Primary Forest and Land Cover Contextual Classification using JERS-1 data in Amazonia, Brazil

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We present a methodology for land cover and primary forest mapping in Amazonia using textural features derived from JERS-1 data and classified with a multi layer perceptron based contextual method. Land cover classification is an important step towards the use of radar data as a tool for land use change studies in Amazonia. Also, primary forest classification is an important issue in ecosystem studies and economical assessment of sustainable timber exploitation. The use of radar data, particularly L-band data, is justifiable as large Amazonian area is permanently cloud covered. Considering a set of primary forest and land use classes of interest in the Tapajós National Forest and adjacent regions, Pará State, Brazil, it was investigated which classes could be distinguished using textural features derived by co-occurrence and matched filtering techniques. Non-discriminating classes were grouped together to form new classes resulting in two classes of primary forest, three classes of land use, water and aquatic vegetation. The feature set with higher overall accuracy was used to classify a small mosaic of the region, using a contextual neural network based classifier with 87% overall accuracy.

INTRODUCTION

Key questions in Amazonian studies are: how do deforested areas evolve? Are these areas left to regenerate after deforestation? Another question is how to classify different types of primary forest. Different types of forest have different potentials for sustainable exploitation. Recent studies based on visual interpretation and usage of established classification techniques exhibited weaknesses concerning correct classification of all classes of interest in Amazonia, particularly different types of primary forest. Sometimes only forest-non forest discrimination is possible. Image texture is a key factor to discriminate primary forests, while L-Band backscatter has the ability to discriminate forest from non-forest.

Field work and prior knowledge of the study area permitted to establish initially 11 classes for Tapajós area. From the original radar image 28 feature images were extracted. Using 2 discrimination ranking coefficients, based on average Jeffries-Matusita distance (JMD) [1] for the classes, 11 features were selected and clusters of classes identified by very small JM distance were grouped. With the new set of classes an exhaustive evaluation of classifier performance on all possible features subsets was executed. The best subset was chosen and the overall accuracy of final classification map obtained. In the following, these steps are explained in deeper detail.

The Tapajós National Forest (FLONA) is located south of city of Santarém, Pará State, Brazil, between the parallels 2:40' to 4:10' and the meridians 54:45' to 55:00. It borders on the east with Santarém-Cuba Highway and the west with Tapajós River. In the last few decades FLONA has presented dynamic alterations resulting from human occupation. Many of these areas have been abandoned and are under regeneration by secondary succession. FLONA is composed by several types of primary forest with different types of soil and soil relief. Initially 11 classes are defined for analysis which are: 1)dense forest – dissected plateau (DFDP); 2)dense forest – high plateau (DFHP); 3)urban areas; 4)open forest (OF); 5)dense forest – sedimentary area (DFSA); 6)mature regeneration; 7)pasture; 8)bare soil; 9)abandoned (dirt) pasture; 10)water; 11)aquatic vegetation. It was used the scenes 405/306 and 405/307 (acquired Aug 13, 1996) and provided by NASDA under the Global Rain Forest Monitoring Project (GRFM). Fig. 1 presents a mosaic of samples of these classes.

FEATURE EXTRACTION

The first step is obtaining texture features from the original image of three different types: local statistics; co-occurrence and variance from inverse matched filtering.

Local Statistics Filters. (calculated in 5x5 window).

f_0 – original backscatter (processed by Lee [2] filter);
f_1 - coefficient of variation for amplitude (CVa);
f_2 - coefficient of variation for intensity (CVi);
f_3 – coeff. of variation for square root of amplitude (CVs);
f_4 – contrast;
f_5 – homogeneity;
f_6 - trimmed range of data in a window (TM).

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Texture features are calculated from unfiltered amplitude image in a 5x5 window. Three kinds of coefficient of variation (standard deviation/average) were used to verify which type is more discriminating. Trimmed range is an order statistics filter and stands for the difference between the second and the next to the last in the sorted list of backscatter values in a 5x5 window.

Co-occurrence Filters.

Grey-level co-occurrence matrices GLCM are derived from pair-wise pixel intensity statistics [3]. We use a single GLCM for angles of 0,45,90 and 135 degrees and d=1 and extract the following features from this undirected GLCM, calculated in an 11x11 sliding window. Pixel values were quantized to 16 levels.

f_7 - Energy	f_{12} - Correlation
f_8 - Entropy	f_{13} - Cluster shade
f_9 - Max. Probability	f_{14} - Cluster prominence
f_{10} - Contrast	f_{15} - Information correlation I
f_{11} - Homogeneity	f_{16} - Information correlation II

Matched Filtering.

Local statistics and co-occurrence filters were unable to provide separation for any type of primary forest. Additional texture information was provided by calculating the output variance of a bank of matched whitening filters. Firstly five feature detectors, e.g. Laws filters [4] of length 9 were applied to the original image. Eigenvalues and corresponding eigenvectors were calculated for each class training region from the Laws filtered feature space. The eigenvector (a weighted average of Laws filters) corresponding to the smallest eigenvalue is equivalent to a matched inverse filter which ensures minimum variance in its output when filtering a region from which the filter was derived. Any unitary linear transformation different from the matched eigenvector, when applied to the region, will give higher variance in the output. The last eigenvector also has the property of whiten the output residues. Five Laws filters were used because it was observed that the rank of covariance matrices was not higher than five if more than five Laws filters are used. 11 Features corresponding to 11 inverse matched filtered channels, where each matched filter corresponds to each one of the studied classes complete the set of 28 features(from feature f_{17} to f_{27}).

FEATURE SELECTION AND CLASS GROUPING

Selection of Features Based on Ranking.

