SINGLE-TREE SPECIES MAPPING USING ONE-CLASS CLASSIFICATION METHODS AND UAV HYPERSPECTRAL IMAGES

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ABSTRACT

Progress in tree species mapping with hyperspectral data usually is limited by the multi-class classification framework, which imposes the requirement of exhaustively defining all species encountered in a landscape. As the research objective may be to map only one or a few species of interest, it is necessary to explore alternative classification methods that may be used to more efficiently detect a single species. In this study, we used UAV hyperspectral data to detect one endangered tree species, *Araucaria angustifolia*, in a subtropical forest area comparing the performance of two one-class classifiers (OCC): OCSVM and OCRF. Besides the 25 spectral bands (SB), we also tested two other datasets: one comprising the first five MNF components, and the other one comprising the first five PCA. Both algorithms and all the datasets reached good results, with F-score varying from 0.81 for OCRF and SB dataset, to 1 for OCSVM associated with the PCA dataset.

Keywords— endangered tree species, Support Vector Machine, Random Forest, Principal Component Analysis, Minimum Noise Fraction.

1. INTRODUCTION

Remote sensing studies designed for tree species mapping play a strategic role in management, monitoring and conservation of forest environments. They consist in an efficient and potentially economic way of inventorying forest resources [1-2]. In this respect, the greater detail reached by the enrichment of the spatial resolution of remote sensors in the last decades enable not only the mapping of forest typologies, but also the identification of isolated trees in forest canopies.

Hyperspectral sensors embedded in manned aircrafts provide data at both high spatial and spectral resolution, being extensively used in tree species classification [1-7]. Recently, the small-format hyperspectral cameras on board Unmanned Aerial Vehicles (UAVs) have been on the spotlight. As they operate at even lower flight heights than conventional aerial platforms, they offer even finer spatial resolutions [8].

Regarding the classification methods at the tree species level, the machine learning algorithms, such as Support Vector Machine (SVM) and Random Forest (RF), have been highlighted [1-2; 6-8]. These methods are considered robust and to work well in the presence of a wide range of class distributions and with high dimensionality and multisource data [2]. However, the progress in mapping certain forest species with spectral data is limited by the traditional multi-class classification structure, which exhaustively needs to define all classes (species) present in the landscape [9]. In this case, single-species classification approaches have considerable advantages over the traditional multi-species classification framework when the interest is in mapping one or a few focal species. These methods are designed to increase the performance in detecting the species of interest while reducing the need for training data collection [6].

In this context, we aim to investigate two single-class classification techniques based on machine learning algorithms to detect and classify one endangered tree species of a subtropical forest area, using hyperspectral data acquired by an UAV. Our specific goals are: a) compare the two classification techniques, one based on the SVM and the other based on RF; b) besides the spectral bands (SB), analyze the use of different features extracted from hyperspectral dataset: minimum noise fraction (MNF) and principal component analysis (PCA).

2. MATERIAL AND METHODS

The study area has approximately 24 ha of extension and comprises one forest fragment of Mixed Ombrophilous Forest (MOF) in a subtropical environment of the Atlantic Rain Forest, located within the municipality of Curitibanos, in the Brazilian southern state of Santa Catarina. The MOF phytophysiognomy is characterized by the presence of the *Araucaria angustifolia* tree species. Currently this species is at risk of extinction, which denotes the importance of granting priority for conservation of these areas.

Hyperspectral images were obtained with a camera based on an Interferometer Fabry-Perot (FPI), model 2014 (DT-0014), belonging to São Paulo State University (UNESP). This commercial camera was constructed in 2014 by Senop Ltd. The images were acquired in December 2017 with a UAV 6 platform (SX4 model). With an adjustable air gap between the FPI, 25 different spectral bands were acquired in the range of 500–900 nm with a minimum spectral resolution of 10 nm at the full width at half maximum (FWHM) [10]. The spatial resolution of the images acquired in this flight was 0.11 m. Details of the camera are given by Oliveira et al. [11].

For the preprocessing, the Digital Numbers (DN) of the hyperspectral images were firstly transformed into radiance values. The software Hyperspectral Imager was used to apply dark current and radiometric corrections and transform the binary raw images into the Environment for Visualizing Images image format file (*.dat), a flat-binary raster file with an American Standard Code for Information Interchange header file as complement.

To correct the misalignments of the individual bands of the hypercubes caused by the time-sequential operating principle of the camera, we orthorectified all bands based on six ground control points acquired with a GPS in the field over sites demarcated with lime, a substance that exhibits high reflectance at all wavelengths and therefore visible on all bands. This procedure automatically corregistered the bands. After that, the orthomosaics generated from each band were joint by the layer stacking procedure in the software ENVI 5.3.

The first processing step was to generate the MNF and PCA features from the SB dataset. The MNF is a well-known technique for hyperspectral imagery denoising. It transforms a noisy data cube into output channel images with steadily increasing noise levels, which means that the MNF output images contain steadily decreasing image quality. PCA can also be used for hyperspectral imagery denoising, however it is defined in such a way that the first principal component has the largest possible variance, and each succeeding component has the highest possible variance under the constraint that it is orthogonal to the preceding components [12]. According to Fassnacht et al. [13] both approaches are commonly applied to reduce dataset for tree species classification purposes. After this procedure, three datasets were formed: one solely composed by the 25 SB of the FPI camera, one composed by the first five MNF, and the last one composed by the first five PCA. The choice of only five components was based on the eigenvalues stats of the data generated in each transformation (MNF and PCA).

