Toward an Optimal Fusion Scheme for Multisource Vegetation Classification

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Abstract - The accuracy of forest classification is generally improved by multisensor data fusion since tree species identification benefits from complementary information. However, hypothesizing multisource fusion can also deteriorate accuracy when a non-relevant source is added, we propose a fusion method for classes in difficulty. When the difficulty threshold we introduce is appropriated, our method outperforms the classical approach consisting in performing fusion for all classes. Moreover, the fusion processing time can widely decrease when several classes are put aside. This method can be used effectively to enhance accuracy and processing speed when analyzing the wealth of information available from remote sensors.

Keywords: Vegetation mapping; Ecosystem; Tropical forests; Image classification; Support vector machines; Multisensor systems; French Polynesia.

1. INTRODUCTION

Today, an increasing number of sensors of greater diversity is available to the remote sensing community. Such a variety of spectral, spatial and temporal resolutions has very useful complementary properties and can therefore outperform conventional single-source approaches (Benediktsson and Kanellopoulos, 1999; Chust *et al*., 2004; Blaes *et al*., 2005; Waske and Benediktsson, 2007). In this way, multisource classification represents a fruitful use of the diversity of remotely sensed data. Finding an optimal method for fusing multisource data is still a very challenging research topic, but only few approaches have been developed (see Hill *et al*., 2005; Tuia *et al*., 2010). One of the most classical studies in this field is probably Waske and Benediktsson (2007). They compare several algorithms, namely maximum likelihood, decision trees, boosted decision trees and support vector machines (SVM) for optical and synthetic aperture radar (SAR) data fusion. They point out that SVM outperforms the other four algorithms and denote that SVM fusion is more successful when applied to single-source decision functions than when applied directly to all sources together. The present paper claims to be in continuity with the latter work since the SVM-based fusion schemes they use is compared with the one we introduce. The aim of this study is thus to find an optimal fusion scheme based on SVM for multisource classification of vegetation.

2. MATERIALS AND METHODS

2.1 Study site and ground data collection

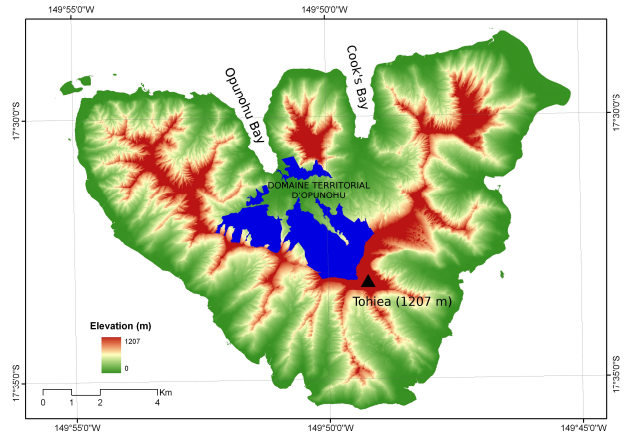Moorea is the fourth highest island in French Polynesia (South

Figure 1. The island of Moorea and its *Domaine Territorial de Opunohu* (in blue) where the study is conducted.

Pacific) with a highest point, mont Tohiea reaching 1207 m. It is a 134 km² island with a shape vaguely resembling a triangle with two nearly symmetrical bays opening to the north side: the Cook's and Opunohu Bays.

This study focuses on tropical forests which is a subject of great interest to scientists around the world. United Nations General Assembly declares 2011 as the International Year of Forests. Indeed, we argue that multisource image fusion is critical to classifying complex structures since each complementary source can contribute to classification success. Optical, infrared, SAR, digital elevation model (DEM) and multi-temporal data can therefore be useful for species identification according to their physico-chemical, anatomical, structural, ecological (via the topography) and phenological properties respectively. Conversely, one source is often satisfactory for classifying simple structures.

The *Domaine territorial de Opunohu* (Territorial Domain of Opunohu) (Figure 1) is ideal for our study since it is highly affected by anthropogenic activities (urbanization, farming, pineapple cultivation and tree plantation), biotic invasions and cyclones leading to a complex mosaic of dominant native, introduced and planted plant species (Table A).

Twelve 260 pixels circular regions of interest are selected and geo-localized with a handheld Trimble® GeoXH[TM] GPS for each of the eight dominating species of the study area. The analysis is therefore based on 24,960 pixels. Half of this area is used for classification training and half for validation. Balance data sets are used to avoid under- or over-representation problems (Waske *et al*., 2009).

