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Random Forest and Rotation Forest for fully polarized SAR image classification using polarimetric and spatial features

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ABSTRACT

Fully Polarimetric Synthetic Aperture Radar (PolSAR) has the advantages of all-weather, day and night observation and high resolution capabilities. The collected data are usually sorted in Sinclair matrix, coherence or covariance matrices which are directly related to physical properties of natural media and backscattering mechanism. Additional information related to the nature of scattering medium can be exploited through polarimetric decomposition theorems. Accordingly, PolSAR image classification gains increasing attentions from remote sensing communities in recent years. However, the above polarimetric measurements or parameters cannot provide sufficient information for accurate PolSAR image classification in some scenarios, e.g. in complex urban areas where different scattering mediums may exhibit similar PolSAR response due to couples of unavoidable reasons. Inspired by the complementarity between spectral and spatial features bringing remarkable improvements in optical image classification, the complementary information between polarimetric and spatial features may also contribute to PolSAR image classification. Therefore, the roles of textural features such as contrast, dissimilarity, homogeneity and local range, morphological profiles (MPs) in PolSAR image classification are investigated using two advanced ensemble learning (EL) classifiers: Random Forest and Rotation Forest. Supervised Wishart classifier and support vector machines (SVMs) are used as benchmark classifiers for the evaluation and comparison purposes. Experimental results with three Radarsat-2 images in quad polarization mode indicate that classification accuracies could be significantly increased by integrating spatial and polarimetric features using ensemble learning strategies. Rotation Forest can get better accuracy than SVM and Random Forest, in the meantime, Random Forest is much faster than Rotation Forest.

1. Introduction

Synthetic aperture radar (SAR) has all-weather, day and night observation and high resolution capabilities. Enhanced SAR systems, including high spatial resolution and increased repetition rates as well as the availability of multi-frequency data of different missions improve the potential applicability of SAR data. In contrast, Polarimetric SAR (PolSAR, also called quad-polarimetric SAR, or fully polarized SAR) is characterized by not only all above advantages of conventional SAR, but also the measured information that can be directly related to physical properties of natural media and backscattering mechanism. Accordingly, PolSAR data processing has attracted growing interests in the context of remote sensing applications, from vegetation to ice, from natural terrain to artificial infrastructure, especially with the newly availability sensors such as Radarsat-2, TerraSAR-X and ALOS PALSAR (Cable et al., 2014; Jin et al., 2014; Jones et al., 2013). In various studies, the impacts of single, dual and fully polarimetric data sets as well as the corresponding polarimetric features and decomposition methods have been discussed (McNairn et al., 2009; Zhu et al., 2012; Dickinson et al., 2013; Jin et al., 2014). However, due to the data acquisition mechanism, complexity of ground surface and the inherent speckles, PolSAR image classification is particularly challenging in urban and suburban areas (Zhu et al., 2012; Niu and Ban, 2013). To overcome these challenges,

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many classifiers and machine learning methods, such as support vector machine (SVM) (Lardeux et al., 2009; Niu and Ban, 2013), ensemble learning (EL) (Qi et al., 2012; Samat et al., 2014; van Beijma et al., 2014), linear discriminative Laplacian eigenmaps (LDLE) (Shi et al., 2013) and artificial neural networks (ANNs) (Pajares et al., 2012) have been adopted for PolSAR image classification, pixel based or object oriented (Niu and Ban, 2013). As a matter of fact, especially in supervised remote sensing image classification community, high classification performance not only depends on the robustness of classifiers, but also relies on the quality of input features and the information sufficiency in training samples (Olofsson et al., 2014). Therefore, as one of the three major components in classification (e.g. classifier, feature and training samples), extraction of effective feature sets has been extensively investigated from different aspects in PolSAR image classification (Qi et al., 2012; He et al., 2013; Niu and Ban, 2013; Jin et al., 2014). In this component, the use of spatial features proves useful to classification process and has been paid more and more attentions. Spatial features can be derived by image segmentation, texture analysis and mathematical morphology, etc. Although the definition of an adequate segmentation level might be critical, a segmentation inherent speckle reduction significantly increases the classification accuracy (Waske and Braun, 2009). Texture is an effective representation of spatial relationship and contextual information. Various texture measures based on histogram statistics, gray level co-occurrence matrix (GLCM), Markov random fields (MRFs) and Gabor wavelets have been widely investigated in SAR and PolSAR image classification (Dell'Acqua and Gamba, 2003; He et al., 2013; Uhlmann and Kiranyaz, 2014). Among these texture extraction methods, GLCM is the most popular one. In spite of GLCM derived features are sensitive to texture boundaries (might be enhanced by speckle noise in PolSAR imagery), the better performance of image classification, segmentation or retrieval can be reached through combining different textures (Clausi and Yue, 2004). Recently, morphological profiles have shown very attractive capability for representing the complementarity information between spectral and spatial features in the context of multispectral and hyperspectral image processing (Benediktsson et al., 2003; Fauvel et al., 2008; Dalla Mura et al., 2010). However, they are not yet applied to classify PolSAR images.

