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Active extreme learning machines for quad-polarimetric SAR imagery classification

Alim Samat[a,b], Paolo Gamba[c], Peijun Du[a,b,*], Jieqiong Luo[a,b]

[a] Key Laboratory for Satellite Mapping Technology and Applications of State Administration of Surveying, Mapping and Geoinformation of China, Nanjing University, China
[b] Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, Nanjing University, China
[c] Department of Electrical, Computer and Biomedical Engineering, University of Pavia, Italy

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ABSTRACT

Supervised classification of quad-polarimetric SAR images is often constrained by the availability of reliable training samples. Active learning (AL) provides a unique capability at selecting samples with high representation quality and low redundancy. The most important part of AL is the criterion for selecting the most informative candidates (pixels) by ranking. In this paper, class supports based on the posterior probability function are approximated by ensemble learning and majority voting. This approximation is statistically meaningful when a large enough classifier ensemble is exploited. In this work, we propose to use extreme learning machines and apply AL to quad-polarimetric SAR image classification. Extreme learning machines are ideal because of their fast operation, straightforward solution and strong generalization. As inputs to the so-called active extreme learning machines, both polarimetric and spatial features (morphological profiles) are considered. In order to validate the proposed method, results and performance are compared with random sampling and state-of-the-art AL methods, such as margin sampling, normalized entropy query-by-bagging and multiclass level uncertainty. Experimental results for four quad-polarimetric SAR images collected by RADARSAT-2, AirSAR and EMISAR indicate that the proposed method achieves promising results in different scenarios. Moreover, the proposed method is faster than existing techniques in both the learning and the classification phases.

Introduction

Polarimetric SAR (PolSAR, also called quad-polarimetric SAR, or fully polarimetric SAR) has not only all the advantages of a conventional SAR, such as all-weather, and day/night observation capabilities, but it is also able to capture more information about the backscattering phenomena through multi-polarization modes. Accordingly, PolSAR has attracted a growing interest in the context of remote sensing applications. The impact of single, dual and fully polarimetric data sets as well as the corresponding polarimetric features and decomposition methods on the characterization of multiple materials, from vegetation to ice, from natural terrain to artificial infrastructures, have been already investigated in various studies (Conradsen et al., 2003; Ainsworth et al., 2009; McNairn et al., 2009; Lonnqvist et al., 2010; van Zyl et al., 2011; Paladini et al., 2013). However, due to the data collection mechanism, the complexity of the interaction between the ground surface and the incident electromagnetic wave, and finally the inherent speckle effect, the classification of PolSAR images is still a challenging research topic. To overcome such challenges and process PolSAR data more effectively, many supervised/unsupervised classifiers have been proposed (Doulgeris et al., 2008; Ferro-Famil et al., 2001; He et al., 2013; Qi et al., 2012). Despite their excellent performances, even the most effective supervised classifiers, such as support vector machines (SVM) (Lardeux et al., 2009), classifiers ensembles (Waske and Braun, 2009), or the Wishart supervised classifier (Lee et al., 1994), rely on the quality, amount and availability of labeled training samples. These training data must represent the actual statistical properties of the land cover classes in the scene. This constraint usually leads to extensive visual interpretation (inherently subjective) or expensive and time-consuming field work. Moreover, due to their redundancy, manually selected training samples do not always guarantee a correct selection. Therefore, training samples with high quality of representation and low redundancy, valid for adequate learning of any supervised classifier, are urgently needed.

* Corresponding author at: Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, Nanjing University, China. Tel.: +86 15905159291.
E-mail addresses: alim.smt@gmail.com (A. Samat), paolo.gamba@unipv.it (P. Gamba), dupjrs@gmail.com (P. Du), luojieqiongyan@126.com (J. Luo).

