Homoskedastic Measures of Distance for Heteroskedastic SAR And POLSAR Data

Thanh-Hai Le

School of Computer Engineering

Nanyang Technological University

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Abstract

In the past decades, the exponential advancement in computational power has made once overly-computational-excessive SAR technology become now a preferred earth observation solution. As state-of-the-art technology, the SAR technique has been extended in a few directions, one of which is the polarimetric SAR or POLSAR. POLSAR is the natural extension from SAR, which exploited the natural polarization property of EM wave. Like the extension from black-and-white images to color imagery, the polarimetric extension brought about the multi-dimensional POLSAR data from the one-dimensional SAR data.

With (POL)SAR data becomes more available and cheaper, the recent emphasis is on using, and therefore understanding the data. Due to the interference of EM wave, SAR measurements are stochastic by nature. Under this condition, it is very important to understand the statistical models for SAR data. It is these models that are used to form the foundation for different SAR data processing techniques, for example speckle filtering, target detection, image segmentation or clustering / classification. central to these machine learning or signal processing techniques, is the need for consistent dis-similarity measures which are derived from the statistical models.

While the SAR heteroskedastic model for homogeneous area has long been developed and widely used, in extending the model toward heterogeneous images, the impact of heteroskedasticity has virtually been ignored. Specifically the concept of distance as a measure of dis-similarity is seriously flawed, as it is widely known that ratio offers a better discrimination measure TODOCITE. This thesis starts off by proposing the logarithmic transformation which is shown converting the SAR data into an homoskedastic

model. From this log-transformed model, a few consistent measures of distance is proposed. in a sense the distance concept is re-emerged, as the log-transformation converts the widely used ratio into standard subtraction, and thus distance.

In extending our statistical understanding of SAR data towards multi-dimensional POLSAR data, the representation problem need to be addressed. The trouble that the high dimensional data bring about is that there exists not one, as the intensity in the one-channel SAR, but many observables quantities. While different statistical models have been developed for different observables or their combination, for a model to be useful, a discrimination measure need to be derived. Practical application for POLSAR data processing requires the measure to be scalar, consistent and preferably homoskedastic on the one hand. at the same time the observable quantity being modelled need to be naturally representative for the high dimensional POLSAR data on the other hand.

In this thesis, the determinant of the POLSAR covariance matrix is proposed as an observable quantity to study. The representative power of this observable is explained as it would transform into the standard SAR intensity, should the multi-dimensional POLSAR data is collapsed into the traditional one-dimensional SAR scenario. The thesis then develop statistical models for this POLSAR determinant and log-determinant, which subsequently leads to the proposal for a few homoskedastic measures of distance for POLSAR. And since POLSAR can be viewed as a multi-dimensional extension of SAR, we show how the standard statistical models for SAR can be put within the natural coverage of this generic models for POLSAR.

There are a few benefits of using the homoskedastic measures of distance for POLSAR. Firstly, compared to the multiplicative dis-similarity measure of ratio, these additive measures of distance fit more naturally with the linear scale nature of digital imagery. Secondly, within the homoskedastic log-transformed domain, where the distance concept as well as the Gauss Markov theorem is again applicable, the universal MSE deserves to be reviewed as a reliable objective function / criteria for (POL)SAR estimators.

This may open up a number of different research directions for future studies of (POL)SAR. As example demonstrations of how these models and distance measures can be used, a novel clustering algorithm, a new speckle filter and various procedures in using MSE to evaluate speckle filters are also presented as part of the thesis.

To those in need,

With love and hard work.

Acknowledgement

"Not many appreciate the ultimate power and potential usefulness of basic knowledge accumulated by obscure, unseen investigators who, in a lifetime of intensive study, may never see any practical use for their findings but who go on seeking answers to the unknown without thought of financial or practical gain."

EUGENIE CLARK

Before anything, I would like to express my gratitude towards my family, specifically my wife, my parents and my kids, whose constant love and unconditional support I have greatly relied upon. Their immeasurable sacrifices together with their continous encouragement have always been the motivation for me to follow this academic pursuit. They are the first and foremost people that this work is dedicated upon.

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"The roots of education are bitter, but the fruit is sweet."
– Aristotle

Contents

List of Symbols

1. Glossary

Polarimetric Synthetic Aperture Radar: the extension of single-channel SAR imaging solution to multiple-channel imagary using polarimetric properties.

POLSAR: Polarimetric Synthetic Aperture Radar

SAR: Synthetic Aperture Radar

Synthetic Aperture Radar: an active side-looking-radar remote sensing solution based on doppler-effect

2. Nomenclatures

C_v: denotes the **polarimetric covariance matrix**

C_h: denotes the **polarimetric coherency matrix**

M^{*T}: denotes the **complex conjugate transpose** of matrix M

$pdf(x; k)$: denotes the **probability density function** of the **random variable** x, given the known and **constant** k

$cdf(x; k)$: denotes the **cumulative distribution function** of the **random variable** x, given the known and **constant** k

$cf(x; k)$: denotes the **characteristic function** of the **random variable** x, given the known and **constant** k

$X \sim Y$: denotes the observable values X, which behaves as a single or a combination of random process(es) Y.

$|M|$: denotes the **determinant** of the matrix M, also denoted as $det|M|$

Z: denotes the **scaled polarimetric covariance matrix**, $Z = LC_v$ (see: C_v)

$\Gamma(x)$: denotes the **Gamma function**.

$tr(M)$: denotes the **trace** of matrix M.

$\chi^2(2L)$: denotes the **Chi-Square distribution** with $2L$ degrees of freedom.

$\Lambda(2L)$: denotes the **Log-Chi-Square distribution** with $2L$ degrees of freedom.

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Chapter 1

Introducing The Research Question

Univariate SAR and multi-variate POLSAR data are multiplicative and heteroskedastic. By definition, heteroskedastic noised data has its variance, and correspondingly its substractive distances, dependent on the main signal. In another line of research, log transformation has been shown to convert the multiplicative nature of SAR data into a more familiar additive nature. We hypothesize that log-transformation also offers several consistent measures of distance in heteroskedastic SAR and POLSAR data. This thesis aims to investigate and validate that hypothesis.

In this chapter: the main research problem and the corresponding hypothesis are explicitly stated. The methodology section explains how the results are obtained and analyzed. Contributions to advance theoretical knowledge are illustrated. Towards the end of the thesis, an application illustrate how the theoretical results can be applied in future research and development activities.

1.1 Background Context and the Motivation to Study

Synthetic Aperture Radar can soon become the preferred choice for continous and autonomous large-scale remote surveillance solutions. Compared to optical remote sensors, which is passive, active SAR sensors provides weather independent and night-inclusive operational capabilities. Compared to other radar based active sensors, for example Real Aperture Radar (RAR), SAR provides a much better resolution, and larger coverage solution. The once-limiting drawback of SAR is the high-demanding signal processing procedures, which is needed to process SAR images, has become obsolete, due to recent and quick advances in computational power [**?**].

EM wave polarization and polarimetric SAR paragraph (page 3)

A paragraph about partial polsar and the extension from (page 3)

Problem: speckle in SAR and POLSAR, especially its heteroskedastic nature. (new)

The motivation then is to provide a probably better understanding about the statistics of speckle. (new)

For SAR data (page 4)

For partial POLSAR data (new)

For full polsar data (new)

The purpose of this section is to illustrate the importance of a computational framework needed in the interpretation and processing targets' stochastic polarimetry signatures. As reviewed in the second chapter, Synthetic Aperture Radar, i.e. SAR, offers a higher resolution, large coverage, weather-independent and night-capable imaging solution. Recent advances in computational power has made the once-limiting high-demanding signal-processing procedures, which are needed to process SAR images, obsolete **?**. Thus we believe, SAR will soon come to be the preferred choice for continuous and autonomous large-scale remote surveillance solutions.

Electromagnetic waves have the intrinsic nature of polarization. Polarimetric SAR, i.e. POLSAR, extends the SAR acquisition information from the traditional single SAR channel to multi-channel polarimetric SAR data, corresponding to different combination of transmitted and received polarizations. Early works from the radar community had focused on the theoretical introduction of scattering matrix, i.e. Sinclair matrix or Mueller matrices, for full, i.e. quad, polarimetric measurements **?**. These works were continued by Boerner, and the first polarimetric images were captured by NASA JPL at Caltech in 1991 **?**.

Systems were then engineered and commercial POLSAR satellites, e.g. RadarSat, TerraSAR, Alos-PalSAR, and so on, were launched. However due to operational restrictions on payload, power and data-downlink, the satellites also offer dual-channel polarimetric SAR modes apparently as a compromise between theoretical polarimetric requirements and practical limitations. Initially to the end user, while dual-channel partial polarimetry may not provide the complete polarimetric signature of the target, the loss is compensated for by either better resolutions or higher coverage and lower cost. Until very recently, these partial polarimetry modes were not formally taken up by scientists and academia. In his pioneer paper in 2005, Souyris**?** introduced the so-called compact polarimetry mode with the suggestion that it may be possible to reconstruct full polarimetric information from compact polarimetric data. Raney**?** showed that dual-channel polarimetry is not only capable of measuring the complete polarization information of the back-scattered EM wave, via Stokes parameters, but also capable of detecting the basic target's polarimetric characters, i.e. odd or even bounce phenomena.

The extensions from single-channel SAR to multi-channel polarimetry can be considered as analogous to the advancement towards colour TV from the black-and-white days. While the future is promising, both SAR and POLSAR suffer from speckle phenomena, which hampers the human capabilities to understand SAR images. Speckle, which arises due to the random interference of many de-phased but coherent back-scattered waves, is inherent in all channels. The effects of speckle is illustrated in Figure **??**.

The motivation for this research then is to reconstruct high-quality grey-scale images from speckled single channel SAR data, and to visualise as colourful images the de-speckled multi-channel POLSAR data. In order to do so, the speckle effects need to be removed as much as possible from original (POL)SAR data.

Due to the random nature of speckle, speckle filtering has been put into the context of statistical estimation theory, which comprises statistical modelling and validation, estimator design and development as well as evaluation of different estimators' accuracy. This proposed research project focuses on developing a computational framework for simulation, evaluation, processing and classification of target polarimetric signatures. The benefits of such a framework are many fold. Firstly, simulation allows one to quickly carry out experiments on small synthesized and well-designed scenarios, without the need for a real expensive satellite imagery. Secondly, simulation provides ground-truth, without which quantitative evaluation of estimators would have been impossible. Last but certainly not least, such a framework allow one to apply estimators repeatedly, and results from different estimators can be statistically and reliably compared.

For single-channel SAR images, our initial observations and experiences indicate that the community has been oblivious to many of the negative effects of statistical heteroskedasticity manifested in the original intensity and amplitude data. In Chapter 4, it is shown that logarithmic transformation can convert SAR's multiplicative stochastic process into a better-understood additive noise model. Thus, the additive-noise domain indicates homoskedasticity as well as offers a consistent sense of distance and variance. As the additive noise PDF in log-domain has been worked out, we hypothesize that the true back-scattering coefficient PDF, also in log-domain, can be estimated through regularized deconvolution algorithms. If an algorithm could be designed to estimate such PDF, we believe this would present an improvement for a whole class of speckle filters, namely the Maximum-A-Priori (MAP) class, which up to now, still assumes the true PDF will follow certain known fixed distributions.

For multi-channel SAR data, as reviewed in Chapter 2, speckle filtering for the off-diagonal element $S_h S_v^*$ of the covariance matrix is still an open question. Our observation has been that these elements are also available in dual-polarization SAR data, they specifically are part of Stokes parameters. As mentioned earlier, Stokes parameters have been largely ignored in polarimetric literature, until recently asserted again by Raney in 2006 **?**. Mathematically, Stokes parameters can be written as:

$$S = \begin{pmatrix} S_h S_h + S_v S_v \\ S_h S_h - S_v S_v \\ 2\Re(S_h S_v^*) \\ 2\Im(S_h S_v^*) \end{pmatrix} = \begin{pmatrix} S_h S_h + S_v S_v \\ S_h S_h - S_v S_v \\ S_+ S_+ - S_- S_- \\ S_l S_l - S_r S_r \end{pmatrix} \tag{1.1}$$

We have evidence, and hypothesize that S_+S_+, S_-S_-, S_rS_r, S_lS_l will have the same physical and statistical properties as the normal S_hS_h, S_vS_v. If our hypothesis can be proven rigorously, it may then be possible to build and validate a statistical model for all elements in the covariance matrix of Polarimetric SAR data, namely S_hS_h, S_vS_v, $\Re(S_hS_v^*)$, $\Im(S_hS_v^*)$. Also, speckle filtering on off-diagonal elements can be carried out using techniques, that were originally developed for single-channel SAR data, and up to now is only applicable to the diagonal elements of the covariance matrix.

