Research Paper

Comparative Analysis of Different Polarimetric Target Decompositions for Land Cover Classification Using Synthetic Aperture Radar Data

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(Received on 20 April 2020; Revised on 19 October 2020; Accepted on 30 November 2020)

For perfect sustainable resource development plans, assessment of the condition of the natural resources and its availability is the prime step. Many studies revealed Synthetic Aperture Radar data (SAR) backscattering is a very useful technique in identification of soil contents and various land cover types. Classification of different features which itself shows direct relation to physical properties of terrain under study. SAR polarimetry has tremendous potential in classifying various elements of land cover and various polarimetric decomposition algorithms have been developed for this purpose. The present study analyze nine different SAR polarimetric decomposition methods, such as Freeman-Durden, Yamaguchi 3 & 4, Van zyl, Nonnegative Eigenvalue Decomposition (NNED), Singh 4, Krogagar, H/ α /A and Multiple Component Scattering Model (MCSM), for land cover classification using C-band SAR data. The RADARSAT-2 image of tropical area of Shivpuri, India with fine quad-pol was used for polarimetric decompositions. These decompositions generates scattering. The results show that Yamaguchi three component decomposition gives better overall accuracy and kappa coefficients of 88.19% and 0.85, followed by Van zyl 88.00% and 0.85, and Krogager 87.86% and 0.85 respectively by employing SVM classifier. Lowest accuracy is registered for MCSM with overall accuracy 75.65% and kappa coefficient 0.70. Three component decompositions provided better accuracy in classification than four or five component decompositions. The present study reveals that in majority of the decompositions, odd bounce produced better discrimination between urban, forest and agricultural areas and volume scattering gives better separation within the vegetation types. From the experimental results obtained it is clear that SAR data have significant potential in classifying various land cover which includes water body, forest/scrub, agriculture, etc.

Keywords : SAR, Polarimetric Decompositions; Land Cover Classification

Introduction

Characterizing and mapping of land use land cover is essential for planning and managing natural resources, modeling environmental variables, and monitoring. Polarimetric analysis is the measurement and interpretation of different polarizations of electromagnetic waves. Polarimetric SAR (Synthetic Aperture Radar) has been used in the retrieval of soil moisture and surface roughness, snow and ice mapping, forest cover and land-cover classification (Haldar *et al.*, 2012; Parihar *et al.*, 2014; Alappat *et*

al., 2011; Varghese and Joshi 2015; Varghese *et al.*, 2016). Due to its sensitivity to the structure of vegetation such as height of plants, size etc and various land-covers, SAR polarimetry has the potential for crop and land-cover classification. Since microwave radar have the penetrating and polarization capabilities, its data contains more information compared to optical or thermal data as per literature study (Shakil& Masanobu, 2001). Target decomposition theorems are used to extract information of fully polarimetric SAR data by decomposing it into various scattering mechanisms (Cloude, 2010) was first formalized by

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Huynen (Huynen, 1970). The polarimetric information is combination of both geometric and physical characteristics of the feature such as height of plants, canopy type, etc., obtained from scattering radar waves.

Decomposition techniques are divided into two types such as coherent decompositions and incoherent decompositions, where the first decompositions derived from the scattering matrix while the others from coherency or covariance matrices (Pottier *et al.*, 2007). Krogager decomposition (Krogager, 1990) is a coherent decomposition of scattering matrix in which rotation operator is altered to balance the misalignment between the antenna and the target orientation and it can be modeled as a combination of sphere, oriented diplane and a right or left wound helix. In incoherent decompositions, the decomposition of covariance and coherency matrices can be employed to decompose partial polarized scattering and distributed targets. Incoherent decompositions is further divided into eigenvalue based decomposition model (Cloude and Pottier, 1996; Cloude and Pottier, 1997; Pottier, 1994), where entropy (H), anisotropy (A) and alpha angle (α) were introduced. The second type is model based decomposition proposed by Freeman-Durden (Freeman and Durden, 1998), in this technique covariance matrix is decomposed in to three scattering mechanism i.e. single bounce, double bounce and volume scattering. This algorithm assumed reflection symmetry for the observation hence it neglected non-negligible power in off-diagonal terms. This limitation was removed by Yamaguchi through adding a fourth component called helix, which represent the off-diagonal terms neglected by Yamaguchi (Yamaguchi *et al.*, 2005). Likewise, Singh (Singh *et al.*, 2013) also proposed a four-component scattering power decomposition scheme by adding helix component. Zhang (Zhang *et al.*, 2008) proposed a multiple component scattering model based on elementary scattering mechanism such as single-bounce, double-bounce, volume, helix scattering and wire scattering. These elementary scattering mechanisms correspond to the asymmetric reflection condition that the co-polar and cross-polar correlations are not close to zero. Van zyl argued that this algorithm shows negative powers to some of scattering components; which resulted into a serious error. So they proposed Nonnegative Eigenvalue Decomposition (NNED) which guarantees that no eigenvalues are

negative. In the present study representative decompositions from coherent, incoherent, eigenvalue, model based and nonnegative eigenvalue decompositions were selected in order to generate inputs for land over classification for a comparative analysis.