Table A. Class set

Dominant species class set	Status
Hibiscus tiliaceus	Indigenous
Inocarpus fagifer	Polynesian introduction
Neonauclea forsteri	Indigenous
Aleurites moluccana	Polynesian introduction
Falcataria moluccana	Exogenous and invasive
Pinus caribaea	Exogenous and invasive
Casuarina equisetifolia	Indigenous
Cloud forest	60% of the native flora is found in CF

2.2 Remotely sensed data

The experiment is carried out on three data sets, namely a multispectral image, a SAR image and a digital elevation model (DEM), projected in the WGS 84 – UTM 6 South coordinate system.

For the first image type, we selected a four-bands and 0.60 m-resolution Quickbird scene from November 9, 2006. It is geometrically corrected using the cubic convolution approximation technique, more suitable than nearest neighbour and bilinear interpolation techniques according to Arif *et al.* (2006). The near infrared band is useful for vegetation studies (Boureau, 2008) and very high spatial resolution is critical for plant species discrimination (Xie *et al.*, 2008; Turner *et al.*, 2003) using texture metrics for example.

Eight gray-level co-occurrence matrix (GLCM) texture metrics are extracted from this data: mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation (Haralick *et al.*, 1973). They are calculated in the 15x15 pixels window size, determined as optimal after several tests. Since GLCM texture metrics have a strongly different nature than the spectral information, they were considered as a separated source.

For the second image type, two 2.5 m-resolution StripMap TerraSAR-X acquisitions were programmed over Moorea on April 30, 2010 in VV-VH polarizations and on August 28, 2010 in HH-HV polarizations. The scenes are geometrically corrected using a 5 m-resolution DEM.

The same eight GLCM texture metrics are again extracted from the TerraSAR-X data. They are also considered as a separate source.

The third data set is the DEM produced from a photogrammetric restitution at a scale of 1/5000 based on aerial photography from 1997 at a scale of 1/15000. It is shifted from the RGPF – Moorea 87 local coordinate system to the WGS 84 – UTM 6 South. With a 5 meter resolution it enables extraction of topographical variables typically impacting plant distribution in montane ecosystems: elevation, slope, aspect and a wetness index (Gessler *et al.*, 2000). The wetness index was used as an index of water drainage. With low wetness index values representing convex positions like mountain crests and with high wetness index values representing concave positions like

coves or hill slope bases. It is a function of the slope angle β (in radians) and the specific catchment area (As) expressed as m² per unit width orthogonal to the flow direction (1).

$$Wetness\ index = \ln\left(\frac{As}{\tan\beta}\right) \qquad (1)$$

2.3 Support vector machine method

SVM is arguably one of the most successful statistical tools for multisource fusion (Waske and Benediktsson, 2007; Halldorsson *et al.*, 2003; Song *et al.*, 2005; Fauvel *et al.*, 2006). SVM consists in projecting vectors into a high dimension feature space by means of a kernel function then fitting an optimal hyperplane that separates classes using an optimization function (2). For a generic pattern $\mathbf{x}$, the corresponding estimated label $\hat{y}$ is given by (2).

$$\hat{y} = \text{sign}[f(\mathbf{x})] = \text{sign}\left(\sum_{i=1}^{N} a_i.y_i.K(\mathbf{x_i}, \mathbf{x}) + b\right) \qquad (2)$$

Wherein N is the number of training points, the label of the ith sample is y_i, b is a bias parameter, $K(\mathbf{x_i},\mathbf{x})$ is the chosen kernel function and a_i denotes the Lagrangian multipliers.

SVM is introduced by Vapnik (1998) and extensively described by Burges (1998), Schölkopf and A. Smola (2002) and Hsu *et al.* (2009). As suggested by the latter and supported by many other papers, we use the radial basis function (RBF) as the kernel. The equation is (3).

$$K(\mathbf{x_i}, \mathbf{x}) = \exp-\frac{\|\mathbf{x_i} - \mathbf{x}\|^2}{2\sigma^2} \qquad (3)$$

Noise in the data can be accounted for by defining a distance tolerating the data scattering, thus relaxing the decision constraint. This regularization parameter C as well as σ are found by cross-validation.

SVM have been created for two-class problem but extensions have been developed to deal with Q class problem. Among them, we choose the One-Against-One algorithm which consists in the construction of $Q(Q-1)/2$ hyperplanes which separate each pair of classes.

