Eigen Value and Eigen Vector Based Decomposition and Wishart Supervised Classification on Fully Polarimetric SAR Data

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Abstract

Objectives: To study the decomposition parameters, target scattering mechanism using Eigen value Eigen vector based decomposition and classifying the filtered datasets with wishart supervised classifier, H-α classification plane on fully Polarimetric Synthetic Aperture Radar (PolSAR) data. Methods/Analysis: Fully PolSAR datasets of Single Look Complex (SLC) product is selected for multiprocessing. As the SLC product contains Speckle, it has to be reduced using speckle filtering techniques, because speckle can degrade the accuracy of image classification. H/A/α decomposition theorem is applied on the dataset for classifying the scattering mechanism. Based on the H-α plane, Polarimetric parameters further classifies the type of target. Wishart supervised classification and H-α classification are performed on the filtered dataset to classify the image. Findings: The entropy is a fundamental key parameter in determining the randomness of the model thus showing the importance of polarimetry in solving remote sensing problems. Supervised Wishart Classification accuracy assessment was made using Confusion matrix. The results of the outcomes are satisfactory. Novelty/Improvement: Classifying SAR data with H/A/α decomposition theorem using decomposition parameters and calculating accuracy assessment using Confusion matrix. Analysing, estimating the physical parameters using eigenvalues $\lambda_i$, entropy $H$, alpha angle $\alpha$ and anisotropy $A$.

Keywords: Eigen Value Eigen Vector Decomposition, Fully Polarimetric, H/A/α Decomposition, Polarimetric Decomposition, Radarsat-2, SAR, Wishart Supervised Classification

1. Introduction

The limitation of optical remote sensing during monsoon seasons leads to loss of periodical data acquisitions and hampers the strategic development updates in day to day life. This limitation can be overcome using imaging radar of good resolution, which has the capability to penetrate through clouds. This can be achieved through Synthetic Aperture Radar (SAR) which has potential to monitor in all weather conditions and also in absence of sunlight. The development of polarimetric systems has led to an increased amount of information acquired by SAR sensors but also to an increased complexity of the data to be analyzed and interpreted. With the launch of Alos-Palsar-2, Radarsat-2, TerraSAR-X, Sentinel-1, Kompsat-5, RISAT-1 the PolSAR data has been so widely available to the remote sensing community. SAR images can also be applied to cities damaged by disasters like floods and earthquakes to assess the contingency measures of post event. Speckle in an image will degrade the information; hence it is suggested to opt for the optimum filter which reduces speckle without degrading the information. The polarimetric information is stored in the form of coherency matrix $[T]$. Polarimetric data allows a better characterization of the scatters based on decomposition theorems.

The rest of the paper is organized as follows: Section II describes the Study area and SAR datasets used. Section III gives a brief view methodology followed in this work. Section IV gives us the details of results obtained in this
work, followed by conclusions and future scope in Section V.

2. Study Area and SAR Datasets

Vancouver is a Canadian province of British Columbia with latitude 49°28′27″ N and longitude 123°12′07″ W in the country of Canada. The data used for this study is RADARSAT-2 fine-beam PolSAR data, which contains HH, HV, VH and VV polarizations. The centre frequency at this beam mode is 5.4GHz, i.e., C-band and the spatial resolution is 8 meters. Table 1 summarizes the system parameters of the quad-polarized mode.

3. Methodology

Figure 1 shows the implementation of proposed work in a flowchart. Polarimetric information is recorded in the form of Scattering matrix(S) from which the coherency matrix T3 was extracted using POLSAR pro. The coherency matrix [T] contains all the polarimetric information. Most of the decomposition parameters were derived from coherency matrix T3. The generated [T] matrix is used for polarimetric speckle filtering and polarimetric decomposition. Polarimetric speckle filtering is performed using refined lee filter with window size 5x5. Filtered datasets are decomposed and are classified using several polarimetric decomposition parameters like H-α classification plane. We attempted an H-A-α decomposition model for full polarimetric data analysis. Using Speckle filtered [T] matrix product as input Wishart supervised classification is performed to group similar pixels into classes. The detailed explanations of polarimetric decomposition along with related equation are provided in subsequent sections.