For the topic of target (ship) detection and classification, we notice that the use of partial polarimetry will provide extra polarimetry data without incurring loss in spatial resolution. We proceed to hypothesize that: partial polarimetry will lead to improved target (ship) detection and classification accuracy in comparision to traditional SAR data. Experiments can be carried out by capturing polarimetric SAR remote sensing imagery and ground truth data which is provided via the ships' locational identification data. Automatic Identification System (AIS), which normally supplements marine radars, is a standard ship tracking system for identifying and locating floating vessels. Empirical evidence can be obtained by applying traditional ship detection and classification on traditional and polarimetric data concurrently, and the results are to be compared.

1.2 Objectives, Methodology and Contributions

Copy the objectives (page 6)

copy the benefits (page 6)

1.2.1 Objectives and Contributions

The purpose of this section is to illustrate the objectives in developing computational frameworks for Stochastic Polarimetric Data. Assuming the framework will be implemented successfully, this section also describes its academic contributions as well as its projected practical benefits.

Even though the research topic spreads across different sub-fields, a common thread that bind them all together is the application and development of statistical estimators. For single channel SAR, it is the estimation of underlying back-scattering coefficients being corrupted with stochastic noise. In the case of multi-channel SAR, it is the estimation of a target's polarimetric signature, being measured in multiple channels simultaneously and stochastically. And for the problem of target detection or classification, it is the likelihood estimation that the target belongs to a certain category.

Thus, the main objective of this research is to derive effective statistical estimators for the reconstruction and classification of the underlying target information in speckled SAR and POLSAR data.

In order to design and evaluate effective estimators, we centre our effort on developing a good computational framework. The objective of such framework being:

1. To build, develop and validate statistical models for different stochastics processes that are inherent within the polarimetric SAR domain.

2. To allow easy, fast and repeatable simulations and experiments of various stochastic processes in designed, focused, as well as broad-based scenarios.

3. To allow easy application of different existing estimators as well as various transformations into focused and simulated scenarios as well as into practical real measured data.

4. To allow development and calculation of good performance indices for estimators.

5. To allow visualization and analysis of the performance of different stochastic estimators.

6. Ultimately, to allow development of better and more accurate estimators, whose results can be verified: not only qualitatively on real life images, but also quantitatively through rigorous simulations.

The possible benefits of the research project are:

1. Practical benefits

    (a) The computational frameworks allow for faster, quicker and more focused experiments. Often, a statistical hypothesis can be observed or rejected by designing and implementing an appropriate computational experiment.

    (b) The framework allows for easier analysis, and thus more insight to be gained, on the performance of an estimator. This, in turn, allows for design and development of better estimators.

    (c) Our research to find evidence, and hopefully rigorous proofs, supporting the advantages of (partial) polarimetric SAR implementations over conventional SAR data also yields high practical interest. Apparently the topic has also received a fair share of attention and supports from EADS [1].

    (d) The investigative research of ship monitoring using polarimetric SAR satellites is also apparently of high interest to EADS, as evidenced by their own in-house investigations.

[1] This PhD research project is run in conjunction with EADS and has an EADS co-supervisor

2. Academic benefits

   (a) The computational framework allows for quantitative evaluation and comparison of estimators. With fast and repeated experiments, the framework allows one to not only compute a single performance value on a single experiment, but also to analyze the whole behaviour of such performance measures over repeated stochastic simulations.

   (b) For the sub-topic of single-channel SAR imagery, we believe an estimate for the PDF of the true underlying coefficient will be an unique research result.

   (c) For the multi-channel POLSAR sub-field, we believe our proposed approach in speckle filtering of the off-diagonal elements in the polarimetry covariance matrix is also a novelty.

   (d) For the specific application of ship detection and classification, we believe our approach of evaluating the performance of higher-resolution and partial polarimetry modes using ground truth from AIS data is also unique.

As a testament on the effectiveness of this research, the work discussed in this report was published as two separate papers in 2010, at ISCCSP**?** and ACRSLe *et al.* [2010].

1.2.2 The Research Questions

Figure **??** shows that: when compared with optical remote sensing images, SAR data suffers from serious degradation. The degraded SAR data almost invariably requires a treatment of speckle filtering to yield more comprehensible images. Recent advances in Polarimetric SAR (POLSAR) have produced multiple channels of SAR data, which are conceptually similar to the multiple channels found in colourful optical images. However, the stochastic effects of speckle on multivariate and correlated data is ever more eminent. The key proposed research question is how to reconstruct clean, colorful visualization of Polarimetric Information from the new but speckled PolSAR satellites. Towards the end of the research project, an optional extended question shall be how this extra de-speckled polarimetric information may help in the tasks of target detection and classification.

The main research question is conceptually divided into the following subsidiary questions to investigate:

1. For single channel SAR data, the main aim would be how best to produce and quantitatively evaluate the de-speckled gray images. The main contributions could be that: for the first time, the PDF for the underlying back-scattering coefficient appears to be estimate-able, at least in the log-transformed domain. It is hoped this new knowledge may help in developing better speckle filters, especially those filters of *Maximum a Posteriori* (MAP) nature. Another possible contribution could be: how the homoskedasticity in the log-transformed domain could help to consistently evaluate the performance of different speckle-filters being applied on heterogeneous spatial variations.

2. For multi-channel SAR data, the main aim would be to produce a smoothed and colourful visualisation of Polarimetric information. The main contributions would be a methodology to extends the results of single-channel SAR speckle filtering towards the issue of estimating the off-diagonal elements in polarimetric covariance matrix. Another fundamental contribution could be: how to model, simulate and visualize the multivariate and correlated channels in POLSAR data.

3. The third portion of this project is to investigate how full polarimetric information could be reconstructed from partial polarimetry modes. The main aim of this section is to fill the gap between practical dual-polarimetric implementations and theoretical established full polarimetric results.

4. An optional collaborative portion is to investigate how the extra information in different polarimetric modes may help in the task of target detection and classification. The main aim of this stage is to demonstrate the capability of (partial) polarimetric information over traditional single-channel SAR data.

1.2.3 Research Methodology

As the speckle phenomena is stochastic in nature, speckle filtering has been put into the framework of statistical estimation. This project's research methodology will be based extensively on a statistical estimation framework. The framework consists of three stages:

1. Stage 1: data statistical analysis. We aim to propose a preferred data transformation and decomposition that may allow applications of existing computer science

techniques. The statistical models built after such a transformation are validated against real-life data.

2. Stage 2: predictor and estimator development. Various statistics based computational intelligence and/or signal processing methods are intended to be applied.

3. Stage 3: results analysis and performance evaluation. Experiment results are evaluated both qualitatively on real images and quantitatively through simulated data.

1.2.3.1 Data Collection

We have used, and plan to keep using simulated data extensively. There appears to have a number of advantages in using simulated experiments:

1. Once the model is validated against real-life data, simulated experiments can be carried out on more focused scenarios. This allows smaller data sets to be generated and analysis can become faster and more accurate.

2. Contrary to real-life images where underlying coefficients are to be estimated, ground truth is readily available in simulated experiments.

3. Quantitative evaluation is possible not only via a single experiment on a single real-image but via repeated stochastic runs.

4. Thus not only single values of mean or mean-squared-error is to be evaluated. As the whole response PDF is available, statistical bias or heteroskedasticity can also be reported.

Besides simulated data, we have gathered a large amount of real-life data. The table below lists data made available to us, courtesy of EADS Innovation Works Singapore.

Furthermore, for the task of ship detection and classification using polarimetric data, we intended to capture ship's location using readily available Automatic Identification System (AIS) systems. The data collection strategy will be synchronized tasks of satellite imagery and AIS data capture. AIS data, in a close-to-port environment, will be used as ultimate ground truth to evaluate different target detection and classification algorithms.

Radar Platform	Polarization Mode	Data Capture Time
RadarSat 2	Full Quad Pol	29 Apr 2009
RadarSat 2	Full Quad Pol	05 Apr 2009
RadarSat 2	Full Quad Pol	12 Mar 2009
RadarSat 2	Full Quad Pol	23 Jan 2009
RadarSat 2	Full Quad Pol	30 Dec 2008
RadarSat 2	Full Quad Pol	06 Dec 2008
RadarSat 2	Full Quad Pol	19 Oct 2008
RadarSat 2	Full Quad Pol	12 Nov 2008
RadarSat 2	Full Quad Pol	25 Sep 2008
TerraSar-X	Dual Pol (HH-VV)	18 Apr 2008
NASA-JPL AirSar	Full Quad Pol	2001

Table 1.1: Collected imagery data

1.2.3.2 Result Interpretation and Evaluation

Simulated experiments allows evaluation of estimators against ground-truth. Errors can be quantitatively analyzed and methods to reduce such errors can be developed. Thus simulated experiments could produce quick results, which may provide faster analysis and further insights for developing more accurate estimators.

Practically in the end, all estimators would always need to be applied on real images. Contrary to experiments on simulated data, experiments on real images can only be compared qualitatively. This however, is critical and will always be used in our investigations. The reason is that this helps to guard against any systematic errors in the used assumptions and approximations made in developing the theoretical models. Towards that end, real-data can help to build and validate statistical models.

1.2.3.3 Theory Development and Research Strategy

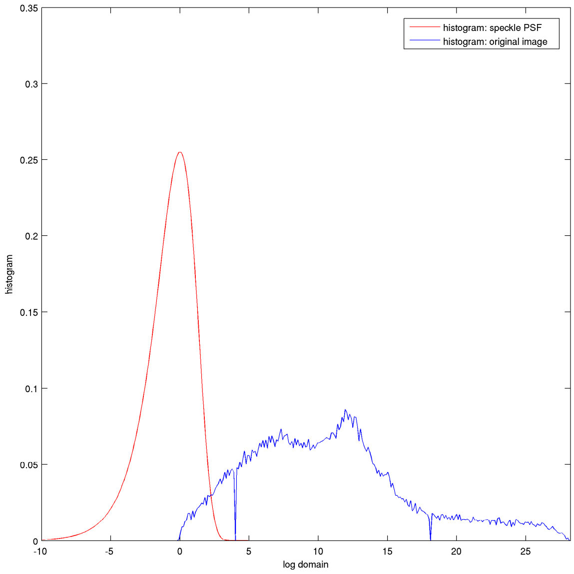
For single channel SAR data, we propose the use of a log transform to evaluate speckle filter's performance. We have proved that homoskedasticity property is indeed manifested in the log-domain. The traditional performance index in comparing speckle filters, i.e. the Equivalent Number of Looks (ENL), has also been shown to be related and calculable from the standard Mean Squared Error (MSE) inside the log-domain. We are working to prove that, with the homoskedastic property asserted, the universal Mean Squared Error can be a good performance indicator, even on heterogeneous spatial variations.

Furthermore, as the point spread function (PSF) is available in the log-transformed domain, it appears that, for the first time, the histogram of the underlying back-scattering coefficient may become estimate-able. In figure 1.1a, the underlying single channel gray image histogram is presented along with the noise PDF, in the log-transformed domain. As the noise is additive, it is expected that the noise PDF will act as a point spread function. This makes the observable speckled image histogram mathematically equivalent to the convolution of the original image's histogram and the noise PDF. This fact is evidenced in figure 1.1b, where except for the un-calibrated shifting, the shapes of theoretical convolution and observed histogram are reasonably similar. We hypothesize that: given the observable SAR data and its histogram, it should be possible to estimate the original underlying signal's histogram through some regularized deconvolution methods. We intended to start by applying the Richardson-Lucy algorithm **??** for such estimations.