2.4 Fusion schemes comparison

We compare the following two fusion schemes based on SVM (Figure 2):
- Waske and Benediktsson (2007) method: a single SVM is trained on each source separately and a rule image is generated for each class on each source. Then an additional SVM is trained on rule images of each single-source classification to perform the fusion;
- fusion for classes in difficulty: The general principle is the same but fusion is performed only when no single source is able to classify satisfactorily a class or a set of classes. A difficulty threshold α is therefore introduced to define whether a class is in difficulty or not. Assuming for a given class that $\alpha > \min(\text{PA}_{source\ i}; \text{UA}_{source\ i})$ (wherein i $\in$ [1,5], PA is the producer accuracies and UA the user accuracies), the class is not considered as in difficulty, the spatial distribution of the considered class is taken from the most accurate single-source classification (the source having the best OA) and the class is expelled from fusion. If a pixel belongs to several classes with this process, the class with the best
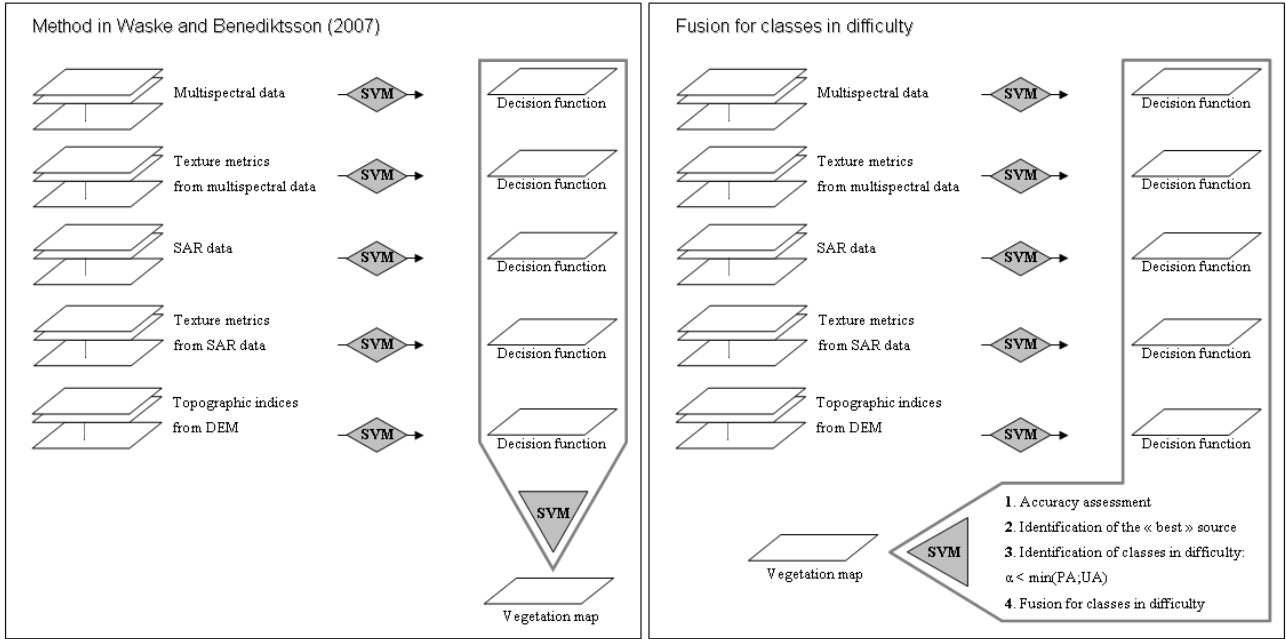
Figure 2. Diagram of fusion method in Waske and Benediktsson (2007) compared with the fusion for classes in difficulty we introduce.

$\min(PA_{source\ i}; UA_{source\ i})$ wins. If $\alpha < \min(PA_{source\ i}; UA_{source\ i})$, the class is considered as in difficulty and fusion is performed.

3. RESULTS AND DISCUSSION

3.1 Accuracy assessment

Comparing the different sources, TerraSAR-X spectral and contextual data performed worst in term of accuracy (Table B). The reason may be that even if it gives useful information on the structure of the vegetation cover, such data is not able to discriminate such a fine class set at the species scale. Classification from DEM gives an OA of 42.5 and a Kappa of 34.3 but these average results hide tremendous differences between classes. In particular, the PA and UA of the cloud forest class are 100 which means that topography is sufficient to explain the spatial distribution of this habitat in the *Domaine Territorial de Opunohu*. The Quickbird imagery achieves the highest accuracies of single-source classifications. GLCM texture metrics appear as highly relevant for tree species discrimination. More probably than their color, it is thus the layout of crowns, branches and leaves that allow the SVM to identify one species from another.