3.1 Speckle Filtering

Speckle filtering of PolSAR images is a critical preprocessing step, where it must reach the best possible comprise between the spatial details preservation and speckle reduction within homogeneous targets. This is very important especially for SLC imagery, where the speckle intensity is the highest when compared to other products. Regularly used filter such as the boxcar filter when opted for speckle filtering it degrades the image quality by smearing edges. The filters Boxcar and Refined Lee filters are good at the preserving polarimetric information for distributed targets, but Refined Lee filter preserves the polarimetric information of point targets better than boxcar filter. We used the refined Lee filter, as this speckle filter uses edge-aligned, non-square windows to preserve edges and Polarimetric information. After speckle filtering, all elements of the covariance matrix will be correlated. Figure 2 shows the comparison between speckle image and filtered image.
3.2 Polarimetric Decomposition

The process of extracting information about the scattering process using various techniques from full polarimetric SAR data is known as target decompositions. The first objective of decomposition theory is to express the average of the scattering mechanism in the resolution cell in a sum of independent elements aiming to associate a physical mechanism to each type of scattering.

These techniques generate polarimetric parameters that can be used for interpretation or classification. A different decomposition technique uses different polarimetric features that are derived from the scattering matrix. H/A/α decomposition uses coherency matrix, Pauli decomposition technique uses covariance matrix derived from scattering matrix. Polarimetric decomposition can be broadly classified into two categories: 1) coherent decomposition technique and 2) incoherent decomposition technique. Coherent techniques utilize the information contained in the scattering matrix [S] whereas incoherent decomposition techniques utilize the covariance matrix [C] or coherency matrix [T]. Furthermore, incoherent decomposition techniques can be subdivided into eigenvalue-eigenvector-based and model-based. Eigen value Eigenvector-based decompositions provide a unique solution in terms of the scattering mechanisms.

3.2.1 Eigen Value-Eigen Vector Based Decomposition: H/α / A Decomposition

H/A/α decomposition was proposed by Cloude and Pottier for extracting average parameters from experimental data using a smoothing algorithm. From coherency matrix T3 matrix decomposition parameters are generated from an eigenvector analysis. The eigenvectors describe different scattering processes, and the eigenvalues indicate their relative magnitudes. Among all the parameters, the averaged Alpha angle (α) relates directly to the underlying average physical scattering mechanisms. The value of Alpha ranges from 0° to 90°, which indicates the dominant scattering varies from surface scattering mechanism (0°), moving into single scattering (45°) by a cloud of anisotropic particles, and finally reaching dihedral scattering (90°). The Entropy (H) describes the randomness of the scatter. The anisotropy (A) corresponds to the relative power of the second and third Eigen vectors. The elements of scattering matrix are defined as

\[
[S] = \begin{bmatrix}
S_{hh} & S_{hv} \\
S_{vh} & S_{vv}
\end{bmatrix}
\]

The coherency matrix is defined as

\[
[T] = \begin{bmatrix}
\langle S_{hh} + S_{vv} \rangle & \langle S_{hh} + S_{vv} \rangle & \langle S_{hh} + S_{vv} \rangle \\
\langle S_{hh} - S_{vv} \rangle & \langle S_{hh} - S_{vv} \rangle & \langle S_{hh} - S_{vv} \rangle \\
\langle 2S_{hv} \rangle & \langle 2S_{hv} \rangle & \langle 4S_{hv} \rangle
\end{bmatrix}
\]

Let \( \lambda_1, \lambda_2, \lambda_3 \) be the Eigen values of the coherency matrix and \( u_1, u_2, u_3 \) are the corresponding Eigen vectors.

\[
[u_3]^T = \begin{bmatrix}
\cos \alpha_1 & \cos \alpha_2 & \cos \alpha_3 \\
\sin \alpha_1 \sin \beta_1 & \sin \alpha_2 \sin \beta_1 & \sin \alpha_3 \sin \beta_1 \\
\sin \alpha_1 \sin \beta_2 & \sin \alpha_2 \sin \beta_2 & \sin \alpha_3 \sin \beta_2
\end{bmatrix}
\]

Polarimetric parameters are derived from H/A/α Decomposition and H-α plot. Parameters used in this classification does not contain any information related to intensity, it only contains information related to scattering mechanisms and the dominance relationship between them. From the parameters, angle and entropy can be calculated for each scattering mechanism. Figure 3 and Figure 4 shows H/α plane segmentation and Haα decomposition parameters.
### 3.3 Classification

Wishart Hα classification and Wishart supervised classification are applied to perform classification on fully polarimetric Radarsat-2 dataset. In supervised classification polarimetric data is classified using maximum likelihood statistics. From the wishart statistics, Classifier learns from the user defined training areas, then the entire dataset is then classified by assigning each pixel to the closest class using maximum likelihood decision rule.

