A Hybrid Approach Classification of Remote Sensing Images

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Abstract. The use of a hybrid approach classification, which combines pixels and objects, has been shown to be suitable for the identification of Landscape Units that contain a variety of land cover objects using VHSR images. However, the pixel-based classification of remote sensing images performed with different classifiers usually produces different results. With the combination of the outputs of a set of classifiers it is possible to obtain a classification that is often more accurate than the individual classifications. In this paper the author analyzes if the use of an output combination of a set of soft classifiers in a hybrid approach classification, can improve the accuracy of the results. To this end, a hybrid classification method was developed that includes the following steps: 1) pixel-based soft classification; 2) computation of the classification uncertainty; 3) development of rules to combine the soft classifications, which incorporate the information provided by the previous pixel-based classification and the results given by the uncertainty measure 4) image segmentation; and 5) object classification based on decision rules which include the results of the combined soft pixel-based classification and its uncertainty. The proposed methodology was applied to an IKONOS image. The overall accuracy of the hybrid approach classification obtained with the proposed methodology was higher than the ones obtained with the individual pixel-based classifications, which shows that the methodology is promising and may be used to increase hybrid classification accuracy.

Keywords. Soft classifiers, uncertainty information, combining soft classifications.

1. Introduction

A large number of classifiers and classification methods are available to automatically extract thematic information from multispectral images. A group of classifiers particularly used are the supervised classifiers, which perform the classification process in two phases: 1) the first phase includes the identification of training areas in the image for each class, which are used as descriptors of the spectral characteristics of the classes; 2) the results obtained in the first phase are used to assign to each spatial unit of the image (usually a pixel or an object) a class, or several classes if soft classifiers are used. However, different classifiers produce different classification results even when they are applied to the same image using the same training sets. This is because classifiers have different capabilities and their performance depends on the application fields and image characteristics.

During the last two decades, considerable research has been carried out, and several approaches have been proposed for combining hard classifications or soft classifications. Through the combination of the outputs of a set of classifiers it is possible to obtain a classification that is often more accurate than the individual classifications ([1], [2], [3], [4], [5]). In addition, several studies showed that traditional pixel-based classification methods are not suitable to identify many types of land cover classes when applied, for example, to VHSR images ([6], [7]). In [8] Wang referred to the fact that its necessary new methods which incorporate shape and context, which are some of the main clues used by a human interpreter. Object-based classification methods and hybrid methods composed of pixel-based and object-based classifications have been proposed to incorporate spatial
information into the classification procedure ([8], [7], [9]). Several researches have also been carried out in the development of soft classifiers to extract information from remote sensing images ([10], [11], [12], [13]). These classifiers enable the generation of probability or possibility distribution, for each pixel or object, depending on the classifiers used, where each probability or possibility degree is associated with a class of the nomenclature. The spatial units (pixel or object) are assigned to the class presenting the larger degree of possibility or probability. This additional information may be used as indicators of the classifiers difficulty to assign only one class to the spatial unit, and, together with the application of uncertainty measures, may provide valuable information that can be used in combined classification methods [5] and in hybrid classification approaches [14]. In [14] Gonçalves et al., for example, a new hybrid classification approach was proposed that integrates combined pixel-based soft classification, objects and includes the uncertainty information associated with the pixel soft classification, into the objects-based classification based on decision rules. The introduction of uncertainty information in the hybrid classification process has proven to increase the accuracy of Land Units classification and enables the identification of the main forest species in Portugal.

This study tests whether the use of an output combination of a set of soft classifiers in a hybrid approach classification can improve the results accuracy. In this new hybrid classification method proposed the uncertainty information was used in two steps. First, for combining the outputs of two pixel-based soft classifications. This was done through the development of rules that incorporate the information provided by the previous pixel-based soft classification and the results given by the application of an uncertainty measure. Second, in the hybrid classification process where the segmented objects obtained, which represent the Land Units existing in the study area, are classified through decision rules which include the results of the combined soft pixel-based classification and its uncertainty. The main objective of integrating uncertainty in the classification process is to avoid the use of misclassified pixels in the classification.

2. Data

The study was conducted in a region in the south of Portugal. The area was occupied mainly by agriculture, pastures, forest and agro-forestry areas. The dominant forest species in the region are eucalyptus, coniferous and cork trees. An image obtained by the IKONOS sensor was used, with a spatial resolution of 4m in the multi-spectral mode (XS) and a dimension of 11.8 km by 8.7 Km. The geometric correction of the multi-spectral image consisted of its orthorectification. The average quadratic error obtained for the geometric correction was of 1.39m, less than half the pixel size, which guarantees an accurate geo-referencing.