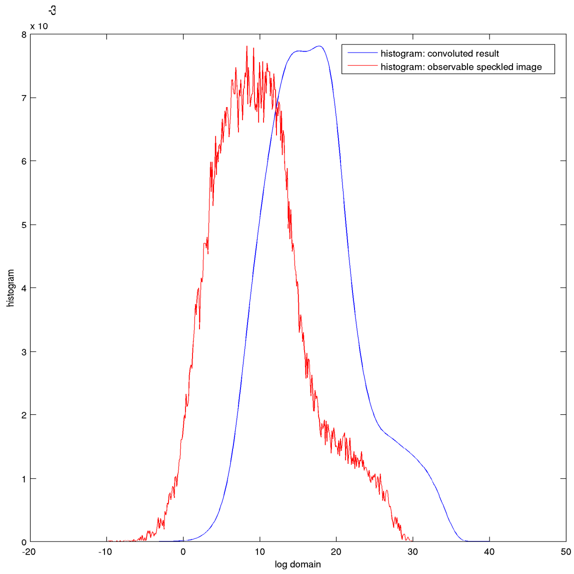
For multi-channel SAR data, we focus on partial polarimetric SAR satellite data. Attempts have been made to model the data, especially the off-diagonal covariance matrix elements, i.e. $S_h S_v^*$. However, the models are overly complicated which made proposed PolSAR speckle suppression algorithms became overly complex (see polarimetric data modelling section in Chapter 2). We preferred an alternative approach. We propose to transform the polarization basis of dual-polarized SAR data to help estimate this element.

We first pick up a recent revelation by Raney, 2006 **?**, that the back scattering waves' polarization captured in dual-pol data can be completely described using Stokes parameters. Furthermore, Stokes parameters can be measured in multiple polarization basis, which can also be synthesized from the given data (see polarization basis transform section in Chapter 2). That is: the measured signal at $\pi/4$ linear polarizer as: $\xi_+ = \frac{\xi_h + \xi_v}{\sqrt{2}}$, at $-\pi/4$ linear polarizer as: $\xi_- = \frac{\xi_h - \xi_v}{\sqrt{2}}$, at left circular polarization as: $\xi_l = \frac{\xi_h + i\xi_v}{\sqrt{2}}$, and at right circular polarization as $\xi_r = \frac{\xi_h - i\xi_v}{\sqrt{2}}$.

The Stokes vectors, when aligned at these transformed projections are given by the



(a) Original image's histogram and PSF



(b) Convoluted and speckled image histogram

Figure 1.1: Observable convolution of PSF

following well-known equation:

$$S_t = \begin{pmatrix} |\xi_h|^2 + |\xi_v|^2 \\ |\xi_h|^2 - |\xi_v|^2 \\ 2\Re(\xi_h \xi_v^*) \\ 2\Im(\xi_h \xi_v^*) \end{pmatrix} = \begin{pmatrix} |\xi_+|^2 + |\xi_-|^2 \\ -2\Re(\xi_+^* \xi_-) \\ |\xi_+|^2 - |\xi_-|^2 \\ 2\Im(\xi_+^* \xi_-) \end{pmatrix} = \begin{pmatrix} |\xi_l|^2 + |\xi_r|^2 \\ 2\Re(\xi_l^* \xi_r) \\ -2\Im(\xi_l^* \xi_r) \\ |\xi_l|^2 - |\xi_r|^2 \end{pmatrix} \tag{1.2}$$

Evidently, the real and imaginary parts of $S_h S_v^*$ is closely related to Stokes Parameters. Specifically they may be considered as the subtraction of two random SAR intensity variables, e.g., $|S_l|^2 - |S_r|^2$. For the same traditional reasoning of $|S_h|^2$ and $|S_v|^2$, we hypothesize that all the four intensities calculated from the transformation of polarization basis, i.e., $|S_+|^2$, $|S_-|^2$, $|S_l|^2$, $|S_r|^2$, follow negative exponential distributions. The hypothesis is supported by our preliminary experiment results, where we synthesize the basis transformed intensity from real-measured polarimetric data. It then follows that $S_h S_v^*$ can be despeckled by independently de-speckling the four synthesized intensities. Read chapter 4 for our work in progress in single-channel SAR speckle filtering. We hope to go further speculating that: the speckle-filtering methodologies in dual-polarization SAR data is extensible to full polarimetric SAR data.

To demonstrate the use of partial polarimetry for target detection and classification tasks, we could proceed with either approach. The first approach being: first full polarimetric information is to be reconstructed from partial polarimetry data. Then standard full polarimetric target detection and classification techniques can be applied on synthesized data. Read Chapter 3 for our published work in extending the reconstruct-ability of full polarimetric information from partial polarimetry data to urban and man-made areas. The second approach would be to invent a totally new target detection algorithm making use of the fact that partial polarimetric data also contains certain basic information about the target's polarimetric signature (see partial polarimetry section in Chapter 2).

1.2.4 Theoretical and Practical Contributions

For SAR data, the main focus is on niches areas like evaluation of filters, estimate of PDF, new filter? For PolSAR data, the main focus is more fundamental: investigation and modelling of PolSAR data channels. The approach is to start from simulation and ENL estimation in multi-variate extension of Gauss Markov theorem, new filters can be developed, initially with limited assumptions in modelling, and is evaluated against an evaluation protocol. Assumptions are made and tested in the process of evaluation of PolSAR speckle filter. Valid assumptions are then checked against mathematical formula and transformations.

The methodology in analysing multi-channel Polarimetric SAR data is to based on target decompositions. The multi-variate data is decomposed into conceptually and physically independent quantities and analysis is conducted on them individually! Another possibility is to find a consistent distance measure from the multi variate, multidimensional SAR data. This distance measure would be useful in the task of target detection from a randomized background. It could also be useful in land cover classification as well as change detection fields of PolSAR

We believe that the main focus of this research, partial polarimetric speckle filtering, has the following advantages:

1. The topic and the concept itself are newly developed and have just recently being introduced into the community.
2. Compared to full polarimetric data, partial polarimetry is much more compact. Yet it still exhibits the same multi-variate correctional statistics properties.
3. The practical application is synchronized with current satellite hardware deployments and trade-offs.

The possible benefits of our proposed research project are:

1. Practical benefits
    (a) The computational frameworks allow for faster, quicker and more focused experiments. Often a point can be proven or rejected by designing and implementing an appropriate computational experiment.
    (b) The framework allows for easier analysis and allows for more insight to be gained in an estimator's performance. This in turn allows for the development of better estimators.
    (c) Our research topic for partial polarimetric SAR has high practical interest, addressing a pressing practical trade-off between the better resolution in partial modes versus the more complete but coarser resolution in theoretical full polarimetry. Apparently the topic also generated practical interest from industry, i.e. from EADS.
    (d) The investigative research of ship monitoring using polarimetric SAR satellites is also apparently of high interest to EADS, as they are themselves working in this area.
2. Academic benefits

(a) The computational framework allows for quantitative evaluation of estimators. And with fast and repeated experiments, the framework allows the computation of not only a single performance counter value on a single experiment, but also allow the full distribution of such performance over repeated stochastic simulations to be inspected.

(b) For our research topic in the SAR community, we believe that obtaining an estimate of the true underlying PDF is a first of such systems.

(c) For multi-channel POLSAR, we believe our approach to tackle speckle filtering of off-diagonal elements in polarimetric covariance matrix is also a novelty.

(d) In the topic of target (ship) detection and classification, we believe our approach of evaluating the trade off between higher-resolution and partial polarimetry using AIS as ground truth is also unique.

1.3 Organisation of the Thesis

The rest of this thesis is organized into 5 chapters, as follows: The next chapter will survey the related publications and state-of-the-art techniques in modeling, processing, filtering and evaluating (POL)SAR speckle filter will be presented. It will also discuss the different measures of distance for both SAR and POLSAR data, together with their extensive applications. Through these discussion, the need for a homoskedatic and scalar model for the multivariate and heteroskedastic polsar is brought forward.

The heart of the thesis lies in chapters **??** and **??**. While chapter **??** presents the initial homoskedastic model for SAR data, chapter **??** illustrates the more recent and more generic model for POLSAR. Chapter **??** also specifically describes how the initial model for SAR can be considered as a special case of the POLSAR model.

Chapter **??** presents several of our published techniques in handling both SAR and POLSAR data. Theses techniques can all be considered as applications of the theoretical model presented in chapters **??** and **??**. Demonstrated applications include, but the possibilities are not limited to: clustering algorithms, speckle filtering techniques or a novel methodology to evaluate (POL)SAR speckle filters. Finally, the contribution of the thesis is discussed in the conclusional chapter 3.

Chapter 2

Current Methods in Processing SAR and POLSAR Data

2.1 The nature of Polarimetric SAR: EM Wave Polarization

Remote sensing introduction paragraph (section 2.1.1)

SAR introduction paragraph (section 2.1.2)

EM Wave polarization (Maxwell law leads to wave equations section 2.1.3.1, choice of origin which leads to polarization basis change eq 2.22)

SAR Polarimetry: and SAR as a special case of POLSAR (send and receive polarizations: 2.1.3.5)

Full Polarimetric SAR and target polarimetric response (also 2.1.3.5)

Partial Polarimetric SAR and EM wave polarization (2.1.3.4)

SAR stochastics nature (new)

2.1.1 Representations of EM Wave Polarizations (Linear, Circular ...)

2.1.1.1 Plane wave and solutions to the EM Wave equations

The general solution to the PDE EM wave equation is a linear superposition of waves each having the form

$$\vec{E}(\vec{r},t) = g(\phi(\vec{r},t)) = g(\omega t - \vec{k}\cdot\vec{r}) \tag{2.1}$$

and

$$\vec{B}(\vec{r},t) = g(\phi(\vec{r},t)) = g(\omega t - \vec{k}\cdot\vec{r}) \tag{2.2}$$

where g is any well-behaved function of a dimensionless argument ϕ, ω is the angular frequency (in radians per second), and $\vec{k} = (k_x, k_y, k_z)$ is the wave vector (in radians per meter).

In addition to the relations above, the wave vector and the angular frequency are not independent; they must adhere to the dispersion relation:

$$k = |\vec{k}| = \frac{\omega}{c} = \frac{2\pi}{\lambda} \tag{2.3}$$

where k is the wave number and λ is the wavelength.

Since any real wave can be considered as a superpositions of several sinusoidal waves, the simplest solution to consider for the EM Wave equations is:

$$\vec{E}(\vec{r},t) = \Re\left(\vec{E}(\vec{r})e^{i\omega t}\right) \tag{2.4}$$

where $\omega = 2\pi f$ is the angular frequency, f is the wave frequency. Assuming the most common case of EM waves travelling in a planar fashion, which is a good approximation of most light waves. For plane waves Maxwell's equations, specifically Gauss's laws, imposes a transversality requirement that the electric and magnetic field be perpendicular to the direction of propagation and to each other. Conventionally, when considering polarization, the electric field vector is described and the magnetic field is ignored since it is perpendicular to the electric field and proportional to it. Thus it is sufficient to just consider electric field, which equals:

$$\vec{E}(\vec{r}) = \vec{E^0}e^{-i\vec{k}\cdot\vec{r}} \tag{2.5}$$

Combining the two equations we have:

$$\vec{E}(\vec{r},t) = \vec{E^0}\Re\left(e^{i(\omega t-\vec{k}\cdot\vec{r})}\right) = \vec{E^0}\cos(wt-\vec{k}\cdot\vec{r}) \tag{2.6}$$

If we define the z direction as the travelling direction of the EM wave, and the electric field is fluctuating in the (x,y) plane, because the divergence of the electric and magnetic fields are zero, there will be no fields in the direction of propagation. Project this into x and y directions:

$$\vec{E}(z,t) = \begin{pmatrix} E_x^0\cos\left(wt-kz+\phi_x^0\right) \\ E_y^0\cos\left(wt-kz+\phi_y^0\right) \\ 0 \end{pmatrix} = \begin{pmatrix} \xi_x(t) \\ \xi_y(t) \\ 0 \end{pmatrix} \tag{2.7}$$

where ϕ_0 is the initial phase angle, that is dependent on the choice of space-time origin.

