GROUND TRUTH METHOD ASSESSMENT FOR SVM BASED LANDSCAPE CLASSIFICATION

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1. INTRODUCTION

Understanding spatial organization of natural and human structures in the context of global changes is a modern challenge. Detailed land cover thematic mapping is a key tool for decision makers. Remotely sensed data becomes a powerful instrument to monitor landscapes, the integration level of management decisions.

Over the past four decades, classification of remote sensing imagery is developed, initially from signal processing methods (e.g. maximum likelihood classifier (MLC)). Then, the development of remote sensing data with increasing spectral and spatial resolution and the enhanced computer processing capability have lead to the development of many new classifying techniques to map more precisely land covers. Numerous comparative studies come to the consensus that support vector machines (SVM) [1] are presently the most efficient classifier [2].

SVM are a semi-supervised method and need thus adapted training sets to be optimally functional. Nevertheless, in order to compare classifiers objectively, training sets have to be specified and adapted. Moreover, the dependence of the classifier to the training sets suggests that they are a key point to outperform the present classification accuracies.

This essay has two major objectives: (i) while the nature of an ideal training set is not clear, to explore this key stage and (ii) to suggest and apply a generic ground truth method to train efficiently our classifications.

2. MATERIAL AND METHODS

The study site is located in mont Marau, at the northwest of Tahiti, French Polynesia. Mont Marau is an endangered area of exceptional ecological value. But in mountainous areas, such as Pacific volcanic islands, access is limited and resources are difficult to evaluate in situ. That's why remotely sensed data represents invaluable information and land cover classification represents a helpful tool for eco-environmental monitoring.

A four channels (R, G, B, NIR) multispectral Quickbird scene from 2006 is used for the analyses. This very high resolution image allows computing efficient analysis on texture [3] to help species discrimination.

By nature, accuracy of a supervised classification depends on the quantity and quality of the data used in the learning and assessment steps. The chosen classifier accuracy may thus be impacted by the used training set.

In a large majority of studies, pure pixels are used for the SVM training stage. Nevertheless, Lesparre and Gorte [4] denote that mixed pixels can successfully be used to train a MLC and consider that this facilitates to estimate the spectra of the pure classes using mixed pixels, provided that the mixture proportions are known. In the same way, Foody and Mathur [5] show that the use of small training sets containing mixed pixels as boundaries between agricultural fields improves SVM classification. Foody and Mathur consider that unlike the conventional classifiers, the aim of SVM training is not to describe accurately the classes, but to provide information that will help fitting the classification decision boundaries - the hyperplanes - to separate them. Such boundaries between agricultural fields are privileged training areas thanks to the aggregation of information on pixels.

Training set size has to maximize accuracy without increasing needlessly ground sampling and computational times. For example, [6] state that the classification overall accuracy (OA) achieved by SVM is affected by the size of the training data set, as noted in the case of other classifiers. This behaviour could be related to the capability of the training pixels to adequately represent the characteristics of their respective classes. As the number of training pixel increases, SVM find pixels that better define inter-classes discriminating surfaces. We formulate the hypothesis that the classification accuracy and the number of training pixels are not linearly correlated because of their redundancy.

Training sets are usually made out of pure pixels characterizing homogenous areas. This traditional training method is compared with training on mixed pixels.

Pure pixels selection is carried out calculating a new proposed purity index.

Because satellite data are spatially correlated, ecotones (the transition area between two adjacent but different plant communities) are privileged areas of mixed spectral responses. Ecotones are often hard to distinguish in imagery when vegetal communities are a complex mosaic of different taxa. Moreover it is difficult to quantify their magnitude. Consequently, ecotones as landscape breakings are located using the Sobel's edge detection algorithm [7] since it proves to have a good accuracy/confusion trade-off [8].

Transects are drawn at 100 m in parallel to a road i.e. near enough for convenient questions and far enough to avoid a bias due to alien species over-representation. When an area is detected i.e. when the transect crosses a very pure area or a marked ecotone, one homogeneous region of interest (ROI) is sampled for the pure pixels sampling method or two ROI, in each side of the detected ecotone and in the transect direction, for the mixed pixels sampling. ROI surface is 450 m² because, according to phytosociologists, the minimal area (designated as the smallest area which can contain an adequate representation of a species association) for tree and shrub communities is more than 400 m² [9].

Validation set is composed by 25,000 pixels, i.e. ~ 1 ‰ of the mont Marau area, equally distributed between classes.

3. RESULTS

The training area - or number of pixels - is not linearly correlated with the OA but their relation is nearly logarithmic. Mixed pixels constitute actually the best training set for both classifiers. If classification schemes give similar results for the smallest training sets i.e. ~ 500 pixels, significant differences appear when this minimal size is outreached. This remark doesn't agree with [5], considering that the use of mixed pixels allows the use of smaller training sets in the set size range they studied. The most interesting point is the synergy between SVM and the training method based on mixed pixels areas.

Comparing classifiers, precisions are sensibly improved by the use of SVM face to the familiar Gaussian maximum likelihood classifier for both sampling methods. The same observation can be found in [10] and [11].

On the other hand, difference between sampling methods for the same classifier are significantly bigger than the inter-classifiers one which clearly shows the importance of training sets comparing classifiers. The optimal OA of 82 % is obtained combining SVM and mixed pixels based training set. Ecotones are thus very informative training areas providing aggregated spectral response of two different classes. Such a training set is particularly capable to bring adjacent classes' support vectors closer, optimizing the fitting of the separating hyperplane. Our results corroborate observations of [4] and [5] and validate the proposed method.

4. DISCUSSION AND CONCLUSION

The proposed comparison method has the advantage to be objective since training sets are not chosen subjectively. Another benefit of the proposed technique is that the selected mixed pixels are the most separable ones on the used imagery because they were chosen in function of their change rate (algorithm of Sobel).

This study proves that the use of mixed pixels is efficient in complex systems such as Polynesian landscapes, where intrusive vegetation cover boundaries represent a large area misclassified with conventional sampling methods. Sampling at the ecotones level consists to "show" to the SVM the most complex spectral situations to guarantee the effectiveness of their classification, hypothesizing that trained in difficult situations, the algorithm will classify easily the simplest cases. Moreover, training on pure pixels doesn't allow knowing precisely where limits between two classes are localized. In contrary, sampling at the ecotones level allows to compel the definition of each class in situ.

Finally, the presented study shows that the training stage could be more influential on classifier accuracy than classifiers themselves.

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