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Polarimetric SAR decomposition parameter subset selection and their optimal dynamic range evaluation for urban area classification using Random Forest

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ABSTRACT

Urban area classification is important for monitoring the ever increasing urbanization and studying its environmental impact. Two NASA JPL's UAVSAR datasets of L-band (wavelength: 23 cm) were used in this study for urban area classification. The two datasets used in this study are different in terms of urban area structures, building patterns, their geometric shapes and sizes. In these datasets, some urban areas appear oriented about the radar line of sight (LOS) while some areas appear non-oriented. In this study, roll invariant polarimetric SAR decomposition parameters were used to classify these urban areas.

Random Forest (RF), which is an ensemble decision tree learning technique, was used in this study. RF performs parameter subset selection as a part of its classification procedure. In this study, parameter subsets were obtained and analyzed to infer scattering mechanisms useful for urban area classification. The Cloude–Pottier α, the Touzi dominant scattering amplitude α_{s_1} and the anisotropy A were among the top six important parameters selected for both the datasets. However, it was observed that these parameters were ranked differently for the two datasets. The urban area classification using RF was compared with the Support Vector Machine (SVM) and the Maximum Likelihood Classifier (MLC) for both the datasets. RF outperforms SVM by 4% and MLC by 12% in Dataset 1. It also outperforms SVM and MLC by 3.5% and 11% respectively in Dataset 2.

1. Introduction

In general, urban area comprises of housing, transportation systems, utilities, commercial buildings and recreational areas (Welch, 1982). Urban area classification is very important for efficient city planning, monitoring the ever increasing urban sprawl and to study its impact on the climate and the environment. For this purpose, remote sensing satellite data for accurate and comprehensive urban area classification are very useful. In our study, all built-up zones were considered as urban areas. Some urban areas appear oriented to the radar line of sight (LOS) while some appear non-oriented to the radar LOS. Non-urban areas consisted of naturally occurring classes such as forests/vegetation and water.

Optical and Synthetic Aperture Radar (SAR) data have been increasingly used for urban area classification over the last decade. Urban area classification studies using optical remote sensing data can be found in Fauvel et al. (2006), Zhong and Wang (2007), Longbotham et al. (2012), and Erener (2013). For classification purpose, SAR images are more desirable than optical since they are less affected by weather conditions. Full-polarimetric SAR uses orthogonal polarizations on transmission and reception which offer additional physical information such as the target geometry, shape and orientation. Significant amount of work has been done in urban area classification using SAR data (Dell'Acqua and Gamba, 2001; Dekker, 2003; Tison et al., 2004; Stilla and Soergel, 2006; Guida et al., 2008; Bhattacharya and Touzi, 2012).

In this study, urban area classification was performed using the Random Forest (RF) classifier (Breiman, 2001). RF is an ensemble classification technique where multiple decision trees are grown from random subsets (known as bootstrap) of the input data. RF performs better than a single decision tree since the result of each decision tree is combined through a voting process for the final classification accuracy. RF has been widely used for classification in many recent applications such as ecology (Cutler et al., 2007), Land Use/Land Cover (LULC) (Pal, 2005; Gislason et al., 2006; Rodriguez-Galiano et al., 2012; Hariharan et al., 2014), crop classification (Ok et al., 2012; Sonobe et al., 2014).

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Some of the unique qualities of RF which were useful in our urban classification study are highlighted below:

- It keeps the parameters in its original form without needing to perform pre-processing steps such as normalization and parameter tuning.
- It is a distribution-free classifier, *i.e.*, it does not assume any underlying probability distribution function associated with the sampled data.
- It provides a parameter subset selection as a part of the classification procedure.
- It has a partial probability plot attribute which can evaluate the optimal dynamic range of the parameters involved in classification.

The urban areas in this study are both oriented as well as non-oriented about the radar LOS. Roll invariant parameters, which remain unaffected by the rotation of the antenna co-ordinate system about the radar LOS, were used in this study. Usually, parameter subset selection studies do not evaluate the range of the parameters that are necessary for classification. In this study, it was important to determine the optimal ranges of the polarimetric parameters to analyze the underlying physical characteristics related to urban target scatterers. The range of the polarimetric parameter where the probability of presence of the urban class was ≥ 0.8 was chosen to be the optimal dynamic range of that parameter in this study. Some urban area classification studies using RF can be found in (Hansch and Hellwich, 2010; Puissant et al., 2014). Since urban area classification is the only aim of this study, each pixel of the datasets used here was classified either as an 'Urban' class or a 'Non-urban' class. Further, the RF classifier was compared with the SVM (Vapnik et al., 1997) and the MLC (Richards and Richards, 1999) classifiers.

This paper has been divided into the following sections: an introduction of the various urban area classification studies conducted using remote sensing datasets is given in Section 1. Section 2 describes in detail, the polarimetric decomposition parameters used in this study. The study area and the two datasets used here are give in Section 3. The RF classification methodology and the McNemar statistical test used in this study are described in Section 4. Section 5 is dedicated to the results and discussions of this study.