3. Methodology

The main goal of the classification is to obtain a Land Unit Map (LUM), where the Land Units (objects) have a mean area of 0.5 ha, using a new hybrid classification approach that integrates the combination of the outputs of two pixel-based soft classifications and their uncertainty information to classify the LU. The two soft classifiers that were used in this application were the following: 1) the neural network Multi-Layer Perceptron (MLP); 2) a pixel-based supervised fuzzy soft classifier based on the underlying logic of Minimum-Distance-to-Means (FMDM). The classifiers were trained using the same sampling protocol that included 100 pixels per-class. The classes used in this study are: Eucalyptus Trees (ET); Cork Trees (CKT), Coniferous Trees (CFT); Shadows (S); Shallow Water (SW), Deep Water (DW), Herbaceous Vegetation (HV), Sparse Herbaceous Vegetation
These classification methods assign different degrees of assignment to each pixel, in the case of MLP, and different degrees of possibility, in the case of FMDM, to the several classes under consideration. This extra data provide additional information at the pixel level which allows the assessment of the classification uncertainty. To analyze if the use of an output combination of a set of soft classifiers in a hybrid approach classification, can improve the results accuracy a similar method, where the combination of the two classifiers and the classification uncertainty was not considered, is also presented. The hybrid classification method that was developed includes the following steps: 1) pixel-based soft classification; 2) computation of the classification uncertainty; 3) development of rules to combine the soft classifications, that incorporate the information provided by the previous pixel-based classification and the results given by the uncertainty measure 4) image segmentation; and 5) object classification based on decision rules which include the results of the combined soft pixel-based classification and its uncertainty. The second method that not takes into consideration the output combination of pixel-based classifications and their uncertainty includes three steps: 1) pixel-based classification of the image; 2) image segmentation and 3) object classification based on decision rules. The paper focuses only on the first methodology since the second one was already presented in [14].

3.1. Combination of soft classifiers

The outputs of the two individual soft classifiers were combined through the use of an uncertainty measure. If the output classes for each individual pixel differed, the uncertainty information was compared and the class assigned with the lower value of uncertainty is chosen to be the one assigned to the pixel. In this approach the uncertainty measure $E$, developed by [15], was used to quantify the uncertainty at each spatial unit. This measure is given by

$$
E = 1 - p(x_i)
$$

where $p(x_i)$ is the largest degree of possibility or probability of the possibility distributions or probability distributions assigned with the pixel. This measure is also called ambiguity measure [16].

The first phase of the algorithm developed to combine classifications checks whether the same class is assigned to each pixel by both classifiers. If this condition is satisfied the class is accepted. If the two classifiers have different results for a certain pixel, the ambiguity information is used to make a judgement. The class with the lower ambiguity value is taken as the output for the pixel.

To evaluate if the combined classification improves the results, the accuracy assessment was made with the same protocol used with the single classifiers and the results were compared.

One of the classifiers used was the MLP neural network which is a non-parametric method and is the most commonly used in remote sensing. Details of the MLP can be found in [17] and in [18]. The MLP provides an activation level for every output class of each pixel, and for hard classifications each pixel is allocated to the class with the largest activation level. A soft classification may be derived from this classifier by considering the activation levels of the network output units for each pixel. These activation levels range from 0 to 1, and may be used as indicators of the uncertainty associated with the pixel allocation to the classes.

The other classifier used was a pixel-based supervised fuzzy classifier based on the underlying logic of the Minimum-Distance-to-Means classifier. Details of the fuzzy classifier can be found in [19]. With this method the image is classified based on the information contained in a series of signatures files and a standard deviation unit (Z-score distance) chosen by the user. The fuzzy set membership is calculated based on a standardized Euclidean distance from each pixel reflectance, on each band, to the mean reflectance for each class signature, using a sigmoid membership func-
tion [20]. The underlying logic is that the mean of a given signature represents the ideal point for the class, where fuzzy set membership is one. When distance increases, fuzzy set membership decreases, until it reaches the user-defined Z-score distance where fuzzy set membership decreases to zero. To determine the value to use for the standard deviation unit, the information of the training data set was used to study the spectral separability of the classes and to determine their average separability.

Unlike traditional hard classifiers, the output obtained with these classifiers is not a single classified map, but rather a set of images (one per class) that expresses the probability, for the first classifier, and the possibility, for the second one, that each pixel belongs to the class in question.

To evaluate the classification accuracy of the two individual soft classifications and the combined results, a stratified random sampling with about 100 pixels per class was selected considering the entire image scene, which also included mixed pixels. The number of pixels was chosen to obtain a standard error of 0.05 for the estimation of the accuracy indexes of each class [21]. Each land cover class was sampled independently and the accuracy assessment was made with an error matrix.

