteristics of the off-diagonal elements of the covariance matrix, i.e. $\Re(S_{HH}S_{VV}^*)$, $\Re(S_{HH}S_{HV}^*)$, $\Re(S_{HV}S_{VV}^*)$, $\Im(S_{HH}S_{VV}^*)$, $\Im(S_{HH}S_{HV}^*)$ and $\Im(S_{HV}S_{VV}^*)$, have to be further investigated. Then, the proposed speckle filter can be refined accordingly by taking the speckle characteristics into account.
- (iii) In the area of region-based segmentation, it was noticed that the segmentation results from both the HSWO and extended hybrid algorithms depend strongly on the desired number of regions, which is used as a termination rule. The perfect setting of this parameter is, however, difficult since the exact number of regions is always unknown. Thus, an automatic termination rule can be further derived for improving both the HSWO and extended hybrid algorithms.
- (iv) The scattering property-based classification algorithms produce only scattering classes and no land cover classes in the final outputs. On the other hand, the supervised complex Wishart classifier generates land cover classes based solely on POLSAR image statistics without taking the underlying scattering properties into account. Thus, a combined use of physical scattering mechanisms and statistical characteristics for improving land cover classification can be developed. In addition, there is a need for further investigation on the scattering characteristics of the river in the selected POLSAR test data.
- (v) The developed image processing techniques can be further assessed using other airborne POLSAR data, such as E-SAR EMISAR, Pi-SAR and so forth. Moreover, the experiments using spaceborne POLSAR data, which are captured by the ALOS and RADARSAT-2 imaging systems, can be considered. In addition, the applications of the developed techniques using circular polarisations can also be examined.

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Appendix A

NASA/JPL POLSAR Data Format

The NASA/JPL POLSAR data are provided in compressed Stokes matrix format. Each pixel in the data consists of ten bytes whereby the 4×4 symmetrical Stokes matrix $\mathbf{M}$ of each pixel can be reconstructed from these ten bytes using the following equations:

$$\mathbf{M} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & m_{14} \\ m_{21} & m_{22} & m_{23} & m_{24} \\ m_{31} & m_{32} & m_{33} & m_{34} \\ m_{41} & m_{42} & m_{43} & m_{44} \end{bmatrix},$$

with

$$m_{11} = \frac{1}{4} (S_{HH} S_{HH}^* + S_{VV} S_{VV}^* + 2S_{HV} S_{HV}^*) = \left(\frac{\text{byte}(2)}{254} + 1.5 \right) \times 2^{\text{byte}(1)},$$

$$m_{12} = \frac{1}{4} (S_{HH} S_{HH}^* - S_{VV} S_{VV}^*) = \text{byte}(3) \times \frac{m_{11}}{127},$$

$$m_{13} = \frac{1}{2} \Re(S_{HH} S_{HV}^*) + \frac{1}{2} \Re(S_{HV} S_{VV}^*) = \text{sign}(\text{byte}(4)) \times \left(\frac{\text{byte}(4)}{127} \right)^2 \times m_{11},$$

$$m_{14} = -\frac{1}{2} \Im(S_{HH} S_{HV}^*) - \frac{1}{2} \Im(S_{HV} S_{VV}^*) = \text{sign}(\text{byte}(5)) \times \left(\frac{\text{byte}(5)}{127} \right)^2 \times m_{11},$$

$$m_{23} = \frac{1}{2} \Re(S_{HH} S_{HV}^*) - \frac{1}{2} \Re(S_{HV} S_{VV}^*) = \text{sign}(\text{byte}(6)) \times \left(\frac{\text{byte}(6)}{127} \right)^2 \times m_{11},$$

$$m_{24} = -\frac{1}{2} \Im(S_{HH} S_{HV}^*) + \frac{1}{2} \Im(S_{HV} S_{VV}^*) = \text{sign}(\text{byte}(7)) \times \left(\frac{\text{byte}(7)}{127} \right)^2 \times m_{11},$$

$$m_{33} = \frac{1}{2} S_{HV} S_{HV}^* + \frac{1}{2} \Re(S_{HH} S_{VV}^*) = \text{byte}(8) \times \frac{m_{11}}{127},$$

$$m_{34} = -\frac{1}{2} \Im(S_{HH} S_{VV}^*) = \text{byte}(9) \times \frac{m_{11}}{127},$$

$$m_{44} = \frac{1}{2} S_{HV} S_{HV}^* - \frac{1}{2} \Re(S_{HH} S_{VV}^*) = \text{byte}(10) \times \frac{m_{11}}{127},$$

$$m_{22} = \frac{1}{4} (S_{HH} S_{HH}^* + S_{VV} S_{VV}^* - 2S_{HV} S_{HV}^*) = m_{11} - m_{33} - m_{44},$$

where S_{pq} refers to the scattering matrix element of q -polarised transmitted and p -polarised received waves. The subscripts H and V represent horizontal and vertical polarisations, respectively. The superscript $*$ denotes the complex conjugate. The symbols $\Re$ and $\Im$ are the real and imaginary parts of the operand, respectively. The function $\text{sign}(\cdot)$ reflects the sign of the quantity in brackets.