Given the high dimensionality of the feature space (28 features) the use of exhaustive evaluation of overall accuracy is not feasible. JMD is widely used to measure separability between distributions and also used as feature selection criterion. JMD, however, is unsuitable to choose a sub-set of features of any possible size because it is monotonic increasing with dimensionality, while overall accuracy (ov. acc.) is not in most of cases. Two ranking coefficients were proposed, one based on presence of the investigated feature in the upper half set of higher JMD subsets, the other is based on the average JMD distances for all subsets containing that particular feature.

Considering both rankings the following set of 11 features was selected: f_0 – original backscatter; f_2 - CVi; f_6 – TM; f_7 – Energy; f_8 – Entropy; f_{10} – Contrast; f_{11} - Homogeneity and the features f_{17}, f_{19}, f_{23} and f_{24} corresponding to matched filters output variance of classes DFDP; urban areas; pasture and bare soil. It is possible to observe that features originating from different groups are represented in this subset. Worthwhile to note that CV for intensity had slightly better performance on both ranks.

Class Grouping.

With eleven features, exhaustive search based on ov. acc. (calculated over validation areas) is feasible. It was observed however that many classes a-priori defined are very close in this feature space. A class grouping method was used to detect and merge those classes.

Using the information of pair-wise JMD calculated in the 11-feature space a graph with classes as nodes can be constructed: fixing one class as a start and looking for the next closest class in terms of JMD, an edge is drawn between these 2 classes. For the last class the next closest class is looked for until the graph is completed. The graph is traversed by selecting the edge of minimum cost measured by JMD until each node was visited exactly once. Grouping of classes is controlled by setting a threshold on the JMD and therefore dividing the graph into components of size greater or equal to one node. Clusters of classes are characterized by JMD below a threshold between closest neighbours. Considering a threshold of 0.7, a new set of classes classes is now used: 1)DFDP; 2)flat forest (FF) which is composed by DFHP, OF, DFSA and mature regeneration; 3)urban areas; 4)pasture + bare soil; 5)abandoned (dirt) pasture; 6)water and 7)aquatic vegetation.

EXHAUSTIVE SEARCH AND CLASSIFICATION

Each possible subset of features from the set with 11 features is used to train a one hidden layer multilayer perceptron (MLP) classifier by resilient back-propagation (RPROP) method. The subset which gives the higher ov. acc. calculated on a validation set is selected. Training and validation sets are composed by 500 randomly chosen points per class. The best subset of features is composed by eight features: f_0 – original backscatter; f_2 – CVi; f_8 – Entropy; f_{10} –

Contrast; f_{11} – Homogeneity and f_{17}, f_{19} and f_{24} corresponding to matched filters output variance of classes DFDP; urban areas and bare soil.

MLP contextual classification.

A particular case of the ICM [5] contextual classification method is adapted to be used with MLP, where the neurons activations are used instead of the statistical likelihoods of classes. The algorithm begins with the initial MLP classification map and iteratively alters the classification result until ov. acc. calculated on the validation set stops increasing or begins to fall. Table 1 presents the ov. acc. together with Tau coefficient of agreement [6] considering the classification result using the best features subset and classifying into the seven grouped classes. For comparison the MLP classifier was trained on basic features, e.g. filtered backscatter image and intensity coefficient of variation, using the same training samples. See first column of Table 1. Fig.2 shows the result of contextual MLP classification.

Table 1: Classifier Performance for MLP (%)

validation sets	Basic Features	Best Subset	Best Subset + Context
Overall Accuracy	53.7	80.2	86.5
Tau	45.6	76.9	84.2

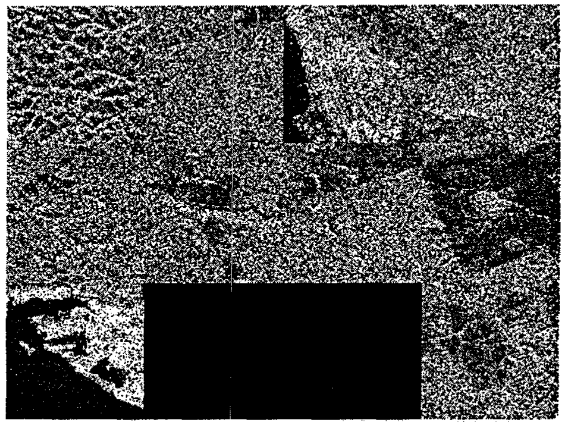

Figure 1: Mosaic of class samples for Tapajós area

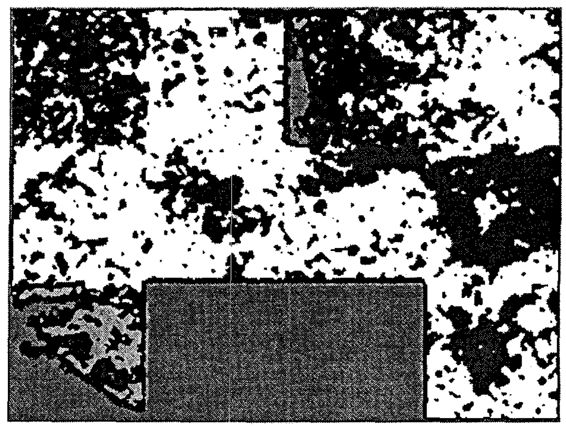

Figure 2: Classification of Tapajós site using MLP

DISCUSSION

As shown in the results texture feature extraction plays an important role in land use classification when using JERS-1 imagery. Particularly, feature extraction from matched filtering allowed a better discrimination of dense forest of dissected plateau, which normally would be confused with most classes because its undulated relief. The proposed method of matched filtering by principal components transformation can be extended to use other type of filter banks, which is now under investigation. We presented also a methodology to class grouping based on JMD and a proposition to contextual classification using MLP classifier based on existing ICM algorithm.

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