2. Polarimetric decomposition parameters

A polarimetric radar transmitting and receiving a linearly polarized wave (horizontal (H) and vertical (V)) can be used to analyze the physical properties of a target using the complex scattering matrix $[\mathbf{S}]$ (Lee and Pottier, 2009),

$$[\mathbf{S}] = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \tag{1}$$

.

The $[\mathbf{S}]$ matrix decomposition is useful to analyze the underlying physical characteristics associated with coherent scattering targets. For incoherent targets, the second order polarimetric descriptors like the covariance $\langle[\mathbf{C}]\rangle$ and coherency $\langle[\mathbf{T}]\rangle$ matrices derived from the $[\mathbf{S}]$ matrix, are used. The coherency matrix $\langle[\mathbf{T}]\rangle$ can be obtained from the ensemble averaged target scattering vector $\underline{\boldsymbol{k}}$ expressed in Pauli basis as follows (Lee and Pottier, 2009):

$$\underline{\boldsymbol{k}} = \begin{bmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ \sqrt{2} S_{HV} \end{bmatrix} \quad \text{and} \quad \langle[\mathbf{T}]\rangle = \langle \underline{\boldsymbol{k}} \cdot \underline{\boldsymbol{k}}^{\dagger} \rangle \tag{2}$$

In order to characterize distributed scatterers, incoherent target decomposition theorems (ICTD) like Cloude–Pottier ($H/A/\bar{\alpha}$) decomposition (Cloude and Pottier, 1997), the Touzi decomposition (Touzi, 2007) and the Yamaguchi 4-component decomposition (Yamaguchi et al., 2005) are needed, which use the covariance or the coherency matrix of the full polarimetric SAR data.

2.1. $H/A/\bar{\alpha}$ decomposition

A method was proposed by Cloude and Pottier (Cloude and Pottier, 1997) for extracting average scattering parameters from the eigen-decomposition of the coherency matrix $\langle[\mathbf{T}]\rangle$. The roll-invariant parameters thus extracted were the scattering entropy H, the anisotropy A and the mean scattering angle $\bar{\alpha}$ defined as:

$$H = -\sum_{i=1}^{3} p_i \log_3(p_i), \quad A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3}, \quad \bar{\alpha} = \sum_{i=1}^{3} p_i \alpha_i; \qquad \text{where} \quad p_i = \frac{\lambda_i}{\sum_{i=1}^{3} \lambda_k} \tag{3}$$

Cloude–Pottier introduced the $\alpha\beta$ model to express the target scattering vector $\underline{\boldsymbol{k}}$ in terms of five parameters under the condition of reciprocity ($S_{HV} = S_{VH}$) where α is the scattering type and β is the target orientation angle. Additionally, information about target's total backscattered power can be determined by the $Span = \sum_{i=1}^{3} \lambda_i$ which is also a roll-invariant parameter as the eigenvalues λ_i are roll-invariant.

2.2. Touzi decomposition

The parameterization of the eigenvectors by Cloude–Pottier's $\alpha\beta$ model may vary with orientation for non-symmetric targets. In order to alleviate this, the target coherent scattering model (TSVM) has been introduced (Touzi, 2004). Unlike the $\alpha\beta$ model, the TSVM is used to parameterize the coherency eigenvectors. Single scattering is characterized by the TSVM-ICTD in terms of the normalized eigenvalues, λ and the roll-invariant parameters; α_s, Φ_{α_s}, τ_m for all the three eigenvectors (Touzi, 2007). These parameters, which do not depend on the wave polarization basis, are target characteristics and permit a unique and roll-invariant decomposition of coherent target scattering. The roll-invariant coherent target decomposition provides an unambiguous description of the symmetric target scattering using the complex scattering type parameters α_s, Φ_{α_s}. The helicity parameter, τ_m permits the measurement of the degree of target scattering symmetry.

2.3. Yamaguchi 4-component decomposition

Model-based decompositions have gained considerable attention after the initial work of Freeman and Durden (Freeman and Durden, 1998). This decomposition which assumes the target to be reflection symmetric (*i.e.*, $S_{HH}S_{HV}^* = S_{VV}S_{VH}^* = 0$) was later relaxed in the Yamaguchi et al. decomposition (Yamaguchi et al., 2005) with the addition of the roll-invariant helix parameter. A helix target generates circular polarization for all linear polarization incident on it. The measured coherency matrix: $\langle[\mathbf{T}]\rangle = P_s[\mathbf{T}]_s + P_d[\mathbf{T}]_d + P_c[\mathbf{T}]_c + P_v\langle[\mathbf{T}]_v\rangle$ can be decomposed into three rank-1 matrices ($[\mathbf{T}]_s$, $[\mathbf{T}]_d$, $[\mathbf{T}]_c$) and a rank-3 matrix ($\langle[\mathbf{T}]_v\rangle$). It can be easily shown that among all the power components of the Yamaguchi 4-component decomposition, only the helix component (P_c) is roll invariant (Yamaguchi et al., 2011).