Wavelet based texture modeling for the classification of very high resolution maritime pine forest images

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WAVELET BASED TEXTURE MODELING FOR THE CLASSIFICATION OF VERY HIGH RESOLUTION MARITIME PINE FOREST IMAGES

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ABSTRACT

This study evaluates the potential of wavelet-based texture modeling for the classification of stand age in a managed maritime pine forest using very high resolution satellite data. A cross-validation approach based on stand age reference data shows that multivariate modeling of the spatial dependence of wavelet coefficients outperforms the use of features derived from co-occurrence matrices. Simultaneously adding features representing the color dependence and leveling the dominant orientation in anisotropic forest stands enhances the classification performances. These results obtained from panchromatic and multispectral PLEIADES data confirm the ability of such wavelet-based multivariate models to efficiently capture the textural properties of very high resolution forest data and opens up perspectives for their use in the mapping of mono-specific forest structure variables.

Index Terms—forest structure, texture analysis, classification, very high resolution, wavelet.

1. INTRODUCTION

Submetric images produced by Very High Resolution (VHR) sensors enable to capture the geometric aspect of small objects which are only observable through their spectral properties at lower resolution. This is for example the case for vegetation rows in vineyards, orchards and young trees in managed stands. Rather than depending on pixel-based information, the classification or the segmentation of such land cover types could therefore be improved by considering inter-pixel dependencies to capture the spatial organization of the vegetation cover. Approaches using textural analysis have proven to be a valuable solution in this VHR classification context with various commonly used tools such as Grey Level Co-occurrence Matrices (GLCMs), variograms or wavelet representations. All these tools enable to statistically analyze the local spatial dependency between a pixel and its neighboring pixels and lead to a small-sized representation of the textural content since only a few descriptors are extracted from the data. These descriptors can then be further used as input in a classifier or a segmentation algorithm.

In applications relative to forest classification, the existence of a correlation between forest structure variables and the tree spatial distribution is often considered. The forest spatial structure at the stand level indeed varies in time as a result of reforestation, tree growth and periodic thinning. In various studies [1-3], GLCM-based descriptors are exploited in this context to describe the tree canopy spatial organization and are further used for the estimation of forest structure variables at the stand scale. Typically, variables retrieved in these studies are: age, tree height, stand density, crown diameter, basal area, etc.

In this paper, we propose to evaluate how texture features extracted from wavelet-based multivariate models can help in the classification of stand age in a managed maritime pine forest. Lately, wavelet decompositions have indeed emerged as an effective tool to describe textures. In [4], Do & Vetterli suggested the use of probabilistic models to describe the distribution of wavelet coefficients. Further studies proposed to work with multivariate models to express the joint distribution of wavelet coefficients located in a neighborhood and thereby better approximate the local dependencies. Such multivariate models are for instance: multivariate Gaussian distribution, Spherically Invariant Random Vectors (SIRVs) [5], or copula based models [6]. Classification performances obtained with these models are compared with results derived from GLCM-based texture descriptors on VHR PLEIADES images of maritime pine forest.

2. STUDY SITE AND DATA

The study site is located in the Landes de Gascogne forest in the South West of France. This ecosystem is mainly dominated by even-aged maritime pine stands (*Pinus pinaster*). The stand age ranges from 0 (clear cuts) to approximately 50 years. Structure variations may appear between stands of the same age due to the site fertility, silvicultural management practices or natural disturbances.

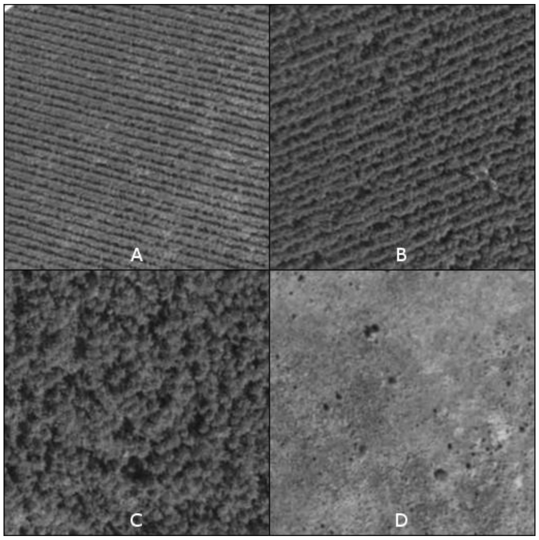

Fig. 1. Extracts of forest stands representing the forest age classes. A – Forest age class 1 (1-9 years), B – Forest age class 2 (10-19 years), C – Forest age class 3 (>19 years), D – Clear cuts.