3.2. Classification of the land units

The Landscape Units Map (LUM) was built using the combined output of the pixel-based classification, its ambiguity information and the objects obtained with the segmentation algorithm. In the segmentation stage the whole image was partitioned into a series of closed objects, corresponding to the spatial patterns. The objects extraction was driven using the “Fractal Net Evolution Approach” (FNEA) segmentation method, implemented in eCognition software, which can be described as a region merging technique [22].

In this study only one segmentation level was considered, chosen from a series of experiments done with different parameters, whose results were visually analyzed. The criteria that led to their choice was the identification of meaningful image-objects i.e., groups of pixels that represented the LU existing in the study area, with a mean area of 0.5 ha. The next step was the development of rules that incorporate the information provided by the combined pixel-based classification within each object and the results given by the ambiguity measure E. The rules construction requires a preliminary analysis of the ambiguity assigned to the classes in order to choose the appropriate thresholds.

The classification of the LU is similar to a decision tree which, for geographical objects, is a hierarchical structure consisting of several levels. At each level a test is applied to one or more attribute values. The application of a rule results either in a leaf, allocating an object to a class, or a new decision node, specifying a further decision rule. In this study eight LU classes were used: Water Bodies (WB), Agriculture and Pasture Areas (A), Non-Vegetated Areas (NVA), Broad-Leaved Forest (BF), Coniferous Forest (CFF), Cork Forest (CF), Agro-Forestry Areas (AFA) and Mixed Forest (MF).

Table 1 shows the classification rules. The aim of rule 1 is to make a distinction between ‘Forest Areas’ and ‘Non-Forest Areas’. Rule 2 assigns the objects considered ‘Non-Forest Areas’, to one of the three LU classes: Water Bodies, Agriculture, and Non-Vegetated Areas. Rule 3 classifies the ‘Forest’ regions into Broad-Leaved Forest, Coniferous Forest, Cork Forest and ‘Mixed or Non-Dense Forest’. Finally, rule 4 assigns the objects considered ‘Mixed or Non-Dense Forest’ to one of two possible LU classes: Agro-Forestry Areas and Mixed Forest. The structure of the rules is based in the ones used on the study performed by [14].

For the accuracy assessment, the sampling unit to assess the accuracy of the LUM was a fixed-area square plot sampling unit with an area of 0.5 ha. A stratified random sampling of about 50 samples per class was chosen, which guarantees a standard error of 0.07 for the CPM and CPR estimates for each class, assuming that the classification accuracy is superior to 50% [23], which is
acceptable because the construction of the LUM already involved a prior pixel-based classification and an analysis of the terrain. The accuracy assessment was made with an error matrix, where the pij entry is the proportion of area that is class i in the map and class j in the reference within the square areas with 0.5 ha. The CPM and CPR accuracy parameters were then derived from the error matrix [24].

Table 1. Classification Rules.

<table>
<thead>
<tr>
<th>Rules</th>
<th>Test</th>
<th>Class if true</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule 1</td>
<td>Objects which have more than 10% of SE classified as tree crowns, regardless of species, with ambiguity less than 0.5</td>
<td>Forest</td>
</tr>
<tr>
<td></td>
<td>Objects which do not satisfy the previous test</td>
<td>Non-Forest</td>
</tr>
<tr>
<td>Rule 2</td>
<td>The mode of the SE, inside the object, with ambiguity less than 0.5 is Deep Water or Shallow Water</td>
<td>Water Bodies</td>
</tr>
<tr>
<td></td>
<td>The mode of the SE, inside the objects, with ambiguity less than 0.5 is Herbaceous Vegetation or Sparse Herbaceous Vegetation</td>
<td>Agriculture</td>
</tr>
<tr>
<td></td>
<td>The mode of the SE, inside the objects, with ambiguity less than 0.5 is Non-Vegetated Area or Shadow</td>
<td>Non-Vegetated Areas</td>
</tr>
<tr>
<td>Rule 3</td>
<td>Eucalyptus Trees represent more than 75% of the trees or objects which have only Broad-Leaved Trees inside</td>
<td>Broad-Leaved Forest</td>
</tr>
<tr>
<td></td>
<td>Coniferous Trees represent more than 75% of the trees or objects which have only Coniferous Trees inside</td>
<td>Coniferous Forest</td>
</tr>
<tr>
<td></td>
<td>Cork Trees represent more than 75% of the trees or objects which have only Cork Trees inside and the percentage of Herbaceous or Sparse Herbaceous is inferior than Cork Trees</td>
<td>Cork Tree Forest</td>
</tr>
<tr>
<td></td>
<td>Objects which do not satisfy the previous test</td>
<td>Mixed or Non-Dense Forest</td>
</tr>
<tr>
<td>Rule 4</td>
<td>The percentage of trees is less than 50%; the percentage of Herbaceous or Sparse Herbaceous is superior than Cork Trees and 80% of trees is Cork Trees with ambiguity less than 0.5</td>
<td>Agro-Forestry Areas</td>
</tr>
<tr>
<td></td>
<td>Objects which do not satisfy the previous test</td>
<td>Mixed Forest</td>
</tr>
</tbody>
</table>