2.1.1.2 Linear, Circular and Elliptical Polarization

The shape traced out in a fixed projective plane by the electric vector as the plane wave passes over it is a description of the polarization state. This shape is characterized by the formula

$$\frac{\xi_x^2(t)}{|E_x^0|^2} + \frac{\xi_y^2(t)}{|E_y^0|^2} - 2\frac{\xi_x\xi_y}{E_x^0E_y^0}\cos(\Delta\phi) = \sin^2(\Delta\phi) \tag{2.8}$$

where $\Delta\phi = \phi_y^0 - \phi_x^0$ The formula characterizes what is termed as the polarization ellipse.

When the two orthogonal components are in phase, i.e. $\phi_x^0 = \phi_y^0$, the ratio of the strengths of the two components is constant. Thus the direction of the electric vector (the vector sum of these two components) is constant. Since the tip of the vector traces out a single line in the plane, this special case is called linear polarization. The direction of this line depends on the relative amplitudes of the two components.

When the two orthogonal components have exactly the same amplitude and are exactly ninety degrees out of phase, i.e. $E_x^0 = E_y^0$ and $|\phi_x^0 - \phi_y^0| = \pi/2$. In this special case the electric vector traces out a circle in the plane, so this special case is called circular polarization. The direction the field's rotation depends on the signed of the difference between the two phases. These cases are called right-hand circular polarizationand left-hand circular polarization, depending on which way the electric vector rotates and the chosen convention.

The general case is when the two components are not in phase and either do not have the same amplitude or are not ninety degrees out of phase, though their phase offset and their amplitude ratio are constant. This kind of polarization is called elliptical polarization because the electric vector traces out an ellipse in the plane (the polarization ellipse).

The parameters that describe the polarization ellipse are:

$$\tan(\theta) = \frac{E_y^0}{E_x^0} \tag{2.9}$$

with $0 \leq \theta \leq \pi/2$. The orientation angle, which is the angle between the major semi-axis of the ellipse and the x-axis, is given by:

$$\tan(\Psi) = \tan(2\theta)\cos(\Delta\phi) \tag{2.10}$$

with $0 \leq \Psi < \pi$. The ellipticity, ϵ is the major-to-minor-axis ratio. The ellipticity angle which is defined as $\chi = \arctan(1/\epsilon)$ can be calculated as:

$$\sin(2\chi) = \sin(2\theta)\sin(\Delta\phi) \tag{2.11}$$

with $0 \leq \chi \leq \pi/2$, and $0 \leq \epsilon \leq \infty$

Ignoring the scale of the electrical fields, the elementary wave polarization can be completely described by two parameters, i.e. E_y^0/E_x^0 and $\Delta\phi = \phi_y^0 - \phi_x^0$. Similarly, ignoring the scale of the ellipse, the polarization ellipse can be completely described by two angles Ψ and χ.

2.1.1.3 Mathematical representations of wave polarizations

Complex polarization ratio This ratio is important in explaining polarization basis changes.

It is defined as:

$$\rho = \frac{E_y^0}{E_x^0}e^{i\Delta\phi} = \frac{\cos(2\chi) + i\sin(2\chi)}{1 - \cos(2\Psi)\cos(2\chi)} \tag{2.12}$$

Jones Vector The Jones vector is defined as

$$J = \begin{pmatrix} \xi_x(t) \\ \xi_y(t) \end{pmatrix} = \xi_x(t) \begin{pmatrix} 1 \\ \rho \end{pmatrix} \tag{2.13}$$

Thus the normalized Jones vector can be given as:

$$J = \begin{pmatrix} \cos(\theta) \cdot e^{i\phi_x^0} \\ \sin(\theta) \cdot e^{i\phi_y^0} \end{pmatrix} = \begin{pmatrix} 1 \\ \tan(\theta) \cdot e^{i\Delta\phi} \end{pmatrix} = \begin{pmatrix} \cos(\Psi)\cos(\chi) - i\sin(\Psi)\sin(\chi) \\ \sin(\Psi)\cos(\chi) + i\cos(\Psi)\sin(\chi) \end{pmatrix} \tag{2.14}$$

The two parameters in the Jones vector can completely describe the polarization state (ellipse) of any elementary wave. This same Jones vector finds extensive use in quantum machenics, and is interpreted as quantum state vector. Its bra-ket notation formula, which is normally used in quantum computation contexts is:

$$J = |\Psi\rangle = \begin{pmatrix} \cos(\theta) \cdot e^{i\phi_x^0} \\ \sin(\theta) \cdot e^{i\phi_y^0} \end{pmatrix} \tag{2.15}$$

By definitions, the horizontal linear polarized wave is defined as: $J_h = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$, similarly the vertical linear polarized wave: $J_v = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$, the $\pm\pi/4$ linear polarized waves $J_\pm = \pm\frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ 1 \end{pmatrix}$, the left circular polarized wave: $J_l = |L\rangle = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ -i \end{pmatrix}$ and the right circular polarized wave: $J_r = |R\rangle = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ i \end{pmatrix}$

Stokes Vector Another way to look at polarization is through the coherency matrix, and equivalently the Stokes matrix. The wave coherency matrix is defined as:

$$W_c = \left\langle \begin{pmatrix} \xi_x \\ \xi_y \end{pmatrix} \begin{pmatrix} \xi_x \\ \xi_y \end{pmatrix}^\dagger \right\rangle = \left\langle \begin{pmatrix} \xi_x\xi_x^* & \xi_x\xi_y^* \\ \xi_y\xi_x^* & \xi_y\xi_y^* \end{pmatrix} \right\rangle = \left\langle \begin{pmatrix} |\xi_x|^2 & |\xi_x||\xi_y|e^{-i\Delta\phi} \\ |\xi_x||\xi_y|e^{i\Delta\phi} & |\xi_y|^2 \end{pmatrix} \right\rangle \tag{2.16}$$

The Stokes vector is then defined as:

$$S_t = \begin{pmatrix} S_0 \\ S_1 \\ S_2 \\ S_3 \end{pmatrix} = \begin{pmatrix} |\xi_x|^2 + |\xi_y|^2 \\ |\xi_x|^2 - |\xi_y|^2 \\ 2\Re(\xi_x \xi_y^*) \\ 2\Im(\xi_x \xi_y^*) \end{pmatrix} \tag{2.17}$$

In the case of elementary (or fully polarized) waves, the Stokes vector can be written as:

$$S_t = \begin{pmatrix} S_0 \\ S_0 \cos(2\Psi)\cos(2\chi) \\ S_0 \sin(2\Psi)\cos(2\chi) \\ S_0 \sin(2\chi) \end{pmatrix} \tag{2.18}$$

At this point, a distinction needs to be highlighted. In comparison to the two-element Jones vector, Stokes vectors have more data, four elements. Jones vector can completely describe the polarization states of an elementary wave, which formulation is based on the assumption that the wave is very well behaved. In practice, that is not normally the case, because reflected waves are generally combinations of multiple waves which ranged over certain areas of time and frequency. As such, the polarization of the waves are normally not fully polarized. One simple analogy is that the field ratio, i.e. ξ_x/ξ_y, or the phase difference, i.e. $\Delta\phi$, are not constant at all times. The phenomena can be loosely called wave depolarization.

The analysis above is especially prevalent in the remote sensing community, where the area of a single resolution cell (pixel) is very large compared with the radar's wave length. In such cases, the wave field is very stochastic and only statistical information about the variations and correlations between polarization components can be gathered.

Degree of polarization Degree of polarization p is a quantity used to describe the portion of an EM wave, which is polarized. A perfectly polarized wave has $p = 100\%$, while a fully depolarized wave is characterized by $p = 0\%$. A wave which is partially polarized can be represented as a superposition of a polarized and another unpolarized component. Thus $0 \leq p \leq 1$.

In fully polarized wave, the following equation holds:

$$S_0^2 = S_1^2 + S_2^2 + S_3^2 \tag{2.19}$$

In depolarized wave, it becomes an in-equation

$$S_0^2 > S_1^2 + S_2^2 + S_3^2 \tag{2.20}$$

Then the degree of polarization is defined as

$$p = \frac{\sqrt{S_1^2 + S_2^2 + S_3^2}}{S_0} \tag{2.21}$$

In such general case, the Stokes Vector is written as:

$$S_t = \begin{pmatrix} I \\ Ip\cos(2\Psi)\cos(2\chi) \\ Ip\sin(2\Psi)\cos(2\chi) \\ Ip\sin(2\chi) \end{pmatrix} = I(1-p)\begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} + Ip\begin{pmatrix} 1 \\ \cos(2\Psi)\cos(2\chi) \\ \sin(2\Psi)\cos(2\chi) \\ \sin(2\chi) \end{pmatrix} \tag{2.22}$$

Or alternatively, if Stokes vector is measured and given, then the polarization characteristics of a wave is given as: I, the total power of the measured beam is $I = S_0$, p, the degree of polarization is calculated as $p = \frac{\sqrt{S_1^2+S_2^2+S_3^2}}{S_0}$, $2\Psi = \tan^{-1}(S_2/S_1)$ and $2\chi = \tan^{-1}(S_3/\sqrt{S_1^2 + S_2^2})$ are the angles that characterize the wave polarization state.

Depolarization phenomena is explained from the fact that most sources of EM radiation contain a large number of "elementary" sources. The polarization of the electric fields produced by the emitters may not be correlated, which leads to depolarization effects. If there is partial correlation among the "elementary" sources, the light is partially polarized. One may then describe the received EM wave polarization in terms of the degree of polarization and the parameters of the polarization ellipse.

2.1.2 Different Modes of Polarimetric SAR

2.1.2.1 Full Polarimetry and the Polarimetric Signatures

This section describes the core concept of POLSAR, i.e. the target's polarimetric signature, and illustrates why research into partial polarimetry is warranted.

POLSAR radar measures the back-scattered echo received as the result of transmitting a signal. The scattering matrix relates the received signal E^{Rx} with the transmitted E^{Tx} signal as:

$$E^{Rx} = \frac{e^{ikr}}{r} S E^{Tx} \tag{2.23}$$

Normally, horizontal and vertical linear polarization are used, thus the scattering matrix, i.e. S, normally have the following expanded form:

$$\begin{pmatrix} E_h^{Rx} \\ E_v^{Rx} \end{pmatrix} = \frac{e^{ikr}}{r} \begin{pmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{pmatrix} \begin{pmatrix} E_h^{Tx} \\ E_v^{Tx} \end{pmatrix} \tag{2.24}$$

The scattering matrix can be called the Jones matrix (relating the Jones vector) in the forward scattering alignment. The matrix is normally called Sinclair matrix in SAR literature, as normally backward scattering alignment are normally used in SAR **?**. In the case of mono-static SAR, i.e. both radar transmitter and receiver can be considered as located in a single place, physical reciprocity leads to $S_{HV} = S_{VH}$ **?**.