In order to classify the forest age classes through textural analysis, we used a PLEIADES image acquired on this area of interest on 8 August 2012.

Stand age reference data were collected in 2013 from local forest land managers in the municipality of Audenge (44°70'N, 0°95'W). These data consist in a shapefile containing contours of 179 forest stands with their corresponding age ranging from 0 to 50 years by age group of 5 years. Clear-cuts are also included in the data. Age groups were rearranged in three classes: class 1 includes young stands of 1 to 9 years, class 2 corresponds to stands of 10 to 19 years, and class 3 covers a range from 20 to over 50 years. A fourth class contains the clear-cuts (Fig. 1).

3. FEATURE EXTRACTION

The purpose of the feature extraction step is to represent the spatial dependence and the color (i.e. spectral) dependence in each stand of the reference data by a finite set of descriptors. In this paper, two approaches are compared for the spatial dependence modeling using panchromatic data: the Grey Level Co-Occurrence Matrix (GLCM) and wavelet-based multivariate modeling. Only the latter is applied for the color dependence using multispectral data.

3.1 Grey-Level Co-Occurrence Matrix

The use of the GLCM involves the setting of two spatial parameters, i.e. the distance and the orientation between the pairs of sites. Previous results obtained on a maritime pine forest texture database in a content-based retrieval framework showed that pairs of sites at a distance of 2 pixels (i.e. 1 m in panchromatic) in four directions (0°, 45°, 90°, and 135°) give the highest retrieval rate [7]. Furthermore, a set of textural features derived from the GLCMs is selected out of the 14 second order statistics proposed by Haralick [8]. To achieve this, a principal component analysis was employed to identify the most discriminant features. As a result, a subset of four descriptors (homogeneity, entropy, correlation, and the Haralick's mean) was selected. For each forest stand of the database, a feature vector containing these four descriptors obtained for each direction (16 descriptors in total) is computed from the PLEIADES panchromatic band.

3.2 Wavelet-Based Multivariate Models

Prior to the modeling and the feature extraction, an orthogonal wavelet transform (Daubechies filter db4) is applied on an extract of the PLEIADES panchromatic band and multispectral data corresponding to the area of interest. Two scales and three orientations of decomposition are applied leading to the production of six wavelet subbands.

Two types of dependencies are considered in the modeling process:

- First, the spatial dependence analysis is carried on the subbands derived from the panchromatic data. The wavelet coefficients located in a 3x3 neighborhoods around the current spatial position are clustered in a random vector.
- Secondly, the color dependence analysis is applied on the wavelet subbands derived from the PLEIADES multispectral data. Here, the observed random vector contains the wavelet coefficients of each spectral band of the data.

The distribution of these observations can be further modeled using multivariate probability density functions (pdf) whose parameters are estimated according to the maximum likelihood principle.

Several multivariate models are compared in this study: the multivariate Gaussian with a Sample Covariance Matrix (SCM) estimator and generalizations of the Gaussian distribution such as the SIRV model with a deterministic multiplier (SIRVgauss), the SIRV model with a G^0 distribution (SIRVg0) [9] and the Gaussian copula [6].

Note that the considered SIRV models (SIRVgauss and SIRVg0) were already applied in texture retrieval experiments on forest texture databases and showed interesting retrieval rates [7]. In the next section, we investigate the potential of such models in a cross-validation classification framework.

