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Object-based land cover classification using a preliminary stratified semantic pixel labeling obtained from a fuzzy spectral prior knowledge classifier

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Abstract. Object-based image analysis has been proposed as an efficient approach to handle the multiscale, hierarchical and non-linear complexity of land cover mapping from remote sensing images. It incorporates a first segmentation step that provides image-objects composed of spectrally homogeneous and spatially neighbored clustered pixels. Image-objects benefit from additional region-based metrics to the spectral features such as shape, texture, structure, size and context. Multiplication of classification features enlarges the class discrimination possibilities but in the same time increases the number of meaningless noisy features and the quantity of large redundant information. Then, preliminary segmentation doesn't simplify the classification process but tend to elongate the conceptual pass from pixels to meaningful semantic objects by multiplying information features with no semantic meaning. We propose as a first step in object-based image analysis an innovative fully automated fuzzy spectral rule-based per-pixel classifier, suitable for mapping radiometrically calibrated satellite images into a discrete and finite set of well-understood spectral categories. This classifier is based on purely spectral-domain prior knowledge taken from a reference dictionary of real world spectral signatures collected from satellite images calibrated into planetary reflectance and at-satellite temperature that requires no training and supervision to run. The output kernel spectral symbolic meaning is intermediate between those of clusters and those of land cover classes. It is used to drive stratified classifications involving in a second stage, complementary spectral indices, textural features and segmentation to calculate morphological, scale and contextual features. The efficiency of the proposed rule-based cascade system is tested in the context of mangrove ecosystems in Senegal.

Key-Words: Object-based image analysis, symbolic meaning of informational primitives, segmentation, Spot, ontology, mangrove.

1. Introduction

In recent years, object-based analysis image (OBIA) has been proposed as a feasible approach to handle the multiscale, hierarchical, and non-linear complexity of land cover mapping from remote sensing (RS) images. Consequently, OBIA has increased strongly its number of expert users and started to be considered as a semi-operational methodology that reproduces the time-consuming manual photo-interpretation of remote sensing data in an acceptable way for operational land cover mapping applications. The advantages of OBIA have to be considered in comparison to the previous pixel-based approaches. It was observed that the map produced from pixel-based methods, in particular when applied on high spatial resolution (HR) images, generally lack of spatial coherence because of spectral heterogeneity and spatial variance and present the well-known « salt and pepper » effect. Blaschke et al. (2000) showed that with per-pixel classification, single pixels are classified differently than the surrounding area and homogenous regions cannot be generated. Blaschke et al. (2001) proposed as an efficient solution the use of OBIA where homogeneous regions are first built up through a segmentation process (segments also called image objects) and in a second step, a classification process is applied to these image objects. OBIA relies upon an image simplification (compression) first-stage called primal sketch in the Marr sense (Marr, 1982) or preliminary mapping. Traditionally, a primal sketch is computed as an image partition (segmentation) whose segments are: i) connected, and ii) characterized by a uniform either brightness (luminance), or color, or textural content. It is well-known that picture segmentation (like data clustering) is a subjective and context-dependent cognitive process; in mathematical terms, this problem is ill-posed (Prechelt, 1996). As a consequence, the concept of pictorial uniformity characterizing image segments is necessarily vague (fuzzy). The same vagueness characterizes edge detection, which is the dual task of image segmentation, where "edge" means the "perceptual subjective notion of a region boundary" (Baraldi et al., 2005). To render the inherently ill-posed segmentation problem well-posed, image segmentation algorithms must employ: i) heuristic (subjective, application-dependent) constraints based on empirical user-defined parameters, and ii) an empirical stopping criterion, if no convergence criterion does exist. As a consequence, a) user-defined segmentation parameters are often provided with no physical meaning and are difficult to use, b) the segmentation algorithm may be not robust to changes in the input parameters, and c) the segmentation solution is suboptimal, i.e., it tends to be over-segmented in some image subsets while other small but genuine image details are lost (under-segmented). In existing literature, many image segmentation algorithms are implemented as fine-to-coarse (agglomerative, region growing) procedures providing a hierarchical (multiresolution) segmentation solution from which the user is let free to choose based on heuristics. In commercial image processing software toolboxes, to account for the subjective appraisal of continuous perceptual features involved with image partitioning, the user is allowed to select among a huge variety of input features, distance metrics, segment merging constraints, stopping criteria, etc. In common practice, RS practitioners provided with no searching criterion in the image segmentation space of solutions, find it difficult to reach image segmentation results suitable (in terms of either ease of use, computation time, or classification accuracy) for being employed as informational primitives by a second-stage object-based classification algorithm. Another limitation of actual OBIA methods is linked to the multiplication of features of all kinds provided with the objects: spectral features, shape features, textural features, scale features, contextual features... The freedom generally given in OBIA commercial softwares to the classification hierarchy and the way of using combinations of object features generally leads to confused and not transparent classification hierarchies that are difficult to reproduce and that lack of conceptual meaning either in the land cover or image cognition domains. To improve the classification hierarchy in OBIA, we propose to use the Shackelford and Davis classification hierarchy as a model for land cover classification (Shackelford and Davis, 2003). To apply such classification hierarchy, we propose here to replace the first step of the segmentation classically used in OBIA by a fuzzy spectral rule-based per-pixel pre-classifier detailed in Baraldi et al. (2005). The fully automated pre-classification used here provides objects and semantic and strata that authorizes the building of a conceptually meaningful, transparent and operational classification hierarchy. To evaluate the quality of the first-stage pre-classification, we test it on the mangrove ecosystems of Senegal.