Study Area

Radarsat-2 image which covers part of Shivpuri District of Madhya Pradesh was taken as the study site for the present investigation. The study area contains plateaus, gentle slopes, which rarely forms steep slopes, and altitude ranges in between 380 to 480 m. It is bounded by geo-coordinates 77°25' to 77°46'E and 25 °15' to 25 °37' N. One side of the area is fully covered by forest land and other land cover classes are agriculture land, water body, settlement and scrub land. The forests in the study area are tropical dry deciduous forests and exhibit considerable variation in species composition and densities.

Methodology

Single Look Complex (SLC) image of RADARSAT-2 in fine quad-pol (FQ5) mode was used in this study. The date selected is such that it is period of peak of vegetative growth, when the incessant rain stops, which will enhance the discrimination between the vegetation classes (Clewley *et al.*, 2015; Liesenberg *et al.*, 2016). The quad-pol (HH, HV, VH, VV) image has resolution of 4.73 m $\times$ 4.96 m in the azimuth and range, respectively. The image was acquired at incidence angle of 25.28 degrees. In order to generate scattering matrix, the RadarSat 2 data of area under study was imported in PolSARpro software (Fig. 1). Terrain correction has been done by range-Doppler terrain correction method with Shuttle Radar Topography Mission (SRTM) data in Next ESA SAR Toolbox (NEST) software. The reflectivity of the area being observed is represented by scattering matrix which contains information of various scattering obtained from different scatterer, from the area under study, for a particular radar wavelength (Ulaby and Elachi, 1990). Scattering matrix is then transformed into coherency or covariance matrix (Cloude and Pottier, 1997), in order to retrieve information about incoherent decompositions. The various elements of the coherency matrix, which is divided into real and imaginary part, contains the information about various

types of scatterer which are related to different scattering mechanisms, and sum of diagonal elements represents the total power of the backscattered wave.

All decompositions were done by employing coherency/covariance matrix except Krogagar which was done on scattering matrix. The outputs generated from Freeman-Durden, Yamaguchi three&four, NNED, Singhfour, MCSM and Van zyl decompositions were analyzed in relation to each land cover unit present in the study area.

A total of six land cover classes such as agricultural land (crop & fallow land), settlement, water body, forest scrub and two forest density classes were identified in the study area. Based on the canopy closure of the trees, forest canopy density was sub divided into three categories such as dense forest (>40%), open forest (10-40%) and degraded forest/scrubs (<10%). Ground truth collection has been carried out using GPS in polygon mode for various classes other than waterbody for which training sites were collected directly on the SAR image.

Classification of the generated datasets were done using Support Vector Machine (SVM) classifier (Vapnik, 1995). The SVM method is based on maximizing the distance separating the training classes by the determination of the optimal hyperplane of the input data space. Training vectors are projected into a higher-dimensional space that is the feature space, when hyperplane cannot be found and steps were repeated to find the optimal hyperplane again. A kernel simplifies the projection problem in the higher dimensional space viz feature space. In the first step SVM model define the hyperplane based on user provided training area under study, then the classification of whole data set is done by assigning pixels to the closest class, using the hyperplane side. In the present study, Radial Basic Function (RBF) kernel was opted for one to one mapping of non-linear decision boundary, into linear one. As compared to other kernels available such as linear, polynomial, RBF and sigmoid, RBF has less numerical difficulties (Hsu, 2003).

Classification accuracy of each decomposition

Fig. 1: Methodology flow chart

theorem was assessed by an error matrix to know the overall accuracy. Error matrix is a square array of numbers laid out in rows and columns that express the number of sample units assigned to a particular class relative to actual class in the field. Information obtained from an error matrix is then evaluated by discrete multivariate analytical statistical techniques called Kappa coefficient (Jensen, 1995).