The matrix can also be "stratified" to define the target scattering vector as:

$$T_{cv} = \begin{pmatrix} S_{HH} \\ \sqrt{2} S_{HV} \\ S_{VV} \end{pmatrix} \tag{2.25}$$

or

$$T_{ch} = \frac{1}{\sqrt{2}} \begin{pmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ S_{HV} \end{pmatrix} \tag{2.26}$$

Similar to the reason that Stokes vector are preferred to Jones vector in wave polarization, second order statistics of target scattering matrix are normally preferred. The covariance matrix is defined as:

$$C_v = \langle T_{cv} T_{cv}^{*T} \rangle = \begin{pmatrix} S_{HH}S_{HH}^* & \sqrt{2}S_{HH}S_{HV}^* & S_{HH}S_{VV}^* \\ \sqrt{2}S_{HV}S_{HH}^* & 2S_{HV}S_{HV}^* & \sqrt{2}S_{HV}S_{VV}^* \\ S_{VV}S_{HH}^* & \sqrt{2}S_{VV}S_{HV}^* & S_{VV}S_{VV}^* \end{pmatrix} \tag{2.27}$$

while the coherency matrix is defined as:

$$C_h = \langle T_{ch} T_{ch}^{*T} \rangle = \frac{1}{2} \begin{pmatrix} (S_{HH}+S_{VV})(S_{HH}+S_{VV})^* & (S_{HH}+S_{VV})(S_{HH}-S_{VV})^* & (S_{HH}+S_{VV})S_{HV}^* \\ (S_{HH}-S_{VV})(S_{HH}+S_{VV})^* & (S_{HH}-S_{VV})(S_{HH}-S_{VV})^* & (S_{HH}-S_{VV})S_{HV}^* \\ 2S_{HV}(S_{HH}+S_{VV})^* & 2S_{HV}(S_{HH}-S_{VV})^* & S_{HV}S_{HV}^* \end{pmatrix} \tag{2.28}$$

Evidently the two matrices are related:

$$C_h = NC_vN^T \tag{2.29}$$

where $N = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 0 & 1 \\ 1 & 0 & -1 \\ 0 & \sqrt{2} & 0 \end{pmatrix}$

The off-diagonal values in both covariance and coherence matrices are normally complex. The equivalent all real-valued matrices which carries the same information are called Mueller matrix and Kennaugh matrix which are to be used in forward and backward scattering alignment respectively **?**. They are defined as the matrix that relates the Stokes matrix of sent and received signals.

$$S_t^{Rx} = KS_t^{Tx} \tag{2.30}$$

Since the Stokes and Jones matrices are related, the Kennaugh and Sinclair matrices are also related and is given by:

$$K = 1/2Q^*S \otimes S^*Q^{T*} \tag{2.31}$$

where $\otimes$ denotes the Kronecker product, and $Q = \begin{pmatrix} 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & -1 \\ 0 & 1 & 1 & 0 \\ 0 & i & i & 0 \end{pmatrix}$

POLSAR aims to measure target's polarimetric response. Typically, the radar will separately send different horizontal and vertical polarized waves, and measure the response also in horizontal and vertical polarizations. The full polarimetric data, will then have four channels, i.e. $\{S_{HH}, S_{VV}, S_{HV}, S_{VH}\}$. The four channel, or quad-pol data, is considered full polarimetric data since it allows one to synthesize the target's response for any given pair of transmitted and received polarization. Such a process is called polarization synthesis. The formula is given as:

$$I^{Rx} = \begin{pmatrix} 1 \\ \cos(2\chi^{Rx})\cos(2\Psi^{Rx}) \\ \cos(2\chi^{Rx})\sin(2\Psi^{Rx}) \\ \sin(2\chi^{Rx}) \end{pmatrix}^T K \begin{pmatrix} 1 \\ \cos(2\chi^{Tx})\cos(2\Psi^{Tx}) \\ \cos(2\chi^{Tx})\sin(2\Psi^{Tx}) \\ \sin(2\chi^{Tx}) \end{pmatrix} \tag{2.32}$$

where I^{Rx} is the intensity of the target's response in a given combination of sent and receive polarizations.

In full polarimetric implementation, normally an alternate pulsing scheme is used to share a single time slot for transmitting two different polarizations' pulses. In partial polarimetry modes only a single polarization is sent. Since the transmitting time-slot no longer needs to be shared, a higher frequency become possible which leads to better (almost double) resolution or coverage. Clearly in such cases only two out of four data channels is available, i.e. either $\{S_{HH}, S_{HV}\}$ or $\{S_{VH}, S_{VV}\}$. This trade-off is based on limitations of physics, and hence is expected to be around for years to come.

2.1.2.2 The Polarization Basis Transformation

Assume that the polarization states are known, the wave representation can be given as:

$$\begin{pmatrix} \xi_x \\ \xi_y \end{pmatrix} = A_0 e^{-i\phi_0} \begin{pmatrix} \cos(\Psi) & -\sin(\Psi) \\ \sin(\Psi) & \cos(\Psi) \end{pmatrix} \begin{pmatrix} \cos(\chi) \\ i\sin(\chi) \end{pmatrix} \tag{2.33}$$

The representation of a wave, however, depends on the choice of orthogonal reference frame basis.

Consider two different orthogonal basis, $\{x, y\}$ and $\{h, v\}$. A given Jones vector can be measured in both basis as: $J_{xy} = \begin{pmatrix} \xi_x \\ \xi_y \end{pmatrix}$ and $J_{hv} = \begin{pmatrix} \xi_h \\ \xi_v \end{pmatrix}$ The transformation from $\{h, v\}$ to $\{x, y\}$ is governed by an unitary transformation matrix U_2. The transformation formula is given as:

$$\begin{pmatrix} \xi_x \\ \xi_y \end{pmatrix} = U_2 \begin{pmatrix} \xi_h \\ \xi_v \end{pmatrix} \tag{2.34}$$

Boerner **?** has given U_2 as:

$$U_2 = \frac{1}{\sqrt{1+\rho\rho^*}} \begin{pmatrix} 1 & -\rho^* \\ \rho & 1 \end{pmatrix} \begin{pmatrix} e^{-i\delta} & 0 \\ 0 & e^{i\delta} \end{pmatrix} \tag{2.35}$$

where ρ is the complex polarisation ratio of the Jones vector for the first new basis, and $\delta = \tan^{-1}(\tan(\Psi)\tan(\chi)) - \phi_0$ is the phase reference for the new basis, and is required for the determination of the initial phase of the Jones vector in the new reference basis.

In the same vein, Ferro-Famil, 2000 gives

$$U_2 = \begin{pmatrix} \cos(\Psi) & -\sin(\Psi) \\ \sin(\Psi) & \cos(\Psi) \end{pmatrix} \begin{pmatrix} \cos(\chi) & i\sin(\chi) \\ i\sin(\chi) & \cos(\chi) \end{pmatrix} \begin{pmatrix} e^{-i\phi_0} & 0 \\ 0 & e^{i\phi_0} \end{pmatrix} \tag{2.36}$$

From these results, it is then possible to derive equations for the transformation of the scattering matrix. Noting that be definition, $J^r_{xy} = S_{xy} J^t_{xy}$, $J^r_{hv} = S_{hv} J^t_{hv}$ and that $J^*_{xy} = U_2 J^*_{hv}$. Noting further that $(U_2)^{-1} = (U_2)^T$. It is then trivial to show that:

$$S_{xy} = U_2 S_{hv} U_2^T \tag{2.37}$$

.

Using the result above, we then have:

$$S_{xx} = \frac{1}{1+\rho\rho^*} \left(S_{HH} e^{-2i\delta} - \rho^*(S_{HV} + S_{VH}) + (\rho^*)^2 S_{VV} e^{2i\delta} \right) \tag{2.38}$$

$$S_{xy} = \frac{1}{1+\rho\rho^*} \left(\rho S_{HH} e^{-2i\delta} + S_{HV} - \rho\rho^* S_{VH} - \rho^* S_{VV} e^{2i\delta} \right) \tag{2.39}$$

$$S_{yx} = \frac{1}{1+\rho\rho^*} \left(\rho S_{HH} e^{-2i\delta} - \rho\rho^* S_{HV} + S_{VH} - \rho^* S_{VV} e^{2i\delta} \right) \tag{2.40}$$

$$S_{yy} = \frac{1}{1+\rho\rho^*} \left(\rho^2 S_{HH} e^{-2i\delta} + \rho(S_{HV} + S_{VH}) + S_{VV} e^{2i\delta} \right) \tag{2.41}$$

In the case of mono-static POLSAR, i.e. $S_{HV} = S_{VH} = S_{XX}$ and $S_{xy} = S_{yx}$, the equations become

$$S_{xx} = \frac{1}{1+\rho\rho^*} \left(S_{HH} e^{-2i\delta} - 2\rho^* S_{XX} + (\rho^*)^2 S_{VV} e^{2i\delta} \right) \tag{2.42}$$

$$S_{yx} = S_{xy} = \frac{1}{1+\rho\rho^*}\left(\rho S_{HH}e^{-2i\delta} + (1-\rho\rho^*)S_{XX} - \rho^* S_{VV}e^{2i\delta}\right) \tag{2.43}$$

$$S_{yy} = \frac{1}{1+\rho\rho^*}\left(\rho^2 S_{HH}e^{-2i\delta} + 2\rho S_{XX} + S_{VV}e^{2i\delta}\right) \tag{2.44}$$

The results here, together with Stokes Vector's formula, can be used to prove the following identity, which form the basis of our approach:

$$S_t = \begin{pmatrix} S_hS_h + S_vS_v \\ S_hS_h - S_vS_v \\ 2\Re(S_hS_v^*) \\ 2\Im(S_hS_v^*) \end{pmatrix} = \begin{pmatrix} S_hS_h + S_vS_v \\ S_hS_h - S_vS_v \\ S_+S_+ - S_-S_- \\ S_lS_l - S_rS_r \end{pmatrix} \tag{2.45}$$

where S_t is the Stokes vector and S_+S_+, S_-S_-, S_rS_r, S_lS_l are the intensity of received signals in $+45^o$ linear, -45^o linear, right circular and left circular polarization respectively.

2.1.2.3 Partial Polarimetry and the traditional SAR

The dual-polarization modes has been practically and operationally available for quite some time. However, partial polarimetry has only recently been investigated in the scientific community. By comparison, partial polarimetry measures dual-polarized response from incoming pulses of a single polarization channel, while full polarimetry measures the same response for two (most of the time orthogonal) polarisation channels. Mathematically, the process is modelled as:

$$\begin{pmatrix} E_h^{Rx} \\ E_v^{Rx} \end{pmatrix} = \frac{e^{ikr}}{r}\begin{pmatrix} S_H \\ S_V \end{pmatrix} E^{Tx} \tag{2.46}$$

Souyris **?** pioneered the field with his paper on compact polarimetry. Compact polarimetry is essentially a partial polarimetry mode in which the incoming pulse is of linear polarization, but is neither of the usual horizontal nor vertical angle. Instead its incoming polarization of linear polarisation with an odd angle of $\pi/4$. The partial polarimetric covariance matrix then is given as

$$J = \begin{pmatrix} |s_{HH}|^2 + |s_{HV}|^2 + 2\Re(s_{HH}s^*_{HV}) & s_{HH}s^*_{VV} + |s_{HV}|^2 + s_{HH}s^*_{HV} + s_{HV}s^*_{VV} \\ s^*_{HH}s_{VV} + |s_{HV}|^2 + s_{HV}s^*_{HH} + s_{VV}s^*_{HV} & |s_{VV}|^2 + |s_{HV}|^2 + 2\Re(s_{VV}s^*_{HV}) \end{pmatrix} \tag{2.47}$$

Raney **?** demonstrated a different perspective by proposing a hybrid architecture. He argued that the dual polarisation measurements effectively capture the polarisation states of the single back-scattered signal resulting from a single incoming pulse. Thus the polarisation choice of the receiving antenna is trivial (as long as they are orthogonal). The important parameter to choose is the use of which polarisation for the incoming pulse. His hybrid architecture is again a kind of partial polarimetry in which the incoming pulse is of circular polarisation, instead of the normally encountered linear polarisation. The partial covariance matrix then become:

$$J = \frac{1}{2}\begin{pmatrix} |s_{HH}|^2 + |s_{HV}|^2 + i(s_{HH}s^*_{HV} - s_{HV}s^*_{VV}) & s_{HH}s^*_{HV} - s_{HV}s^*_{VV} - i(|s_{HV}|^2 + s_{HH}s^*_{VV}) \\ s_{HH}s^*_{HV} - s_{HV}s^*_{VV} + i(|s_{HV}|^2 + s_{HH}s^*_{VV}) & |s_{VV}|^2 + |s_{HV}|^2 + i(s_{HV}s^*_{VV} - s_{VV}s^*_{HV}) \end{pmatrix} \tag{2.48}$$

The benefits of this hybrid architecture, according to Raney being: this partial polarimetric measurements can measures certain physical polarimetric phenomena like odd and even bounce phenomena. The suggestion is evidenced by calculating the response of known odd-bounce trihedral and even-bounce dihedral when the incident wave is right circular polarized.

$$\Gamma_{tri} = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \tag{2.49}$$

Then the response will be reversed as it can be calculated as:

$$J_r = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ -i \end{pmatrix} = \begin{pmatrix} 1 \\ i \end{pmatrix} \tag{2.50}$$

with $\begin{pmatrix} 1 \\ -i \end{pmatrix}$ indicating right circular polarization transmitted, and $\begin{pmatrix} 1 \\ i \end{pmatrix}$ indicating left circular polarization received.