2. Study area

The study area is the estuary of Low Casamance in South-western Senegal. The estuary is the downstream part of the catchment formed by the river Casamance. It is an almost flat area about 5 100 sqkm wide located between 12°10’ and 13° 06’ latitude North and 16° 15’ to 16° 48’ longitude West. The region is characterised by a sub-tropical climate with marked dry and wet season pattern. The estuary is composed of tidal floodplains with a multitude of mangrove-fringed channels (Bos et al., 2006). Behind and within mangrove stands there are large bare zones (*tannes)* occurring on slightly higher ground between the channels (Tappan et al., 2004). Herbaceous halophytes such as *Sesuvium portulacastrum* and *Paspalum vaginatum* or even salt crusts cover the *tannes*. Rice paddies which are mainly located in the tidal lowlands behind mangroves represent the largest agricultural surface. Since the late 1960s, the rainfall deficit linked to the 'Sahel drought' contributed to modify the physical-chemical conditions of ground and river water. The estuary has become inverse and hypersaline. Several authors reported the expansion of *tannes* and a die back of mangrove as consequence of salinity levels beyond species tolerance (Aizpuru et al., 2000; Bertrand, 1999; Cormier-Salem, 1999). Soil salinisation as consequence of drought has negatively affected rice cultivation thus contributing to land cover and land use dynamics in the area.

3. Satellite imagery and reference data set

The land cover mapping used a mosaic of SPOT images acquired in march of 2006. The spatial resolution of the multi-spectral images is 10m. Access to SPOT images was freely granted in the framework of the "Optimizing Access to SPOT Infrastructure for Science" program (OASIS) funded by the European Commission. Based on literature research and field knowledge, the following land cover classes were identified: mangroves; salt mud flats; *tannes*; herbaceous crops; tree savannah and tree cover. The last is a land use/land cover class since it corresponds to open forest of palm trees interspersed by fruit trees such as cashew nuts and mangos.

The classification was validated using a reference data set composed partly of ground truth points (November and December 2006 fieldwork campaigns) and of points collected from visual inspection of high resolution images available on the web (©2006Google Earth™). Google Earth™ combines different resolution images and update them on a rolling basis. In 2006, the coverage of the study area was updated with 5 m resolution images. The reference data set is composed of 1360 points; for each land cover class a minimum set of 150 reference points was obtained.

4. Methods

The objective of this paper is to verify that the first-stage semantic pre-classifier proposed by Baraldi et al. (2005) simplify, accelerates, clarify and improves the possibilities of a second-stage classification solution by reducing the complexity and the dimensionality of the image information content. Our method to check such hypotheses is to compare a supervised classification applied directly to the image with a supervised classification applied in cascade to the preliminary spectral rule-based classifier.