Regarding fusion methods, accuracies are improved when multiple sources are used for classification. The experimental results clearly show the positive impact of complementary multisensor imagery for forest classification. Comparing the different fusion methods, fusion for classes in difficulty slightly outperform the method in Waske and Benediktsson (2007) when the difficulty threshold α is fixed between 87.0 and 96.8 (Figure 3). At this threshold, fusion is performed for each classes except for *Aleurites moluccana* which has a PA=96.8 and a UA=97.5 from the texture extracted from the Quickbird data only and the cloud forest which has a PA=100.0 and a UA=100.0 from the DEM only. For these two classes, we pointed out that fusion can deteriorate accuracy when not used appropriately. Indeed the addition of non-relevant sources acts as a bias in the classification process. Fusion for classes in difficulty has as main advantage to select classes which can

Table B. Accuracies (%) achieved by SVM using different source

Source	OA	Kappa
Quickbird	64.8	60.4
Texture metrics from Quickbird	84.6	82.7
TerraSAR-X	23.0	12.0
Texture metrics from TerraSAR-X	42.0	33.9
DEM	42.5	34.3
Method in Waske and Benediktsson (2007)	93.9	93.0
Fusion for classes in difficulty	95.4	94.7

benefit from multiple information sources and thus to be not too global.

By performing fusion for classes in difficulty, we only tested seven combinations of classes for fusion. In reality, 240 other combinations of classes exist and should be tested since we can suppose that at least one of them performs better than the optimal combination of classes we used, namely all classes except *Aleurites moluccana* trained on texture extracted from the Quickbird data only and cloud forest trained on the DEM only. Such a test may be computationally demanding but should be implemented in the future.

3.2 Fusion processing time assessment

The fusion processing time and the number of classes considered for SVM fusion can be fitted by a quadratic regression giving an $r^2=99.9\%$ (data not shown). As a result, by limiting the number of classes in the fusion, processing time can be significantly reduced. For example when $Q=6$ i.e. in the optimal combination of classes we tested, fusion processing time is half the time when $Q=8$.
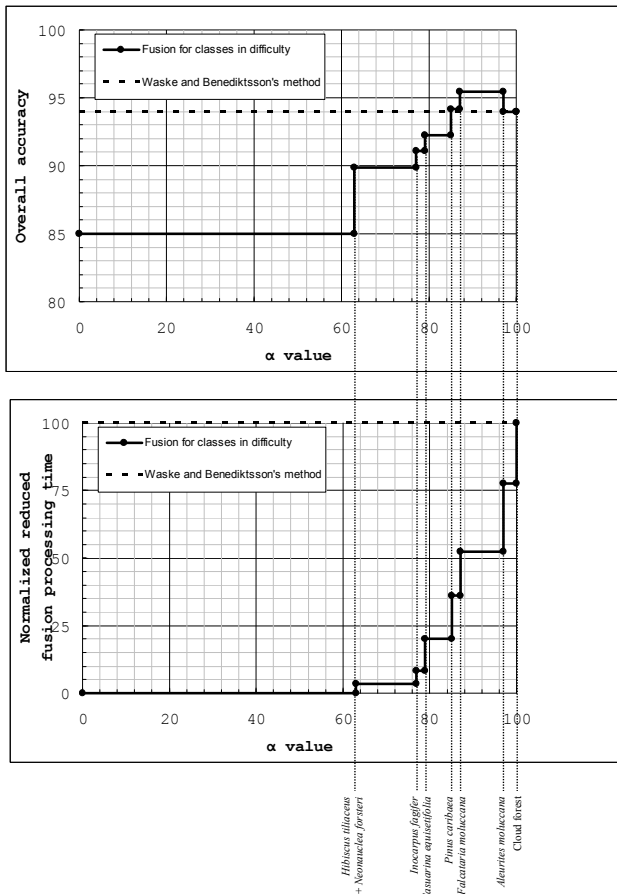
Figure 3. Evolution of the overall accuracy and the fusion processing time according to the difficulty threshold (α) introduced with the "fusion for classes in difficulty" method. Regarding its value, classes are considered as in difficulty and fusion is performed or not. Here, the optimal value of α is in the range 87.0-96.8.

4   CONCLUSIONS

In this study, two fusion schemes based on SVM were compared for multisource classification of French Polynesian tropical forests. Contrary to the classical global approaches, we proposed to use fusion for classes in difficulty only. Classes accurately classified with a single-source are expelled from fusion since we show that fusion can perform worse than single-source classification for some classes. Our method slightly outperformed the classical global approaches in term of accuracy and reduced by a factor 2 fusion processing time in our study case.

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