For a dihedral target, whose main axis at an angle θ with respect to the horizontal direction, the Sinclair matrix is given as:

$$\Gamma_{dih} = \begin{pmatrix} \cos(2\theta) & \sin(2\theta) \\ \sin(2\theta) & \cos(2\theta) \end{pmatrix} \tag{2.51}$$

The even bounce phenomena is detectable as its polarimetric response is then:

$$J_r = \begin{pmatrix} \cos(2\theta) & \sin(2\theta) \\ \sin(2\theta) & \cos(2\theta) \end{pmatrix} \cdot \begin{pmatrix} 1 \\ -i \end{pmatrix} = \begin{pmatrix} 1 \\ -i \end{pmatrix} \tag{2.52}$$

In **?**, Raney shows that hybrid circular modes bring many conviniences to hardware calibration. Also in a follow up study **?**, he demonstrate the classification power of hybrid polarimetry. Furthermore, Lardeux **?** found that for target classification using SVM techniques, compact polarimetry mode shows comparable results to full polarimetric data. Notably, the hybrid architectural concepts has been adopted and brought towards implementation by NASA's upcoming Desdynl satellite **?**.

The research into partial polarimetry is convenient as its data can be simulated using polarisation basis transformation described above. Hardware realisation may not be needed until the final physical prototype stages. This methodology has been demonstrated and is widely used in the community. We hypothesize that the partial polarimetric covariance matrix, which is essentially a variant of the Stokes vector, can be speckle filtered, using the familiar intensity speckle filtering algorithms. The focus into partial polarimetry allow analysis into a smaller matrix, while its implication can be extended not only to full polarimetry modes but also towards bi-static polarimetric scenarios. Besides that, a number of research questions in this new field are still open, relevant and exciting.

Souyris, in 2005, published a paper **?** which claimed and presented an algorithm to reconstruct full polarimetric information from the given partial compact polarimetric data. The algorithm is claimed to work on natural surfaces. In **?**, Nord reviewed the reconstruction problem for various different partial polarimetry modes, and an improved algorithm is given. In **?**, Ainsworth reviewed performance of target classification on different partial modes, reconstructed pseudo-full mode and full polarimetric data. Chapter 3 reviews of this sub-topic further and introduces our work on expanding the reconstruction to urban man-made structures and surfaces.

For the tasks of target detection and classification, we believe that partial dual polarization provides a unique offer. Compared with single-channel, dual channel provide extra polarimetric information. Compared with full polarimetric data, the better spatial resolution could makes up for the loss of reconstructed polarimetric information, especially for the purpose of target detection and classification.

In fact, this project is intended to provide help for a new project at EADS Innovation Works Singapore to investigate the use of polarimertic data in ship monitoring over the oceans. It is hypothesized that using polarimetric information would improve the possibilities of detecting ships travelling in the open seas. Evidently partial polarimetric modes are good candidates for better detection rates.

The scientific application of POLSAR include: oil slick detection **??**, ship monitoring **?**, sea ice monitoring **??**, volcano lava-flow monitoring **?**, agricultural crop monitoring **??**, planetary exploration **?** and other surface parameter estimations **???**. The remaining text of this chapter briefly look at recent literature in the context of ship detection and monitoring. The topic of ship detection and monitoring has already been tackled quite extensively for single channel SAR data **??**. In fact, a number of countries have reported to implement such systems, and some uses them in everyday operations. The countries includes: USA **?**, Canada **?**, France **?**, Norway **?** and Spain **?**. The common scenarios in use are normally: a designated area is continuously monitored through the use of some automatic ship detection algorithm. If an unknown ship is detected, some manual intervention is to be applied, normally in the form of a navy ship being sent to further investigate. The reports however did not elaborate about the accuracy of the detection algorithms.

A recent trend that is reported in the literature is the use of AIS (Automatic Identification System). In 2007, Vachon **?** reported his study in Canada, which aimed to match ships detectable in SAR images with AIS reported locations. In 2009, Grasso **?** evaluated the performance of ship detection algorithms using AIS as ground truth. In our planned approach, we are prepared to study the performance improvement through using partial polarimetry data in comparison to normal single-channel SAR approaches. Ground truth for such study will also be using synchronized AIS data.

2.2 The Stochastics and Multivariate Nature of (POL)SAR data

2.2.1 The Stochastic nature of SAR and SAR speckle filtering

This section starts with a description of the stochastic nature of SAR data. SAR speckle filtering is then reviewed within a statistical estimation theory framework. Various different approaches to SAR speckle filtering are reviewed, ranging from Generalized Least Squared Error algorithms to the more convoluted Maximum A Posteriori (MAP) approaches.

Although speckle has been extensively studied for decades, speckle reduction remains one of the major issue in SAR imaging process. Many reconstruction filters have been proposed and they can be classified into two main categories: minimum mean-square error (MMSE) de-speckling using the speckle model; and maximum a posteriori (MAP) de-speckling using the product model.

In the first category the speckle random process is assumed to be stationary over the whole image. Then speckle models are proposed, the multiplicative speckle model is first approximated by a linear model, then a speckle reduction filter is formulated The formula is as follows:

$$\hat{R}(t) = I(t) \cdot W(t) + \bar{I}(t) \cdot (1 - W(t)) \tag{2.53}$$

where $\hat{R}(t)$ is the filter response, $I(t)$ is the intensity at the center of the moving window, $\bar{I}(t)$ is the averaged intensity for the whole processing window, $W(t)$ is the weight function,

For the Lee filter **?**, the weight function is proposed to be:

$$W(t) = 1 - \frac{C_u^2}{C_I^2} \tag{2.54}$$

where C_u is the variational coefficient of noise, i.e. $C_u = std(u)/avg(u)$, and C_I is the variational coefficient of the true image, i.e. $C_I = std(I)/avg(I)$.

In the approach of the Kuan filter **?**, the multiplicative speckle model is first transformed into a single-dependent additive noise model, and then the MMSE criterion is applied.

The speckle filter has the same form as the Lee filter but with a different weighting function

$$W(t) = \frac{1 - \frac{C_u^2}{C_I^2}}{1 + C_u^2} \tag{2.55}$$

The Kuan filter takes into account the dependency of noise into signal. In the special case of noise being independent of the underlying signal, the Kuan filter would be exactly the same as the Lee filter. From this point of view, it can be considered to be superior to the Lee filter.

The Frost filter **?** is different from the Lee and Kuan filters with respect that the scene reflectivity is estimated by convolving the observed image with the impulse response of the SAR system. The impulse response of the SAR system is obtained by minimizing the mean square error between the observed image and the scene reflectivity model which is assumed to be an autoregressive process. The filter impulse response can, after some simplification, be written as:

$$H(t) = K_1 e^{-K_2 C_I^2(t)} \tag{2.56}$$

where K_1 is some normalizing coefficient to allow preservation of signal mean values, K_2 is a user chosen filter parameter.

As can be seen from all the three most recognized algorithms in this field, they share the same principles: When the variation coefficient C_I is small, the filter behaves like an low pass filter smoothing out the speckles. When C_I is large, it has a tendency to preserve the original observed image. The choice of functions relating speckle suppression power to local variations may be different, the weighted average as well as the weighted least square principles are apparently common.

As discussed at length in Chapter 4, SAR data is heteroskedastic. Our literature search yielded only a single article **?** tackling SAR data's heteroskedastic feature, suggesting a lack of appropriate attention within the research community about such characteristic and its effects. Under such conditions, Ordinary Least Square methods may not provide optimal results **?**. In fact as is shown by the mathematical formula above, weighted average formula were being used. This is consistent with the knowledge that, when variance of heteroskedastic data is available, weighted least squares is an optimal estimator. As is a fact in SAR data, this variance however is not available directly and can only be estimated (note the concept of variation coefficient). Our analysis then shows that estimating variance is as hard as estimating the un-speckled signal itself! We believe that log transformation could help to break through this circle of ambiguity.

In the second approach, the filters assume that speckle is not stationary globally but is only stationary locally within the moving processing window. The filters operate based on MAP principle, which is given as:

$$f(x|z) = \frac{f(z|x)f(x)}{f(z)} \tag{2.57}$$

where x is the underlying signal that need to be estimated, and z is the observed signal. The underlying signal is found by

$$x = argmax\{\log(f(z|x)) + \log(f(x))\} \tag{2.58}$$

As evidenced, these classes of filter require the knowledge of the *a-priori* PDF $f(x)$. Various PDFs for the underlying back-scattering coefficient have been assumed.

In case Normal distribution is assumed **?**

$$f(x) = \frac{1}{\sigma_x\sqrt{2\pi}} e^{\frac{1}{2}\left(\frac{x-\mu}{\sigma_x}\right)^2} \tag{2.59}$$

the underlying signal is found by solving the equation

$$x^4\Gamma^2(N) - x^3\Gamma^2(N)\mu_x + x^2\Gamma^2(N)2N\sigma_x^2 - 2\sigma_x^2 z^2\Gamma^2(N+1/2) = 0 \tag{2.60}$$

In the case of Gamma distribution is assumed **?**

$$f(x) = \frac{\sigma_x}{\Gamma(\lambda)}(x\sigma_x)^{\lambda-1}e^{-x\sigma_x} \tag{2.61}$$

For $\lambda = 1$, the Gamma distribution is identical to the exponential distribution. For $\lambda = n/2$ and $\sigma = 1/2$ Gamma distribution is equivalent to the chi-square distribution. The underlying signal is found by solving the equation:

$$x^3\Gamma^2(N)\sigma_x + x^2\Gamma^2(N)(2N - \lambda + 1) - 2z^2\Gamma^2(N+1/2) = 0 \tag{2.62}$$

In case exponential distribution is assumed

$$f(x) = \sigma_x e^{-x\sigma_x} \tag{2.63}$$

then the underlying signal is found by solving the equations

$$x^3\Gamma^2(N)\sigma_x + x^2\Gamma^2(N)2N - 2z^2\Gamma^2(N+1/2) = 0 \tag{2.64}$$

In case Chi square distribution is assumed

$$f(x) = \frac{1}{2^{n/2}\Gamma(n/2)} x^{n/2-1} e^{(-x/2)} \tag{2.65}$$

then the true signal is found by solving the equation

$$x^3\Gamma^2(N) + x^2\Gamma^2(N)(4N - n + 2) - 4z^2\Gamma^2(N+1/2) = 0 \tag{2.66}$$

If log-normal distribution is assumed **?**

$$f(x) = \frac{1}{\sigma_x\sqrt{2\pi}} x^{-1} e^{\frac{-1}{2\sigma_x}(\ln(x)-\mu_x)^2} \tag{2.67}$$

$$x^2\Gamma^2(N)(-2N\sigma_x^2 - \sigma_x^2 - \log(x) + \mu_x) + 2z^2\Gamma^2(N+1/2) = 0 \tag{2.68}$$

Other distributions that has been assumed include: heavy tailed Rayleigh distribution **?**, Weibull distribution **?**, beta distribution **?**, Rician distribution **?** ... Evidently, the performance of these filters are dependent on the underlying distribution of the back-scattering coefficient on the particular surface being imaged. In this context, the community appears to focus on using Bayesian inference to choose the most suitable distributions **?**. We hypothesize that the underlying distribution of the back scattering coefficient is estimable, at least in log-transformed domain.

Other approaches, that recently has been actively pursuit in the community include: wavelet **????????**, curvelet **???**, contourlet **?**, ridgelet **?**, fuzzy logic **?**, anisotropic kernels **?**, and autoregressive conditional heteroskedasticity **?**. Central to wavelet techniques is the discoveries of a consistent and optimal choice for the wavelet coefficients. Similarly the development of kernel methods depends strongly on the discoveries of consistent predictive kernels. Evidently the choice of such coefficients are dependent on the underlying statistical characteristics of SAR signals. This further emphasizes the importance of investigating consistent statistical properties of SAR signals. Note only that statistical analysis is important in speckle filtering, the technique is also important in the development of information extraction **?**, target detection **?**, classification Nyoungui *et al.* [2002] techniques.