We used for both classifications a non-parametric k-nearest neighbor (k-NN) supervised classifier that is considered as an important benchmark classifier for its conceptual and computational simplicity and its effectiveness in many experimental environments (Bishop, 1995). The drawback of the k-NN classifier is that it requires all reference samples to be retained in memory (Nabney, 2002). This requirement may become a problem when the reference dataset size is large, which is not the case in this experiment where the small sample size problem is rather likely to occur (Baraldi et al., 2003). To optimize the selection of parameter k when the small reference sample size problem occurs, N-fold cross-validation is recommended. In this latter case, for any given k parameter, the finite reference dataset is randomly split into N parts, the (N -1) parts for training one specific k-NN classifier implementation and one part for testing the trained classifier. This training/testing process is repeated N times for each of the possible choices of the part omitted from the training process. In our case, N is set equal to 3.

For the two-stage classification procedure, the first-stage is constituted by a fully automated preliminary spectral rule-based classification (SRC). Details on the SRC classification algorithms are available in Baraldi et al. (2005) and Baraldi et al. (Submitted). The SRC is a primal sketch alternative to image segmentation pursued by means of a pixel-based spectral rule-based fuzzy classifier. Its decision rules consist of a set of prior knowledge-based fuzzy if-then rules whose activation domains provide an irregular but complete partition of the multi-spectral measurement space. Prior spectral knowledge, i.e., knowledge acquired before observing the data at hand, may be defined solely on analyst expertise and must be acquired (off-line) from reference datasets which must be well understood and well behaved. In our implementation, the reference dataset consists of a dictionary of spectral signatures radiometrically calibrated into top-of-atmosphere reflectance values. These reference spectral signatures are capable of characterizing a discrete and finite set of real-world land cover types as observed from a RS observing platform. Since it relies upon a well behaved and well understood real-world reference dataset, the fuzzy rule-based classifier at hand is non-adaptive (i.e., there is no system free parameter to set). In operational terms, this classifier is fully automated, i.e., it requires neither user-defined parameter nor ground truth data sample to run. As output, it generates a classification map whose pixels altogether with map segments altogether with map strata are provided with a semantic meaning (e.g., vegetation) intermediate between that (null) of clusters and segments and that (high, e.g., forest) of the land cover types.

To combine the semantic pre-classifier and the k-nn classifier, we adopted a stratified two-stage classification strategy. The first-stage pre-classifier provides in output a class-specific image stratification. The second-stage k-nn classifier is then applied to the class-specific strata selected according to Table 1. The overall accuracy are 88% and 93% and kappa statistics are 0.86 and 0.92 respectively for the non-stratified and SRC-based stratified classification processes. These results provide evidence that the SRC-based stratified classifier gives better classification results than a non-stratified classifier. The low standard deviation between the three training/testing combinations shows that this result is robust and that the sample set is of good quality.

	Ref. Samples	Prelim. Spectral Types
Mangroves	265	AVLNIR: 130 ; WVLNIR: 129 ; WE: 6
Tree cover	171	AVMNIR: 123 ; AVLNIR: 38 ; ASRLNIR: 10
Tree Savanna	188	WE: 130 ; TNCL: 45 ; ASRLNIR: 13
Herbaceous Crop	190	TNCL: 108 ; WE: 52 ; DBBF: 30
Tannes	177	DBBF: 115 ; WE: 45 ; TNCL: 17
Salt Mud Flat	106	DBBF: 63 ; TNCL: 40 ; TWASHSN: 3
Water	213	TNCL: 196 ; TWASHSN: 11 ; SLWASH: 6

Table 1: Semantic-based convergence-of-evidence between the reference samples and the preliminary spectral map. For acronym signification, refer to Baraldi et al. (2005).

5. Results and discussion

The figure 1 presents the pre-classification result of the first-stage preliminary spectral rule-based classifier and the results of the two classification results (for the one-stage and two-stage classification procedures) of a specific k-nn N-fold cross-validation. Finally Table 2 and 3 give the error matrices for the three training/testing combinations of the two classification procedures.