4. APPLICATION

For each stand of the reference data, feature sets describing the spatial dependence (SP) were extracted using the GLCM and the four wavelet-based multivariate models: SCM, SIRVgauss, SIRVg0 and copulas. In parallel, feature sets describing the color dependence (COL) were computed

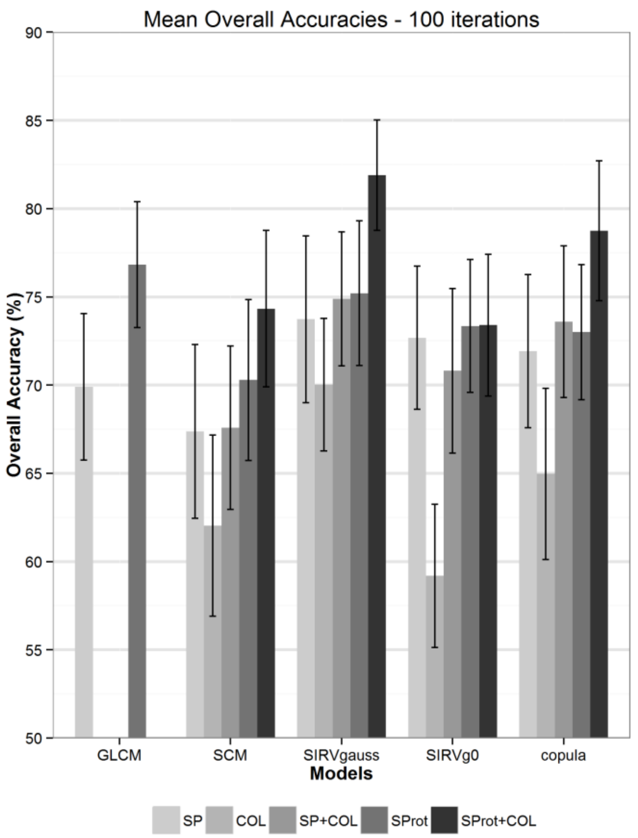

Fig. 2. Mean overall accuracies obtained by cross-validation. SP = spatial dependency, COL = color dependency, SP+COL = combination of spatial and color dependencies, SProt = spatial dependency after rotation of oriented stands, SProt+COL = combination of spatial dependency after rotation of oriented stands and color dependency.

using the same four models. In a third modality, spatial dependence features and color dependence features are concatenated in a unique vector (SP+COL).

Anisotropy is an important texture property, especially when investigating row-planted vegetation. For both investigated approaches (GLCM and multivariate models), computed texture features are not rotation invariant as they are by definition specific to a particular orientation. To evaluate the impact of this lack of rotation invariance on classification accuracy, a second reference image database was produced by rotating each stand displaying an anisotropic texture so that its orientation is forced to 0°. New sets of features describing the spatial dependence of this new database were then extracted for the GLCM and multivariate models (SProt). These new sets of features were also combined with color dependence features in a fifth and last modality (SProt+COL).

To compare the classification accuracies of the proposed models and assess the pertinence of spatial and color dependence modeling, we chose a cross-validation approach. For each iteration of this procedure, the reference database is randomly split in training data (50%) and validation data (50%). A distance matrix is then built between feature sets of the training data and those of the validation data. For multivariate models, a Rao geodesic distance is chosen as it exists in a closed form for all the proposed multivariate models. In the case of similarity measurement between GLCM features, a Mahalanobis distance is applied. The classification is next performed using a k Nearest Neighbor classifier (kNN). The class of a stand is set to the most represented class in the kNN stands of the training data (k=5). The classification performances are next evaluated in terms of average overall accuracy over a hundred Monte Carlo runs.

5. RESULTS AND DISCUSSION

Cross-validation results are presented in Fig. 2 for the five tested modalities and for the five considered texture models.

The modeling of the spatial dependence (SP) is best achieved using SIRV-based models with slightly better classification performances for the SIRVgauss model. Overall, multivariate models are displaying higher performances than the GLCM with the exception of the SCM estimator. This confirms the interest of multiscale wavelet-based approach to describe the texture. The scales of the spatial distribution explored by the GLCM and the multivariate models are indeed different due to the parameterization we have chosen for both approaches. Where GLCM achieve its highest performances by only investigating short distances (1 m), wavelet-based approaches explore larger ranges of object size and are probably more appropriate to describe the variation of tree crown size depending on the stand age.

Besides, once the row orientation is forced to 0° in the SProt modality, the performances of the GLCM descriptors are significantly increased and exceed those of the multivariate models whereas results obtained with multivariate models are only moderately improved. Even though both GLCM-based and wavelet-based features are not rotation invariant due to the orientations considered during their computation, the latter probably better describes orientation-specific characteristics of the textures than the former. Also, the diversity of orientations present in the database could be enough to balance the lack of rotation invariance for both approaches. This could explain why rotation does not significantly improve the performances in the case of multivariate models. Nonetheless, once training and validation data display the same orientation, GLCM approach is more reliable.