With different speckle filtering approaches presented, it is crucial to have a framework for (a) modelling and simulation which provide the ground-truth data in different scenarios of underlying distribution, and (b) analysing the interdependency between noise and the underlying signal, as well as the dependence of each filter's performance on the different underlying distribution scenarios and (c) establishing consistent criteria to evaluate speckle suppression power as well as the adaptive capabilities in reconstructing the underlying signal.

2.2.2 The Multivariate Nature and The Observables in POLSAR data

2.3 Current methods in SAR and POLSAR speckle filtering

2.3.1 Current Statistical Models for SAR and POLSAR data

2.3.2 Current Methods for SAR speckle filtering

(2.2.1)

2.3.3 Current Methods for POLSAR speckle filtering

Compared to SAR technologies, most POLSAR techniques have only recently been developed. The state of POLSAR speckle filtering is reviewed and filtering the covariance matrix off-diagonal elements is shown to be an open problem. The problem can be traced back to the lack of a statistical model for the covariance matrix in polarimetry.

In the first systems that captured POLSAR data, multi-look processing was used as a method of choice for speckle filtering, at the cost of spatial resolution. Novak **?** pioneered the area of speckle reduction and proposed the polarimetric whitening filter

(PWF) to produce a single speckle reduced intensity image. The disadvantages of PWF filter is that the polarimetric information is not well-preserved. Multi-look processing's polarimetric result also exhibits bias and distortion **?**.

Lee **?** proposed a new filtering algorithm which does suppress speckle for the diagonal elements, the off-diagonal elements however remain un-filtered. Later, Touzi **?** drew out the principles of speckle filtering of POLSAR data. They are

1. Speckle can be filtered if ALL elements of its covariance matrix are filtered.

2. Single-channel SAR speckle filtering is only applicable to diagonal elements of the covariance matrix

3. Speckle filtering need to be performed also on off-diagonal elements, as correlation among the elements need to be exploited and the elements do not exists independently.

In 1999, Lee **?** extended his refined-Lee filters on POLSAR data, and argues that all covariance matrix elements should be filtered by the same amount to preserve polarimetric properties. He then proposed to apply the weighted averaging on the full covariance matrix instead of single-channel intensities values.

$$C_{out} = C_{avg} + w(C_{curr} - C_{avg}) \tag{2.69}$$

where C_{out} is the filtered covariance matrix output, C_{avg} is the average covariance matrix using an edge-aligned window, C_{curr} is the covariance matrix of the current processing pixel. The weight w is computed within the edge aligned window from the total power image y as:

$$w = \frac{\sigma_y^2 - \mu_y^2\sigma_v^2}{\sigma_y^2 - \sigma_y^2\sigma_n^2} \tag{2.70}$$

where σ_y^2 and μ_y are the variance and mean computed within the edge aligned window, respectively, σ_n^2 is the user specified noise variance.

Further attempts has been made towards statistical modelling the off-diagonal elements but the applications of these results towards the problem of speckle suppression for off-diagonal element have been non-conclusive. Based on his 2003 paper **?** on POLSAR statistical analysis, in 2008, Martinez **?** proposed a model based polarimetric filter. He first proposed to model $S_h S_v^*$ as having both additive and multiplicative components.

$$S_p S_q^* = \psi|\rho|e^{i\theta} + \psi\bar{z}_n N_c(1-n_m)e^{i\theta} + \psi(n_{ar} + in_{ai}) \tag{2.71}$$

where $\psi = \sqrt{E\left(|S_p|^2\right)E\left(|S_q|^2\right)}$ represents the average joint power in the two channels, $\rho = |\rho|e^{i\theta} = \frac{E\left(S_p S_q^*\right)}{\sqrt{E(|S_p|^2)E(|S_q|^2)}}$ is the complex correlation coefficient that characterize the correlation among the channels, $N_c = \frac{\pi}{4}|\rho|F_{1,2}(1/2, 1/2, 2, |\rho|^2)$ basically contains the same information as the complex correlation coefficient, and $F_{1,2}(a, b, c, d)$ is the Gauss hyper-geometric function, n_m is the first speckle noise component that is multiplicative with $E(n_m) = 1$ and $var(n_m) = 1$, $n_{ar} + in_{ai}$ is the second additive speckle noise component with $E(n_{ar}) = E(n_{ai}) = 0$ and $var(n_{ar}) = var(n_{ai}) = \frac{1}{2}(1-|\rho|^2)^{1.32}$. The model is overly complicated and to do speckle filtering, various approximations has to be used.

In 2009, Lee **?** proposed to model $S_h S_v^*$ in a different approach. The phase difference is defined as:

$$\phi = \arg\left(S_p S_q^*\right) \tag{2.72}$$

Lee gives the PDF for the phase difference as:

$$pdf(\phi) = \frac{\Gamma(3/2)(1-|\rho|^2)\beta}{2\sqrt{\pi}\Gamma(1)(1-\beta^2)} + \frac{(1-|\rho|^2)}{2\pi}F_{1,2}(1, 1, 1/2, \beta^2) \tag{2.73}$$

with $\beta = |\rho|cos(\phi - \theta)$ and $F_{1,2}(a, b, c, d)$ is the Gauss hyper-geometric function.

The normalized magnitude which is defined as

$$\xi = \frac{E\left(S_p S_q^*\right)}{\sqrt{E\left(|S_p|^2\right)E\left(|S_q|^2\right)}} \tag{2.74}$$

and the PDF is given as

$$pdf(\xi) = \frac{4\xi}{\Gamma(1)(1-|\rho|^2)} I_0\left(\frac{2|\rho|\xi}{1-|\rho|^2}\right) K_0\left(\frac{2\xi}{1-|\rho|^2}\right) \tag{2.75}$$

with I_0 and K_0 are modified Bessel functions. Again the equations looks overwhelmingly complex, and as admitted by the authors themselves: this do not allow for easy speckle filtering as the model is too complex and the complex correlation coefficient ρ is not easy to be estimated **?**

There are several other attempts to filter POLSAR data. Vasile, 2006 proposed to region growing adaptive neighborhood approach, where averaging is performed on an adaptive homogenous neighbor. The draw back of the approach is that only the intensity was used to determine homogeneity and primitivev averaging filter is performed on off-diagonal elements **?**. In **?**, J.S. Lee proposed to group homogenous pixels based on their underlying scattering model. While the work is interesting, it is believed that pixels having similar underlying model, says volume scattering, can still be of very different nature. Similar to Lee's previous work, simple weighted average filtering is applied on both diagonal and off-diagonal elements. Vasile, 2010, published a complicated spherically invariant random vector estimation scheme to estimate the underlying target POLSAR signature **?**. While polarimetric information is estimated independently from the power span, its output results no longer follow established Wishart distribution.

In summary, while off-diagonal elements, which carries phase information, is important in intepreting POLSAR data **?**, their estimation and filtering is under-developed. We will discuss our approach based on polarization basis transformation in the next section.

2.3.4 Current Methods to Evaluate (POL)SAR Speckle Filters

It is customary to divide the performance evaluation of speckle filters into two distinct classes of homogeneous and heterogeneous region evaluation. Across homogeneous areas, speckle filters are expected to estimate with negligible radiometric bias. As such, evaluating speckle filters over homogeneous areas has traditionally been focused on evaluating the variation of the estimators' output (a.k.a the speckle suppression power). In contrast, the methodologies used to evaluate speckle filters over heterogeneous areas are much more complicated, due in part to the following difficulties. The first is that of determining an absolute ground-truth against which quantitative criteria can be measured. The second challenge is to then define a quantifiable metric that allows the performance of different speckle filters to be measured and compared.

In general, any metric to evaluate speckle filters should be relevant to the normal usage of such filters. Furthermore, the application of any speckle filter in a SAR processing framework should enable an improvement in the measurement, detection or classification of the underlying radiometric features. As shown in the subsequent sections, by applying log-transformation, this overall requirement of speckle filtering can be further broken down into two smaller requirements. On the one hand, speckle filters should preserve the underlying radiometric signal (namely the radiometric preservation requirement). On the other hand, they should reduce the variation of the additive noise (i.e. speckle suppression power). These requirements can be measured and evaluated by determining, also in the log-transformed domain, the bias and variance error of the output. As the MSE evaluation is a combination of bias and variance error, it is therefore capable of evaluating the general requirements of speckle filtering.

For homogeneous scenes where the underlying radiometry is assumed to be constant, the filtered results are considered, statistically speaking, to be samples of a single but complex stochastic process. From a logarithmic transformation perspective, the radiometric preservation and speckle suppression requirements of speckle filters can be judged using the familiar bias and variance evaluation.

One metric that can be used to detect radiometric distortion is the ratio between the estimated and the original value $r = X_{est}/X_{org}$ **?** **?**. A somewhat similar metric is used in **?** as $r_w = (X_{est} - X_{org})/X_{org}$. In the log-transformed domain, the equivalent criteria for evaluation could be performed by a simple subtraction. In other words, it is clear that the bias evaluation in the log-transformed domain can be used to evaluate the radiometric preservation requirement of speckle filters.

Specifically for homogeneous scenes, Shi et al. **?** found that in the original domain the "standard" filters (boxcar, Lee**?**, Kuan **?**, Frost**?**, MAP**?**) and their enhanced versions Lopes *et al.* [1990] can achieve negligible bias. In this paper, we will also show that all of these standard filters preserve not only the expected radiometric values but also a number of subtractive and consistent measures of distance exhibited in the log-transformed domain.

Several metrics have been developed to evaluate speckle suppression power. The most common measure is the Equivalent Number of Looks (ENL) index $ENL = avg(I)^2/var(I)$ that was proposed by Lee **?**. Another very similar metric is the ratio of mean to standard deviation, $R = avg(I)/std(I)$ **?** In Section **??**, it will be shown that, for homogeneous areas, ENL is mathematically related to variance in the log-transformed domain. Subsequently, we propose the use of log-variance to evaluate the noise suppression power of speckle filters, which is the primary criteria used to evaluate speckle filters over homogeneous area.

Real-life and practical images, however, are not homogeneous. Thus there are a number of associated difficulties in evaluating speckle filters over heterogeneous scenes. The first difficulty in evaluating speckle filters for heterogeneous scenes is to select the basis for comparison. It is trivially easy to estimate the underlying radiometric coefficient if an area is known to be homogeneous. However, without simulation or access to solid ground-truth, it is practically impossible to do so for real-life images. And hence, the need for speckle filters estimation is warranted.

Without ground truth, one way to evaluate radiometric preservation of filters is to compute the ratio image mentioned above. Under a multiplicative model, the ratio image is expected to comprise solely of the noise being removed (i.e. it should be completely random). Being random, this should display as little "visible" structure as possible. However, when displaying such images for visual evaluation, the ratios that are smaller than unity are much harder to distinguish than those that are bigger **?**. We therefore propose to adopt a log-transformed domain perspective where the multiplicative noise would then be transformed into a more familiar additive model. More importantly, the ratio image would then become a simple subtraction image. The evaluation methodology for such adoption would not change. Only that the residual image would become linear and additive. And thus it would be more natural to be displayed and evaluated visually (see **??**).

Another way to evaluate speckle filters is by comparing the feature preservation characteristics of the original noised data and those of the filtered image. When there is no ground-truth given, the feature are estimated in both the original noised and the filtered images. Evaluation would then determine how closely related the two feature maps are. Various methods may be applied to extract features; examples of those that have been used are the Hough Transform **?**, Robert gradient edge detector **?** and edge map **?**. While significant effort has been spent on these evaluations, serious doubts remain concerning the precision of these methodologies. This is because feature extraction algorithms are only approximations, whose accuracy is not only dependent upon the characteristics of the original image but also heavily affected by the inherent noise. Unfortunately, speckle filters invariably alter the noise characteristics. Thus, without a clear understanding of these dependencies and no absolute ground truth, using feature extraction algorithms to evaluate speckle filters would leave serious questions on how to interpret the results, especially its accuracy.

Since SAR statistical models are quite well understood, simulation experiments with known ground-truth can be employed to evaluate speckle filters. In this paper, we also make use of a methodology similar to the ones discussed above with two important changes. Firstly, our simulated experiments offer absolute ground-truth. Secondly, our threshold-based feature extraction algorithm is extremely simple. More importantly, the dependency between the performance of the algorithm and the level of noise is well established. This performance can be conveniently visualized by plotting the Receiver Operating Characteristics Curve (ROC). It can also be objectively quantified by measuring the Area Under this Curve (AUC). As shown in section **??**, this standard and normalized criteria allows a comparative evaluation of feature preservation capabilities for different speckle filters.