#### Figure 4. Hα decomposition parameters.

- (a) Hα decomposition
- (b) Hα decomposition alpha
- (c) Hα decomposition entropy
- (d) Hα decomposition anisotropy
- (e) Wishart H_α classification
- (f) Wishart H-A-α classification
- (g) H-alpha classification
- (h) Hαλ classification
- (i) H α occurrence plane
- (j) H α classified plane

### 4. Results and Discussion

From the Figure 4 (b), Figure 4 (c) and Figure 4 (d) the Hα decomposition parameters like Entropy, Alpha and Anisotropy are calculated from the equations 4 and 5. Based on the values of $\alpha$, scattering mechanism is categorized. When the value of $\alpha = 0^\circ$, then the scattering mechanism is called as single bounce scattering, single bounce scattering is produced by rough surface such as water, ice, smooth bare soil etc. When the value of $\alpha = \frac{\pi}{4}$, then the scattering mechanism is called as volume scattering, and it is observed in forests. When the value of $\alpha = \frac{\pi}{2}$, then the scattering mechanism is called as double bounce scattering, it is generally observed in urban areas. Similarly the value of $\lambda$ is calculated from equation 2. If

| Zone | Entropy, $H$ | $\alpha$ (°) | Scattering Type |
|------|-------------|-------------|-----------------|
| 1    | 0-1.1       | 40-55       | High Entropy Multiple Scattering |
| 2    | 0.1-1.6     | 0-40        | High Entropy Vegetation Scattering |
| 3    | 0.1-1.6     | 0-40        | High Entropy Surface Scattering |
| 4    | 0.5-0.9     | 50-90       | Medium Entropy Multiple Scattering |
| 5    | 0.5-0.9     | 40-50       | Medium Entropy Vegetation Scattering |
| 6    | 0.5-0.9     | 0-40        | Medium Entropy Surface Scattering |
| 7    | 0-0.5       | 47.5-90     | Low Entropy Multiple Scattering |
| 8    | 0-0.5       | 42.5-47.5   | Low Entropy Single Scattering |
| 9    | 0-0.5       | 0-42.5      | Low Entropy Surface Scattering |
the value of $\lambda_1 = \text{Span}/3$ then it is said to be distributed target. Similarly if $\lambda_1 = \text{Span}$, $\lambda_2, \lambda_3 = 0$ then it is said to be pure target. For homogenous targets the Anisotropy value will be low. From the Figure 4 (j) Ha classification plane, water bodies and smooth land surface are categorized to zone 9 with blue color. The urban area is categorized to zone 7 with red color. Low vegetation area is categorized into zone 8 with green color. The entropy image provides information on the scattering degree of randomness. Scattering over the sea is characterized by a low degree of randomness. The mixing of different scattering mechanisms over built up areas results in intermediate entropy values. On forested zones the scattering process is random. Figure 4 (f) shows the wishart HAa classification, where the violet color represents water, light green color represents vegetation, dark green represents mountains, orange color represents urban area and the white color represents metal structures like Multistoried buildings. Figure 4 (e) and Figure 4 (f) clearly shows the difference i.e. the urban area was not classified properly due to the absence of decomposition parameter anisotropy. Figure 5 shows us the supervised classification of filtered image with 4 classes. The red color represents the water body, green color represents the Crop fields, blue color represents the urban area and the yellow color represents the vegetation.

### 4.1 Accuracy Assessment: Confusion Matrix

The confusion matrix is a table that gives the agreement between the classifier and the ground truth data. In this paper the columns will represent the user defined clusters and the rows represent segmented clusters. A number located at a position $I>J$ represents the amount of pixel in the percent belonging to the user defined area $I$ that were assigned to cluster $J$ during supervised classification. The confusion matrix has $n \times n$ elements where $n$ is the number of classes, which in this study is 4. The form of the confusion matrix is given in Table 2. From the confusion matrix it is possible to calculate various accuracy measurements.

|     | C1    | C2  | C3  | C4  | Class population |
|-----|-------|-----|-----|-----|-----------------|
| C1  | 99.98 | 0.02| 0.00| 0.00| 17113           |
| C2  | 0.09  | 90.7| 0.45| 8.76| 3355            |
| C3  | 0.00  | 6.71| 60.75|32.54|3577             |
| C4  | 0.00  | 12.64|1.27|86.09|1891             |

### 5. Conclusions

To summarize, the entropy and anisotropy parameters are interpreted as a level of dominance between the scattering mechanisms. The entropy is the level of dominance of the first scattering mechanism versus the two others, hence it is a useful parameter to determine whether there is one or more scattering mechanisms are present. The anisotropy is the level of dominance between the second and third scattering mechanism, hence it is a useful parameter to determine whether there is two or three scattering mechanisms are present. This paper reported on the results from the analysis of polarimetric decomposition parameters, classification using decomposition parameters and wishart supervised classification.

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