Adding color dependence features to spatial dependence parameters (SP+COL) does not increase overall classification performances for any wavelet-based models. However, when combining color dependence with the removal of the orientation factor (SProt+COL), a synergetic effect is revealed for all multivariate models with the notable exception of SIRVg0. This modality displays the highest overall accuracy.

To better understand classification errors, it is also worth mentioning that a significant part of the reference data (approximately 15%) is composed of outliers in terms of texture content. These stands are not aberrant in terms of age but display a textural content that makes them look different from the average visual aspect of the class they belong to. Various local phenomena could be the source of these discrepancies. For instance, in stands of over 10 years (age classes 2 and 3), forest thinning operations induce changes in forest density and crown growth which consequently alter texture patterns. Residuals of storm damages also cause local changes in forest density. Middle-aged damaged forest stands (class 2) can thereby share common features with older forests with the appearance of large clearing patches. Forest management practices such as plantation density vary sometimes from one land owner to the other and differences in forest patterns occur between young tree stands. Finally, practices may also change within the same stand or the satellite data can be acquired during an ongoing clearing operation. Hence, different patterns may be observed within one stand.

All these phenomena illustrate the limits of the main a priori assumption of this study which is to consider that the relation between the age of a stand and the tree canopy spatial distribution is simple. Local management practices, site fertility and the past history of the studied stands are not to be neglected in the analysis. But, this also means that classification accuracies higher than 85% would be difficult to reach only through automatic textural analysis.

6. CONCLUSION

We investigated the interest of wavelet-based texture modeling for the classification of stand age in a managed mono-specific forest. Multivariate model based on the Gaussian SIRV configuration was confirmed as an interesting candidate approach for spatial dependence modeling in this context. Adding color dependence features and leveling the orientation in the database also proved to enhance the discrimination of age classes when used simultaneously. Nonetheless, the diversity of management practices, the site fertility or the past history of the studied stands will invariably introduce discrepancies between the observed texture of the stands and their actual age. Yet, the proposed models do most of the time fit the displayed texture and misclassifications are mainly due to these discrepancies. This suggests the potential interest of multivariate approaches for the estimation of other forest structure variables that are more directly related to the texture. For instance, the crown diameter, also a good indicator of the forest development stage, has a direct impact on the size of the object to be described and is related to the spatial distribution of these objects.

7. ACKNOWLEDGMENT

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8. REFERENCES

[1] Lévesque J., King D.J., "Spatial analysis of radiometric fractions from high-resolution multispectral imagery for modeling individual tree crown and forest canopy structure and health", *Remote Sens. Environ.*, 84(4), 589-602, 2003.

[2] Kayitakire F., Hamel C., Defourny P., "Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery", *Remote Sens. Environ.*, 102(3), 390-401, 2006.

[3] Béguet B., Chehata N., Boukir S., Guyon D., "Retrieving forest structure variables from very high resolution satellite images using an automatic method", *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci.*, I-7, 1-6, 2012.

[4] Do M.N., Vetterli M., "Wavelet-based texture retrieval using generalized Gaussian density and Kullback-Leibler distance", *IEEE Trans. Image Process.*, 11, 146-158, 2002.

[5] Yao K., "A representation theorem and its applications to spherically-invariant processes", *IEEE Trans. Inf. Theory*, IT-19(5), 600-608, 1973.

[6] Kwitt, R., Uhl A., "A joint model of complex wavelet coefficients for texture retrieval", *16th IEEE Int. Conf. on Image Processing (ICIP)*, 1877-1880, 2009.

[7] Regniers O., Da Costa J.-P., Grenier G., Germain C., Bombrun L., "Texture based image retrieval and classification of very high resolution maritime pine forest images," *IEEE Int. Geoscience and Remote Sensing Symp.(IGARSS)*, 4038-4041, 2013.

[8] Haralick R.M., Shanmugam K., Dinstein I., "Textural features for image classification", *IEEE Trans. Syst., Man, Cybern., Syst..*, 6, 610-621, 1973.

[9] Freitas C., Frery A., Correia A., "The polarimetric G distribution for SAR data analysis," *Environmetrics*, 16, 13-31, 2005.