Even with known ground-truth, evaluating metrics need to be defined for quantitative measurements. This is the second difficulty in evaluating speckle filters for heterogeneous scenes. Under the conditions of heterogeneity, the standard speckle filters still introduce radiometric loss, normally at local or regional levels. In fact, the common consensus is that a powerful speckle suppression filter (for example the boxcar filter) is likely to perform poorly in terms of preserving underlying radiometric differences (e.g. causing excessive blurring). Furthermore, we have not found many published articles combining the evaluation of these two seemingly contradicting requirements.

Overall, many different methods and metrics have been proposed to evaluate various aspects of speckle filters. However it is clearly advantageous to have a single metric that is able to judge if one filter is better than another. Wang **?** proposed using fuzzy membership to weight opinions of an expert panel. Although this provides a potential solution, we consider it to be tedious in implementation, fuzzy in concept and subjective in nature.

Another approach is to apply a universal mean squared error criteria into the context of SAR data. However since SAR data is heteroskedastic, which violates the assumptions of the Gauss-Markov theorem, the use of MSE is not straightforward. Thus Gagnon **?** suggested the use of the ratio between the expected mean of the signal and the RMSE of the removed noise. The metric is argued to be similar in interpretation to the standard signal-to-noise ratio (SNR). Others have suggested the use of normalized MSE, which is essentially the ratio between MSE and the expected mean.

In this paper, homoskedastic property is shown to be available after logarithmic transformation of SAR data. As the important Gauss-Markov theorem becomes applicable in this transformed domain, the use of MSE is shown to be again relevant for evaluating statistical estimators (i.e. speckle filters). Intuitively, each components of the MSE measure, namely bias and variance evaluation, can be mapped into the requirements of radiometric preservation and speckle suppression for speckle filters. Before the details of our evaluation methodology is presented and discussed, Section **??** provides a brief discussion on logarithmic transformation for SAR images.

2.4 Existing Measures of Distance for (POL)SAR data and their applications

to detect if the two scaled multi-look POLSAR covariance matrix Z_x and Z_y, which have L_x and L_y as the corresponding number of looks, come from the same underlying stochastic process, Conradsen considered **?** the following POLSAR statistics

$$Q = \frac{(L_x + L_y)^{d\cdot(L_x+L_y)}}{L_x^{d\cdot L_x} L_y^{d\cdot L_y}} \frac{|Z_x|^{L_x}|Z_y|^{L_y}}{|Z_x + Z_y|^{(L_x+L_y)}} \tag{2.76}$$

Taking the log-transformation of the above statistics, and note that $C_{vx} = Z_x/L_x$, $C_{vy} = Z_y/L_y$ and $C_{vxy} = (Z_x + Z_y)/(L_x + L_y)$ then we have

$$\begin{aligned} Q &= \frac{|C_{vx}|^{L_x} \cdot |C_{vy}|^{L_y}}{|C_{vxy}|^{L_x+L_y}} \\ \ln Q &= L_x \ln |C_{vx}| + L_y \ln |C_{vy}| - (L_x + L_y) \ln |C_{vxy}| \end{aligned}$$

Since both Z_x and Z_y follow complex wishart distribution with L_x and L_y degrees of freedom, $Z_x + Z_y$ also follows the complex wishart distribution with $L_x + L_y$ degrees of freedom. In view of the models denoted in Eqn. **??**, it is evident that not only the bound for $\ln Q$, or equivalently Q, can be derived but the whole statistical distribution for it can be simulated as well:

$$\ln Q \sim q + L_x\Lambda^d_{L_x} + L_y\Lambda^d_{L_y} - (L_x + L_y)\Lambda^d_{(L_x+L_y)} \tag{2.77}$$

$$Q \sim e^q \frac{(\chi^d_{L_x})^{L_x} \cdot (\chi^d_{L_y})^{L_y}}{(\chi^d_{L_x+L_y})^{L_x+L_y}} \tag{2.78}$$

where $q = d\,[(L_x + L_y)\ln(L_x + L_y) - L_x \ln L_x - L_y \ln L_y]$.

In the special case of $L_x = L_y$, the Conradsen statistics become $\ln Q = \ln |C_{vx}| + \ln |C_{vy}| - 2|\ln C_{vxy}|$. The contrast model which is written as $\mathbb{C} = \ln C_{vx} - \ln C_{vy}$

and presented above should, under exactly the same assumptions, provides another consistent and equivalent approach, with probably simpler conceptual model and computational derivations. The details application of this in edge-detection however is outside the scope of this paper.

2.5 The need for Scalar Consistent Measures of Distance

We will show our originality and significance here!

This section surveys recent developments in the research landscape. First, the stochastic nature of SAR speckle phenomena is explained. Then, the topic of SAR speckle is reviewed from the perspective of statistical estimation theory. An opportunity for contribution in proposing a stochastic simulation and evaluation framework is identified. Next, the applications of such a framework into the problem of POLSAR speckle filtering is described. Recently, the practicality of Partial Polarimetry has been noticed and studied. The need for reconstruction of Full Polarimetric signatures is highlighted and the possible application of the proposed framework is described. Last but not least will be an illustration on the applicability of such a framework to the topic of target detection and classification.

Chapter 3

Discussion and Conclusions

3.1 Result Evaluation and Discussion

In this thesis, a new model is developed for POLSAR data. The theory development is based in the principles of statistical mathematic and is visualized using computer simulations. The theory has shown its capabilities through a number of applications, though further studies should unearth even more interesting results.

The main assumption used in this paper is the independent and circular complex Gaussian model for POLSAR data. While the model may not be perfectly matched with practical data, it is apparently the most-widely accepted model. In the following paragraphs, the imperfect practice of over-sampling data in SAR and POLSAR processing is discussed.

The practice of over-sampling in SAR (and hence POLSAR) data processing may affects the choice of nominal ENL for showing the match between real-life data and the proposed model. Specifically, the over-sampling practice would normally be indicated a reduction of the ENL number. This is for example evidenced in our experiment for the RADARSAT2 dataset. The RADARSAT2 given to us is in its Single-Look format, and nine-look processing is applied before the dispersion histogram in log-transformed domain is computed for an homogeneous area. The histograms for both one-dimensional SAR and two-dimensional partial POLSAR data are plotted in Fig ??? against the theoretical model for the nominal ENL value of 9. Even though the shapes of the histograms do look similar, the match however is not very good. A better match can be achieved by estimating the ENL from the observable variance of the log-determinant, and the theoretical model for the estimated ENL indicated a much better consistency. This procedure can always be carried out for any given dataset, since the sample variance of the log-determinant can always be measured and hence the effective ENL can always be estimated using Eqn. ???.

The use of covariance matrix log-determinant may be related to the standard eigen-decomposition method of the second order statsitics POLSAR matrices. In fact, the log-determinant can also be computed as the sum of log-eigen values. Specifically:

$$\ln |M| = \sum \ln \lambda_M \tag{3.1}$$

where λ_M denotes all the eigen-values of M. Similar to other eigen-value based approach (e.g. Entropy/Anisotropy, ...), the models presented here is roll-invariant.

The methodology presented in this paper call for the reduction of the multi-dimensional POLSAR data into a scalar value. While this is probably desirable for a wide range of application where a one-dimensional number is required to represents the complex multi-dimensional data, such reduction is probably not lossless. Thus similar to the way the Wishart Classifier is employed, the use of this technique should be complemented with some high-dimensional POLSAR target-decomposition techniques (e.g. Freeman Durden or entropy/anisotropy TODO:REF ...)

3.2 Contributions of the Thesis

In conclusion, several scalar and consistent measures-of-distance for multi-variate POLSAR data were proposed in this paper. The dis-similarity measures are computed for the determinant of the POLSAR covariance matrix, which when converted into one-dimensional data is gracefully transformed into the traditional SAR intensity. Consequently, these measures of dis-similarity may be employed in a wide range of application where a scalar number is required to represent the complex multi-dimensional POLSAR data. Just like it is shown for the simpler case of SAR data processingLe *et al.* [2010], when these distances are computed in the log-transformed domain, their theoretical statistic models become additive and homoskedastic. The models are shown to be theoretically powerful. Not only they can provide alternative and sometimes simpler explainations to a range of theoretical concepts: i.e. change detection test statistics or

ENL estimation but also a number of results for one-dimensional SAR can be shown as special cases of the POLSAR models. They are also pratically versatile enough capable of explaining the imperfect over-sampling practice evident in RADARSAT2 data. Finally, to extend our previous work in evaluating SAR speckle filters, the applicaton of these additive and homoskedastic distances in the context of evaluating POLSAR speckle filters is briefly explored with promising results reported.

3.3 Possible Future Work and Conclusion

3.3.1 Possibilities for Future Work

A fair amount of work has been carried out, published in two conference papers in 2010. Still, as described in this report, the opportunities for further investigation are abundant.

In the field of single channel SAR, further exploitation from the results of log-transformation should be achievable and publishable. An immediate opportunity is identified as the estimation of the PDF of the underlying signal in SAR images. The mathematical construction and conceptualization was presented earlier, with implementation underway. In the medium term, a possible protocol for evaluation using homoskedastic mean squared error under various scenarios, made possible through simulation of different ground-truth PDFs is being conceptualized.

On the POLSAR front, the short term focus is to implement speckle filtering for the off-diagonal element in the target's covariance matrix. The mathematical conceptualization has been given earlier, with a presentation planned as a paper for IGARSS 2011. In a longer time frame, we are hoping to be able to apply log-transformation's homoskedastic features into POLSAR data to find a consistent measure of distance for one of the matrices representing the target's polarimetry signature. We are also prepared to render help toward EADS's in-house project investigating the problem of ship identification / classification, ground-truth using AIS data.

3.3.2 Conclusion

In conclusion, recent advances in computational power have made SAR and multiple-channel SAR become the preferred choice for continuous and autonomous global-scale earth observation and monitoring. Some primitive systems have been implemented and become operational for such purposes, e.g. ship monitoring, which have show-cased the capability of the technology. Recent advances in multi-channels polarimetric SAR have captured attention, not only within the academic community, but also from industrial players.

There are however certain issues need to be resolved to ensure the extra-information available in POLSAR data leads to better practical implementations. Our studies have exposed the need for a computation framework, to simulate, experiment, carry out statistical analysis, modelling, validation and evaluation of various SAR and POLSAR processing techniques, most of which can be put within the framework of statistical estimations. Our work thus far has developed one such framework for the processing of single-channel SAR data. In the next phase of the project, we aim to develop a more elaborated framework for multi-channel POLSAR data processing.

With the availability of such fundamental research, we can probably afford to follow a wider range of subsidiary research questions. For the traditional single channel SAR, one sub-topic is our hypothesis that it is possible to estimate the PDF of the true, underlying back-scattering coefficient, at least in the log-transformed domain. Should we succeed in such a task, the technique could be an invaluable contributions to the whole class of MAP speckle filters.

Compared to single-channel SAR, the field of multi-channel POLSAR is much less mature. Thus the application of our intended framework can be expected to bring even better impact publications. The first sub-topic that we aim for immediate experiment is the hypothesis that off-diagonal element in the polarimetric covariance matrix element can be speckle filtered through the application of standard SAR techniques on transformed polarization basis intensities. In the longer term, we hope to investigate the extension of our homoskedastic log-transformation techniques towards finding a consistent measure for the multi-variate and stochastic POLSAR data.

Presented here, and in the previous chapter, are just a few of a whole range of possibilities. With such a diversity available, one of our priorities is to be focused to achieve tangible results. We merely choose to present only the sub-topics which showed the greatest potential and which we believe would provide the most impact and leverage for our future work. For such tasks, a snap-shot of the project status and the amount of remaining activities is planned and presented in the previous section. With continued assistance from EADS Innovation Works Singapore, who is a collaborator of this project and has provided us numerous valuable data and discussion, we believe that the remaining tasks are highly feasible. The academic contribution was discussed earlier while the endorsement of EADS speaks volumes about the practical contributions of our research.

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