Results and Discussion

The polarimetric information of a target is stored in a scattering matrix. The information about pure or isolated scatters can be directly extracted using the scattering matrix. Whereas for distributed scatters the second order statistics of the scattering matrix, covariance or coherency matrix, is used to store the complete scattering information about the target. Lee *et al.*, 2001, described methods for interpretations of the off-diagonal terms of the coherency matrix. The $\langle (S_{HH} - S_{VV})S_{HV}^* \rangle$ i.e. the $[T_{23}]$ element of the coherency matrix is affected by the polarisation orientation angle shifts as well as the phase difference between the like polarized responses i.e. HH and VV. The real part of $\langle (S_{HH} - S_{VV})S_{HV}^* \rangle$ contain the information about the polarisation orientation angle shifts induced by terrain slopes in azimuthal direction and man-made structures, whereas the imagery part of $\langle (S_{HH} - S_{VV})S_{HV}^* \rangle$ contains the information about the helicity as described by the polarimetric sphere, diplane and helicity decomposition theory of Krogager (1990). The plane of $\langle (S_{HH} - S_{VV})S_{HV}^* \rangle$ was also found to be affected by the terrain azimuthal slopes. This also resulted in increases in the real part of $\langle (S_{HH} - S_{VV})S_{HV}^* \rangle$. The correlation between the surface scattering and the double bounce scattering is represented by the term $\langle (S_{HH} - S_{VV})(S_{HH} - S_{VV})^* \rangle$. The Eigen values of both the covariance and the coherency matrix are always real and are identical in which the sum of the diagonal elements of each matrix represents the total power of the backscattered wave is also same.

The present study analyzed the performance of each decomposition output by using SVM classifier based on the same training areas. In a comparative evaluation, it is observed that Yamaguchi 3 decomposition shows highest accuracy followed by Van zyl and Krogagar (Table 1). Water body registered very good accuracy in all decompositions

with 100% correctly classified pixels, except in MCSM, followed by scrub/forest scrub with above 99% accuracy. In majority of decompositions, odd bounce produced better discrimination between urban, forest and agricultural areas and volume scattering provided better separation within the vegetation types. The helix and wire scattering, which supposed to give better separation between urban and the rest of the classes, failed to provide better classification accuracy.

Analysis of result obtained from each decomposition theorem gives more information about the physical scattering of land units. Yamaguchi 3 component classification (Yamaguchi *et al.*, 2005) provided the best accuracy among all decompositions with an overall accuracy of 88.19% and 0.85 kappa coefficient. In odd and volume scattering well separation can be seen within vegetation density. Double bounce gives good separation between urban areas and the rest of the class, but failed to produce separation between other classes. Because of these, comparatively high accuracy is obtained in vegetation classes (Table 1). In order to accommodate the decomposition scheme for more complicated geometric scattering structures, Yamaguchi *et al.*, 2005 have added a helix scattering term and proposed the four-component decomposition. This helix power is generated by the imaginary part of $T^{23} = \langle (S_{HH} - S_{VV})S_{HV}^* \rangle$ in the coherency matrix. Yamaguchi's helix component failed to provide a better classification result for urban class, as there is major presence of the co-polarized and cross polarized co-relations in the case of urban scattering. This is mainly because the reflection symmetry condition which was assumed for three component model does not hold for helix scattering. SVM classification of forest density using Yamaguchi 4 components decomposition registered less accuracy than Yamaguchi 3 components with an overall accuracy of 86.73% and 0.83 kappa coefficient.

Van zyl decomposition is based on eigen vector analysis of coherency matrix in which the first two eigen vectors can be interpreted in terms of odd and even number of reflections. Unlike in other decompositions, Van zyl double bounce gives well separation between classes. All three scattering components of the Van zyl decomposition give better discrimination between classes. Even through Van zyl decomposition only has three components, it is

