RANDOM FORESTS FOR BUILDING DETECTION IN POLARIMETRIC SAR DATA

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1. ABSTRACT

Synthetic Aperture Radar (SAR) measures the echo of a microwave signal transmitted from an airplane or satellite and backscattered from the ground. As active sensor it is independent from daylight and less influenced by weather conditions due to the electro-magnetic properties of microwaves. Polarimetric SAR uses different polarizations during emission and reception, which offers additional sources of information. Those advantages have lead to a steady increase of importance of PolSAR based imagery for the last decades. However, due to difficult intrinsic characteristics of PolSAR data, which are quite different compared to optical data, there is still a lack of powerful tools for analysis and interpretation of PolSAR images. Most of contemporary methods for object recognition in PolSAR data still rely on pixel-based features or only consider a small neighborhood. Only few works (e.g. [1]) use more sophisticated features or methods.

Building detection in PolSAR data is an especially important and difficult task. Contemporary space-born sensors are able to provide images with a resolution high enough to enable a successful distinction between single buildings even in very dense urban areas (see Fig.1a). Unfortunately, many of most basic assumptions of SAR image analysis are not longer valid in urban areas. It is e.g. unlikely to find an infinite amount of randomly distributed scatterers with similar characteristics in one resolution cell. That is why fully developed speckle is less probable in high-resolution SAR data of urban areas than in e.g. images of agricultural fields obtained in a low resolution. Methods will tend to fail, if they only rely on some basic features like polarimetric properties. In contrary to land use classification, which is relatively successfully possible by usage of radiometric properties described by single pixels alone or small pixel neighborhoods, building detection has to rely on geometric features to a larger extend.

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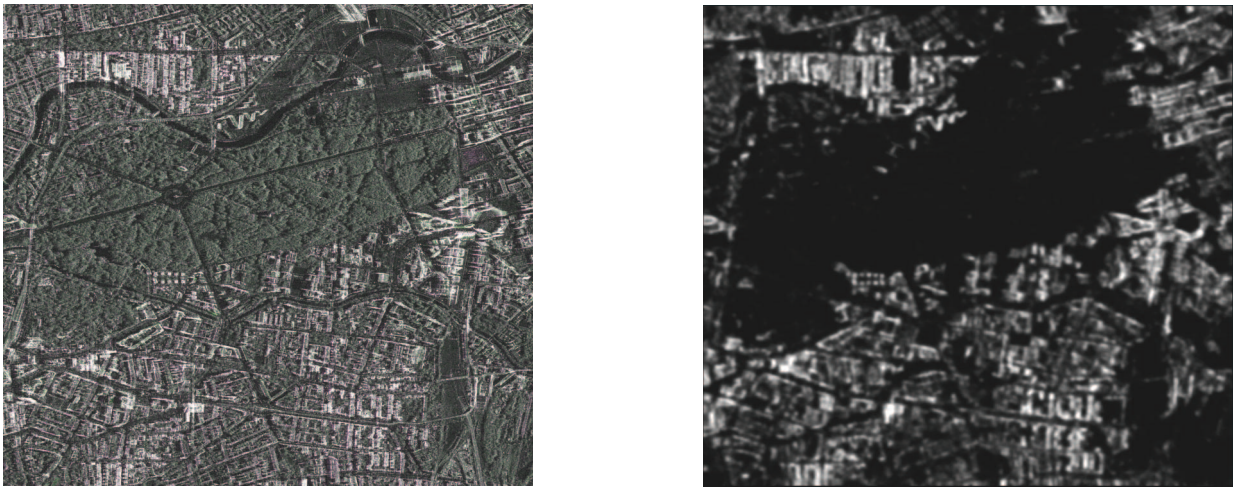

(a) Original PolSAR image (TerraSAR-X, DLR) (b) Classification Result

Fig. 1. Original PolSAR image (TerraSAR-X, DLR) and classification result.

This paper proposes the use of Random Forests (e.g. [2]) as classification method, which are one type of ensemble classifiers. An ensemble consists of a set of simple classifiers and their individual outputs are combined to a final classification result, which is on average better than the result of each individual classifier alone. In the case of Random Forests the individual classifiers are binary decision trees. Each non-terminal node n of tree t performs a simple binary test $f_{(t,n)}(\mathbf{x})$ on the subset $D_{(t,n)}$ of the data which reached this specific node ($\mathbf{x} \in D_{(t,n)}$). Therefore, each non-terminal node splits the data into two disjoint subsets $D^T_{(t,n)}$ and $D^F_{(t,n)}$:

$$D^T_{(t,n)} \cup D^F_{(t,n)} = D_{(t,n)} \tag{1}$$

$$D^T_{(t,n)} \cap D^F_{(t,n)} = \emptyset \tag{2}$$

$$\forall \mathbf{x} \in D_{(t,n)} : \mathbf{x} \in D^T_{(t,n)} \Leftrightarrow f_{(t,n)}(\mathbf{x}) = 1 \vee \mathbf{x} \in D^F_{(t,n)} \Leftrightarrow f_{(t,n)}(\mathbf{x}) = 0 \tag{3}$$

This recursive splitting stops if a user-defined maximal depth is reached or the number of samples at this node is smaller than a given threshold. At this point a terminal node l is created and the a posteriori distribution $P_{(t,l)}(c)$ over class labels c is estimated given the data points that fall into this node:

$$P_{(t,l)}(c) = \frac{|\{\mathbf{x} \in D_{(t,l)} : label(\mathbf{x}) = c\}|}{|D_{(t,l)}|} \tag{4}$$

During application each data point is propagated from the root node down to the terminal nodes in all T trees. The estimated distributions $P_{(t,l)}(c)$ of terminal node l reached by data point $\mathbf{x}$ in all trees t are combined and used to derive the final classification result $P(c|\mathbf{x})$:

$$P(c|\mathbf{x}) = \frac{1}{T} \sum_{t=1}^{T} P_{(t,l)}(c) \tag{5}$$

Random Forests are known to be able to provide high classification rates and to have good convergence properties. Furthermore, they are neither subject to over-fitting nor to the curse of dimensionality. On the contrary, they are able to exploit many different features without any simplifying assumptions about their statistical properties.

Other sophisticated classification methods like neural networks often lack the possibility to give a deeper insight into the calculated solution. Random Forests on the other hand can be utilized to measure the relative importance of single features used during the classification task, as well as estimate the generalization error without disjoint training and test sets. Furthermore, they are easy to train and their application to large data sets is considerably fast (and can be further accelerated by parallel processing).

Fig.1a shows a false color composite of a PolSAR image of Berlin obtained by TerraSAR-X (DLR). The proposed classification method uses various features, e.g. intensity, image gradient, polarimetric correlation, entropy, sublook coherence. The investigation of spatial correlations is done implicitely by the node tests. In Fig.1b a preliminary classification result is shown obtained by two hundred trees, trained only on a small part of the available image data.

The obtained error rates are compared to a simple maximum likelihood classifier as baseline algorithm and support vector machines as state-of-the-art method, to show the superiority of the proposed method.

2. REFERENCES

[1] W. He, A. Reigber, and O. Hellwich, "Building extraction from polarimetric sar data using mean shift and conditional random fields," in *Proceedings of EUSAR 2008*. EUSAR, 2008, vol. 3, pp. 439–442.

[2] L. Breiman, "Random forests," in *Machine Learning*, 2001, pp. 5–32.