In general, in addition to polarimetric features, adding the textural and other spatial features in vector composite way always bring additional information to handle classification task more promisingly. However, critically, vector composite process also brings redundancy and high dimensionality problem. To surpass such problems, plenty of feature extraction (FE) and feature selection (FS) methods have been developed for stressing the discrimination ability. For full PolSAR image classification more accurately and overcome the "observed variation of the same category" (OVSC) phenomenon effect purposes, many FE and FS methods have been investigated as well. For instance, since many polarimetric decomposition methods can provide feasible solution averaging the disaster effect of OVSC, Loosvelt et al. (2012) tried to select the useful PolSAR features by the Random Forest algorithm. And the linear discriminative Laplacian eigenmaps (LDLE) dimensionality reduction (DR) algorithm was introduced to C-band Polarimetric Synthetic Aperture Radar (PolSAR) agricultural classification by Shi et al. (2013). The power of mutual information (MI) for selecting the optimum features from Touzi decomposition parameters was explored by Banerjee et al. (2014) for polarimetric SAR image classification. Here, considering the facts that human–computer interaction way is a favorable solution for selecting the most representative features from those GLCM texture measures, specifically the original dimensionality is lower than 10, it will be adopted in the experiments. On the other hand, the morphological profiles are also used in composite way.

As a matter of fact, in addition to the use of the input images and adopted features, the statistical and/or geometrical properties of training set have obvious impacts on the final classification results (Foody, 2002; Olofsson et al., 2014). For instance, a training set that could be used to deduce preferred classification accuracy from one classifier may yield an undesired accuracy for another classifier. Furthermore, plenty of classifiers haven been proposed in the field of pattern recognition and machine learning (ML). Most of them show strong performance in different scenarios of practical remote sensing applications. However, there is no guarantee that one classifier is robust and suitable in all cases (Richards, 2005; Olofsson et al., 2014). Fortunately, a more stable result can usually be achieved by combining individual classifiers within a multiple classifier system, also named as classifier ensemble or ensemble learning (EL) (Breiman, 1996). The advantage of classifier ensemble on generalizing the capability of classifier has also been investigated for PolSAR image classification (Zou et al., 2010; Qi et al., 2012; Samat et al., 2014; van Beijma et al., 2014). For example, the performance of a maximum likelihood classifier (MLC), a single decision tree (DT), and two ensemble methods, i.e., a boosted decision tree and Random Forests are compared by Waske and Braun (2009) for the classification of a multi-temporal ERS-2 SAR and ENVISAT ASAR data. The results showed that the Random Forest outperform other approaches in terms of the classification accuracy. In other studies SVM and boosted decision trees also proved effective for classifying polarimetric SAR data (McNairn et al., 2009; Lardeux et al., 2009).

Random Forest is a committee of weak learners (e.g. decision tree) for solving classification and regression problems. Due to its generalized performance, high prediction accuracy and fast operation speed, Random Forest attracted many attentions from the context of remote sensing fields, especially for classification tasks, including multispectral (Gislason et al., 2004; Pal, 2005; Gislason et al., 2006; Rodriguez-Galiano et al., 2012), hyperspectral (Ham et al., 2005; Chan and Paelinckx, 2008), SAR and PolSAR image classification (Loosvelt et al., 2012; Qi et al., 2012; Waske and Braun, 2009). In this period, in comparison with Bagging, Boosting, Adaboost, neural network classifier, SVM and classification and regression tree (CART) classifiers, the superiors of Random Forest in terms of classification accuracy and computational efficiency were claimed in many studies of classification of multisource remote sensing and geographic datasets.

Recently, Rotation Forest has been proposed as a new classifier ensemble method by Rodriguez et al. (2006) and their experimental results with 33 data sets from UCI Machine Learning Repository showed that Rotation Forest outperformed other ensemble methods like Bagging, AdaBoost and Random Forest by a large margin. Also, Rotation Forest shown strong generalization performance in cancer classification (Liu and Huang, 2008), regressors improvement (Zhang et al., 2008) and optical and PolSAR remote sensing image classification (Kavzoglu and Colkesen, 2013; Samat et al., 2014; Xia et al., 2014). In above studies, the effectiveness of Rotation Forest in terms of classification accuracy was comparatively investigated in comparison with Bagging, Adaboost, random subspace, Random Forest and SVM.

Generally speaking, the main difference between Random Forest and Rotation Forest is, the latter one adopts PCA on feature subtest to reconstruct full feature space and improve the diversity among all member classifiers. However, in literature, Random Forest and Rotation Forest have not been deeply investigated in PolSAR remote sensing image classification context with polarimetric, textual and spatial features, in terms of classification accuracy, computation efficiency, impacts of training samples size and the numbers of base classifiers in ensemble. To this end, in this paper, these two classifiers are comparatively investigated in PolSAR image classification with multiple features, including