Table 1: Confusion matrices of classifications based on different decompositions

Decomposition Land cover class		Yamaguchi3						Van zyl						Krogarar					
		1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
1	Water body	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0
2	Settlement	0	82.8	6	9.5	1.7	0	0	81.99	7.26	9.5	1.25	0	0	81.18	5.02	12.19	1.61	0
3	Agriculture	0	1.67	82.17	5.17	10.83	0.17	0	1.33	82.17	5.83	10.33	0.33	0	0.67	83.67	4	11.67	0
4	Dense forest	0	4.99	3.24	87.28	4.49	0	0	4.49	3.24	88.28	3.99	0	0	6.23	3.49	85.91	4.36	0
5	Open forest	0	0	7.89	7.72	83.89	0.5	0	0	7.55	8.72	82.89	0.84	0	0	8.05	6.88	84.9	0.17
6	Scrub / Forest scrub	0	0	0	0	0.2	99.8	0	0	0	0	0.39	99.61	0	0	0	0	0.2	99.8
		Overall accuracy 88.19Kappa coefficient 0.85						Overall accuracy 88.00Kappa coefficient 0.85						Overall accuracy 87.86 Kappa coefficient 0.85					
		H/ α /A						Freeman-Durden						Yamaguchi4					
1	Water body	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0
2	Settlement	0	82.53	4.66	11.11	1.7	0	0	82.08	6.72	9.59	1.61	0	0	80.02	9.32	8.87	1.79	0
3	Agriculture	0	1.17	83.17	4.5	10.83	0.33	0	2.33	80.83	6.33	10.33	0.17	0	2.33	80	7.33	10.17	0.17
4	Dense forest	0	4.99	3.37	83.42	8.23	0	0	5.11	3.49	84.54	6.86	0	0	4.61	3.24	86.53	5.61	0
5	Open forest	0	1.01	7.89	7.38	83.22	0.5	0	0	7.21	10.74	81.21	0.84	0	0	6.54	10.91	82.21	0.34
6	Scrub / Forest scrub	0	0	0	0	0.2	99.8	0	0	0	0	0.2	99.8	0	0	0	0	0.59	99.41
		Overall accuracy 87.43Kappa coefficient 0.84						Overall accuracy 86.91 Kappa coefficient 0.84						Overall accuracy 86.73Kappa coefficient 0.83					
		NNED						Sing4						MCSM					
1	Water body	100	0	0	0	0	0	100	0	0	0	0	0	99.5	0	0	0.34	0.17	0
2	Settlement	0	81.18	7.26	10.13	1.43	0	0	80.29	9.14	9.05	1.52	0	0	69.8	12.81	13.71	3.49	0.18
3	Agriculture	0	2.83	78	7.83	10.83	0.5	0	2	79.83	8.17	9.83	0.17	0	2.83	79.33	5.5	12.17	0.17
4	Dense forest	0	4.24	2.99	85.79	6.98	0	0	4.49	4.61	83.79	7.11	0	0.37	2.99	8.73	63.47	21.82	2.62
5	Open forest	0	0	7.21	8.39	83.05	1.34	0	0.17	6.38	11.74	81.04	0.67	0.17	0	9.4	12.75	68.46	9.23
6	Scrub/Forest scrub	0	0	0	0	0.59	99.41	0	0	0	0	0.59	99.41	1.77	0	0.59	0.79	12.97	83.89
		Overall accuracy 86.72Kappa coefficient 0.83						Overall accuracy 86.03 Kappa coefficient 0.83						Overall accuracy 75.65 Kappa coefficient 0.70

Fig. 2: RGB image of Yamaguchi3 decomposition

Fig. 3: Classified output of Yamaguchi3 decomposition

registered the second highest classification accuracy (overall accuracy 88% and kappa 0.85). Pentaet *al.*, (2012) also reported better visual separability among the land cover classes in Van zyl decomposition when compared to Krogagar and Freeman Durden.

To study coherent targets or point targets, Krogagar decomposition (Krogager, 1990) method is employed. In this decomposition (Krogager, 1990), a scattering matrix is decomposed into three coherent components which are interpreted as scattering from a sphere, diplane, and helix targets. It is also important to note that the three Krogager decomposition parameters are independent of orientation, in other words, roll-invariant parameters. This roll-invariant characteristic gives a more stable characterization of a target of interest. Even though Krogagar decomposition model is used to study coherent targets or point targets, the present study provided a good classification accuracy which includes land cover classes of distributed targets with overall accuracy of 87.86% and kappa coefficient of 0.84.

H/A/ α (Cloude and Pottier, 1996; Cloude and Pottier, 1997; Pottier, 1994) polarimetric decomposition theorem is based on analysis of the eigen value-eigen vector of Coherency matrix. Eigen vector analysis gives information about the scattering taking place

from different types of scatterer, whereas Eigen value analysis provide information about the relative magnitude of different types of scattering process. The physical scattering of forest area of the present study site represents mainly volume scattering and shows alpha angle value above 45 degree, because of depolarization. Some places in the forest area show multiple scattering also, the presence of two scattering mechanism implies moderately high entropy and low anisotropy values. Some areas of forest show moderate entropy because of dominant dipole type scattering mechanism, here the scattering is from vegetated surface with anisotropic scatters and moderate correlation of scattered orientations. Low values of α angle are registered in agriculture lands and scrublands mainly due to single bounce scattering. When α angle values approach 90° it is interpreted as double bounce as can be observed in settlement areas. Results obtained from H/A/ α polarimetric decomposition, shows overall accuracy of 87.43% and kappa of 0.84.