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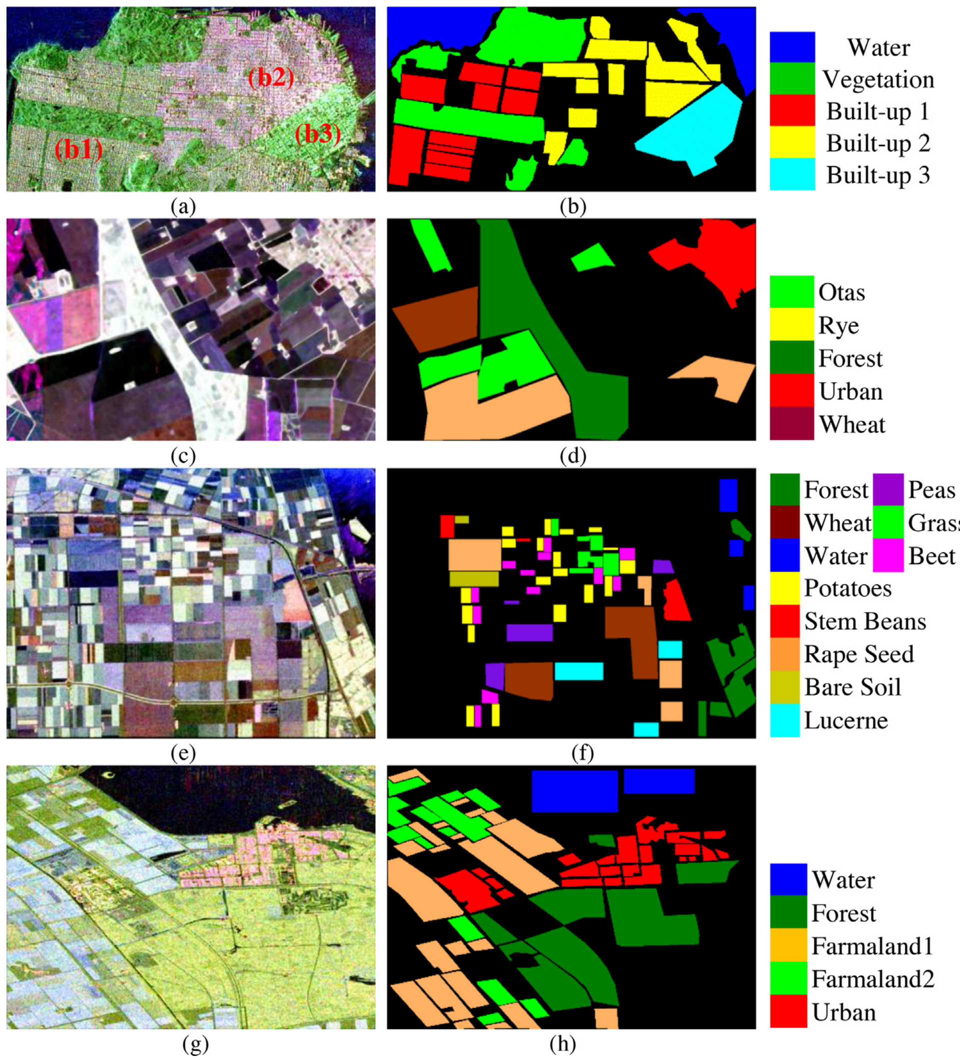

Fig. 1. False colored RGB images obtained using the Pauli decomposition (R = |S11 + S22|, G = |S12 + S21|, B = |S11 − S22|) as well as reference maps for each of the four considered data sets. First row: San Francisco (C-band, Radarsat-2); second row: Foulum (L-Band, AirSAR); third row: Flevoland (L-band, EMISAR); Forth row: Flevoland (C-band, Radarsat-2).

Recently, active learning (AL) techniques have been extensively investigated due to their ability to select additional informative samples from unlabeled data. AL selects samples from a pool of unlabeled samples via query strategies suited to the properties of the classifier, the current labeled sample set and auxiliary unlabeled data (Tuia et al., 2011a,b). So far, several AL algorithms have been introduced, with promising results in multi- and hyperspectral image classification (Rajan et al., 2008; Tuia et al., 2009, 2011a,b). As a form of sampling technique, AL focuses on human–machine interaction under the assumption that the samples that are most informative for the user will generalize the classification capabilities.

According to the selected query strategy, AL methods can be categorized into three main groups: (1) methods relying on the classifier features (e.g., the geometrical features of SVM – Tong and Koller, 2002; Demir et al., 2011); (2) methods based on the estimation of the class posterior probability functions (Roy and McCallum, 2001; Mitra et al., 2004); and (3) methods based on the query-by-committee paradigm (Freund et al., 1997; Copa et al., 2010). The first group includes margin sampling (Tuia et al., 2011a,b), multi-class level uncertainty (Demir et al., 2011) and significance space construction (SSC) (Pasolli et al., 2011). These approaches mainly take advantages of geometrical properties of SVM, but also share their sensitiveness to model parameters. The second group, including KL-max (Rajan et al., 2008) and the breaking ties (BTs – Luo et al., 2004), is more computational efficient, but the training sample selection criterion relies on approximations of the posterior probabilities, and is highly likely to fail when the initial training samples count is very limited. The last group, including query-by-bagging (Freund et al., 1997; Copa et al., 2010), entropy query-by-bagging (EQB), and normalized entropy query-by-bagging (Tuia et al., 2009) is applicable to any kinds of model or combination of models, but models with strong generalization and small computational cost are usually preferred (Tuia et al., 2011a,b). Summing up, there is still a need for AL algorithms with small computational costs and generalized performances, able to work efficiently on very small initial training samples without approximations of the posterior probabilities.

In this regard, our idea is to exploit the potentials of extreme learning machines (ELM) in an active learning framework. ELM was proposed as a generalized algorithm for single-hidden layer feed-forward neural networks, performing well in both regression and classification (Huang et al., 2006a,b). Due to its remarkable advantages, such as fast operation, straightforward solution and strong generalization, ELM has attracted a lot of attentions in the pattern recognition field (Suresh et al., 2009; Minhas et al., 2010;