User Class \ Sample	HC	M.	SMF	T.	TC	TS	W.	Sum
Herbaceous crop	157	0	7	11	0	23	0	198
Mangrove	0	252	0	0	0	0	1	253
Salt mud flat	2	5	77	15	0	0	17	116
Tannes	4	4	18	149	0	0	3	178
Tree cover	0	0	0	0	165	8	0	173
Tree savannah	26	0	0	0	6	155	0	187
Water	0	3	6	2	0	0	192	203
Sum	189	264	108	177	171	186	213	1308
Producer	0,83	0,95	0,71	0,84	0,96	0,83	0,90	
User	0,79	1,00	0,66	0,84	0,95	0,83	0,95	
Overall Accuracy	0,88							
KIA	0,86							
Overall Accuracy Std Dev	0,020							

Table 2: Error matrix for the one-stage non-stratified k-nn classification. HC: Herbaceous Crop, M.: Mangrove, SMF: Salt Mud Flat, T.: Tannes, TC: Tree Cover, TS: Tree Savannah, W.: Water.

User Class \ Sample	HC	M.	SMF	T.	TC	TS	W.	Sum
Herbaceous crop	169	1	3	7	0	16	0	196
Mangrove	0	263	4	0	0	0	0	267
Salt mud flat	1	0	78	9	0	0	5	93
Tannes	7	0	11	160	0	2	1	181
Tree cover	0	0	0	0	170	0	0	170
Tree savannah	12	0	1	0	1	168	0	182
Water	0	0	11	1	0	0	207	219
Sum	189	264	108	177	171	186	213	1308
Producer	0,89	1,00	0,72	0,90	0,99	0,90	0,97	
User	0,86	0,99	0,84	0,88	1,00	0,92	0,95	
Overall Accuracy	0,93							
KIA	0,92							
Overall Accuracy Std Dev	0,034							

Table 3: Error matrix for the two-stage stratified k-nn classification. HC: Herbaceous Crop, M.: Mangrove, SMF: Salt Mud Flat, T.: Tannes, TC: Tree Cover, TS: Tree Savannah, W.: Water.

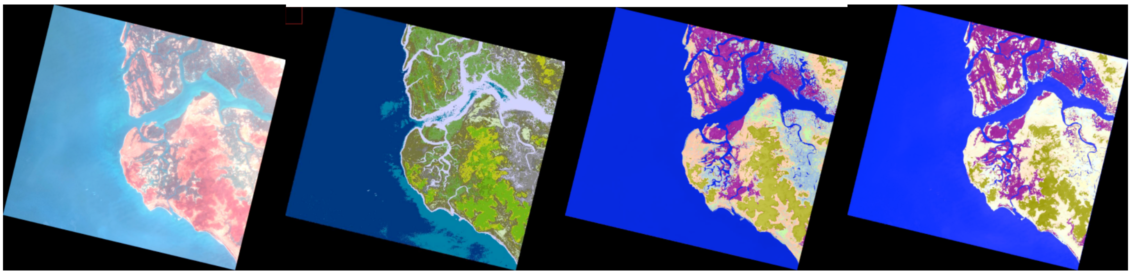

Figure 1. a) Spot 5 image ; b) Spectral primitives ; c) Classification result for the k-nn one-stage classifier ; d) Classification result for the two-stage stratified classifier

6. Conclusions

This study demonstrates that a two-stage SRC-based classifier which incorporates the "stratified" or "layered" approach achieve greater precision than a non-stratified classification approach. According to theory, this result implies that spectral data detected by SRC are "kernel" informational primitives which remain consistent with the spectral characteristics of interest. This test was based on mangroves mapping observed with SPOT data that have demonstrated in the past that they are suitable to study this type of ecosystem (Conchedda et al., 2008). Further studies must be conducted to define the second classification stage that will incorporate the "stratified" approach, where the input feature selection and the classification module implementation are class-specific. Second-stage class-specific stratified classification modules can exploit as input information:

- Semantic strata provided by the first-stage preliminary spectral classification.
- Color properties.
- Achromatic (brightness) properties.
- Textural properties.
- Morphological properties (investigated by means of morphological filters, where the target object's shape and size are known a priori and the target object is a bright object in a dark background, or vice versa).
- Geometric properties of an image object (e.g., area, perimeter, non-compactness, elongatedness, rectangularity, directionality, straightness of boundaries).
- Spatial non-topological relations among image objects , e.g., distance, orientation, etc.
- Spatial topological relations among image objects, e.g., inclusion, adjacency, overlap, etc.

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