The Freeman-Durden (Freeman and Durden, 1998) model is based on three scattering mechanisms: firstly modeled from a cloud of randomly oriented dipoles, the volume scattering; second modeled from a pair of orthogonal surfaces with different dielectric constants, the even or double-bounce scattering, and

third modeled from a Bragg scatter i.e. scattering from a moderately rough surface viz., the odd or single bounce scattering. Freeman-Durden assumed that volume scattering generates cross-polarized response hence there is no correlation between co-polarized and cross polarized radar returns and this assumptions was proved correct by experimental results obtained for natural areas. Hence Freeman-Durden scattering model gives correct analysis of natural distributed areas. Freeman-Durden odd bounce gives well separation between forest and agricultural areas and volume scattering gives better separation within vegetation types. Double bounce failed to produce much separation between classes. Results obtained from Freeman-Durden decomposition shows much better accuracy with an overall accuracy of 86.91% and kappa coefficients of 0.84, in classifying the elements.

Van zyl consider that Freeman-Durden and Yamaguchi theoremen countered serious flaw by overestimating the volume component and produced negative eigen values for other components, so he proposed the non-negative eigen value decomposition (Van zyl *et al.*, 2011). NNED decomposition gives comparatively low classification accuracy with an overall accuracy of 86.72% and kappa value of 0.83. In NNED outputs, odd bounce gives well separation between forest and agricultural areas and volume scattering gives well discrimination with vegetation density.

Singh *et al.* 2013, proposed a four-component scattering power decomposition scheme that is surface, double bounce, volume, and helix. These scattering components are derived from the seven independent polarimetric parameters available in the coherency matrix, therefore, this method uses full polarimetric information in the decomposition. Singh odd bounce gives well separation between forest and agricultural areas and volume scattering gives better separation within vegetation types. The double bounce component, which is enhanced over the urban areas, has not given good separation between urban and the rest of the class. Overall accuracy obtained for this classification is 86.03% with a kappa coefficient of 0.83, which shows comparatively low accuracy.

The MCSM (Zhang *et al.*, 2008) extends the three-component scattering model into five

components by adding helix and wire scattering as elementary scattering mechanisms. Scattering from urban area involves double bounce, helix scattering and wire scattering, corresponds to the symmetric reflection conditions which implies co-polarized and cross-polarized correlations are not close to zero. In urban area wire scattering takes place from the buildings of certain shape and size with sharp edges and with certain orientations. Therefore, wire scattering is supposed to be a specific scattering component in urban areas connected with the generation of cross-polarized response (Krogager, 1990). It is observed that helix component of this decomposition has not provided adequate separation between urban and rest of the class, while wire component gives better discrimination than helix in this regard. Even through the MCSM is five component decomposition, it generated lowest accuracy in classification (75.65% and 0.70) among all the decompositions.

The present study gives comparatively better result in classifying various elements of the land cover by using SAR polarimetry (Sakshaug, 2013; Freitas *et al.*, 2008). Sakshaug, 2013, reported a global accuracy of 79.59% and 59.45% for Yamaguchi4 and H/A/ α decompositions respectively in Tanzania by using L band Advanced Land Observing Satellite. An overall accuracy of 70% and kappa coefficients of 0.74 obtained from Textural analysis of C band Envisat ASAR data (Vyjayanthi *et al.*, 2010). Qi *et al.* (2010) integrated polarimetric decomposition, object-oriented image analysis, and decision tree algorithms and compared the result with the Wishart supervised classification method in land cover classification using Radarsat 2 C band data. The overall accuracies of this proposed method and the Wishart supervised classification were 89.34% and 79.36%, respectively. So the experimental result obtained for land cover classification in the present study using SAR data provides great significance.

Conclusion

The present study examined different SAR polarimetric decomposition methods for land cover classification in a tropical Indian site by using SVM classifier. Even though the study attempted four components and five components scattering mechanisms as inputs for classification, three

component decompositions registered highest accuracies in classification (Yamaguchi3, Van zyl). Coherent Krogarar decomposition is also performed well in classification even though the study area contained distributed targets. Water body registered very good accuracy in all decompositions with 100% correctly classified pixels, except for MCSM, followed by scrub/forest scrub with above 99% accuracy. In majority of the decompositions, odd bounce produce better discrimination between urban, forest and agricultural areas and volume scattering gives better

separation within the vegetation types. Double bounce scattering fails to produce sufficient separation between classes in many of the decompositions.

Acknowledgements

We place our sincere thanks to Santanu Chowdhury, Director, NRSC and Uday Raj, Chief General Manager, RCs, Hyderabad for their constant encouragement and valuable suggestions throughout the study. Special thanks are due to Arun Suryavanshi for the help rendered while executing the work.

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