4. Results

4.1. Combined classification

The accuracy assessment of the combined classification was made with the same testing datasets used to evaluate the individual classifications. The error matrices are generated assigning each pixel to the class with the highest degree of possibility or activation level (in the case of the MLP classifier), corresponding to hard versions of the classifiers. The Global Accuracy (GA) was computed as well as the Users’ Accuracy (UA) and the Producers’ Accuracy (PA) for all classes. The GA of the classification performed with the FMDM classifier was 65.5% and with the MLP classifier 64.5%. The GA of the combined classification was 70% which represent an increase of 4.5% more than that of the most accurate individual classification. Fig. 1 shows the classification results when each pixel is assigned to the class with a higher degree of possibility with the FMDM classifier, and with the largest activation level with the MLP classifier. Fig. 2 shows the spatial distribution of the ambiguity E committed when the pixel is assigned to the class corresponding to the largest degree of
assignment. The regions with larger ambiguity (dark zones) are the ones where the assignment degrees were lower.

Figure 1: a) Ikonos image (RGB:432); b) hard version of the classification results with FMDM classifier and c) with MLP classifier.

Figure 2: Spatial distribution of ambiguity for the classifications obtained with: a) FMDM classifier, b) MLP classifier.

The comparison of the mean ambiguity per class shows that forest species, such as CKT and CFT, were assigned to the pixels with similar ambiguity by both classifiers. The class DW was assigned to the pixels with lower ambiguity with FMDM classifier, but all the other classes present higher values of ambiguity with this classifier.

Fig. 3 allows the comparison between the results of the UA and PA accuracies for the classifications obtained with both classifiers and the combined classification (COMB).

Figure 3: User’s Accuracy and Producer’s Accuracy of the classes obtained with the FMDM, MLP and combined classifications (COMB).

The results presented in Fig. 3 revealed that with the combined classification the UA of the classes SW, NVA, HV, CKT, SHV shows a slight increase when compared with those of the most accurate individual classification. However, for some classes, the UA and PA of the combined classification didn’t improve, for example, the UA of the class ET when compared with the UA obtained with the MLP, or the UA of the class S when compared with the UA obtained with the FMDM. Although, the mean value of the UA and PA of all classes is higher than the mean values obtained for either of the initial classifications.

4.2. Land Unit Map

The Global Probability (GP) classification accuracy for the LUM, obtained with the hybrid approach which classify the LU (segmented object) using the combined classification and the ambigu-
ity information, was 70%. The best result for the GP classification with the hybrid approach, using an individual classification (the ones that had the best GA results) and without the ambiguity information, was 59%. This shows that the accuracy increased significantly with the combined classification and the inclusion of the ambiguity information.

Fig. 4 allows the comparison between the results of the CPR and CPM accuracies for the LUM obtained with both hybrid classification approaches. These show that the classification results obtained with the method using uncertainty are considerably better for almost all LU classes and this improvement is more evident for the forest classes. Fig. 5 shows the final results of the classification with the proposed hybrid classification method.

![Figure 4: Conditional probability of reference (CPR) and Conditional probability of map (CPM) obtained with the hybrid approach (LUM) with and without combined classification and uncertainty.](image1)

![Figure 5: Land Unit Map](image2)

5. Conclusions

The goal of this study was to highlight: a) the usefulness of the uncertainty information associated with the pixel-based soft classification for integrating the results of individual soft classifications; and b) the influence that the combined classification and the uncertainty information have in the classification of Landscape Units. With the hybrid pixel-object classification proposed, the global accuracy of the classification of Mediterranean Landscape Unit class’s increases by 11% when compared to a similar classification method that does not take combined classification and the ambiguity information into consideration. These results show that the information provided by the uncertainty measure was useful for the combined classification process because it allowed the deter-
minimization of the best class to assign to the pixels and in the construction of the Landscape Unit Map avoided the use of misclassified pixels.

References


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