The next stage was the collection of training and validation samples. Based on the field surveys and visual interpretation of the image, we collected about 12,000 pixels belonging to 30 individual tree crowns (ITCs) of araucaria species (our "focal class") (Figure 1) for the training samples, and further 9,500 pixels of 15 araucarias trees which were later randomly selected for the validation procedure. We also collected about 15,000 pixels belonging to other different tree species in order to compose the *outlier* or "non-focal" class. This class was only used in the validation procedure.

After that, the features of the training samples of the *araucaria* class were extracted using the eCognition software to compose the training dataset. A segmentation process was necessary to form the database to apply the classification models. In this procedure, a multiresolution segmentation was applied to three original bands of the hyperspectral data with wavelengths respectively centered at 535 nm, 679 nm and 769 nm. The segmentation parameters were heuristically defined; the scale factor was set to 30, the shape factor to 0.3 and the smoothness factor to 0.5. From the generated segments, the spectral mean corresponding to the features of each dataset were extracted: 25 SB, five MNF and five PCA.

In the sequence, three databases were created in Attribute-Relation File Format (ARFF) in order to perform the one-class classification (OCC) in the software Waikato Environment Knowledge Analysis (WEKA). The OCC is a unary classification technique where information from one class is used to establish a boundary between one class and all other classes [14]. Thus, the training dataset contains only the features of the target at issue or focal class, in this case, the araucaria tree species. We tested two classifiers: the one-class SVM (OCSVM) [15] with a Radial Basis Function, available in the LibSVM package, and the OneClassClassifier [16], in which we set the RF classifier (OCRF). For parameters selection, we carried out a 10 cross-validation process. The best combination of parameters was selected for the final classifications.

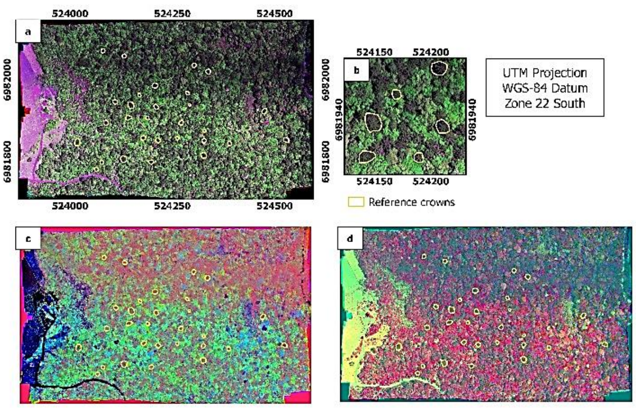

Figure 1. Hyperspectral UAV image of the study area: R(535 nm) G(769 nm) B(679 nm) composition (a); Detail of the focal-class *araucaria* (b); MNF dataset: three first components composition (c); PCA dataset: three first components composition (d).

For the results evaluation, we calculated the F-score for the focal class ($F = 2[(pr)/(p+r)]$, where r = recall accuracy and p = precision). This measure represents an appropriate choice of an optimization criterion in a single-class classification [6; 17]. Recall is the proportion of focal class samples that are correctly assigned by the classifier to the focal class (i.e., the producer's accuracy for the focal class), and precision is the proportion of samples assigned to the focal class that truly belong to the focal class (i.e., the user's accuracy for the focal class). For a given class, differences in precision and recall accuracy indicate if the species is more or less abundant in test data predictions relative to its true abundance [17]. In this process, it was necessary to use the *outlier* samples to compute the recall.

3. RESULTS AND DISCUSSION

Figure 2 shows the results evaluation. It can be observed that the PCA dataset reached the best results for both classifiers, with F-scores of 1 and 0.96 for OCSVM (Figure 3b) and OCRF, respectively. The MNF dataset attained the second best result, with an F-score of 0.97 for OCSVM (Figure 3c) and of 0.88 for OCRF. The SB dataset had the worst result, with F-scores of 0.87 (OCSVM) and 0.81 (OCRF) (Figure 3d). This dataset had the lowest values of precision metrics when compared with the other datasets, indicating that samples classified as *araucaria* not always truly belong to this class. In Figure 3d, one can notice that problems mainly occurred in shadows located between the trees and other darker areas, which were erroneously assigned to the *araucaria* class. In general, the araucaria species present a darker color than other species, what may have caused confusion between this class and shaded areas. When the transformed datasets were employed (PCA and MNF), the problems associated with differences in scene illumination tended to be reduced, and hence, led to a better accuracy in the araucaria detection and classification.

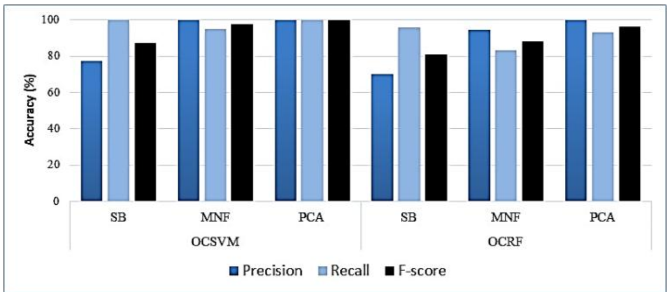

Figure2. F-score, precision and recall metrics (in percentage) reached by each classifier/dataset.

Other studies have shown that the use of MNF components led to better results in tree species classification when compared with studies employing the original bands for tree species mapping [2; 18-22]. According to Zhang and Xie [18], since the MNF transformation reduces both noise and dimensionality of the hyperspectral dataset, it does make the classification process more effective. Not only MNF but also PCA components significantly decrease the classifier complexity and are very effective in similar situations with a reduced number of training samples. Despite the fact that the use of MNF components is more common than PCA when dealing with hyperspectral image, our study showed a slightly better performance when PCA is applied, what can be ascribed to some specific characteristics of our data.

Regarding the classifiers, the OCSVM presented a slightly better accuracy for all tested datasets. Shi et al. [22] tested the OCSVM, the OCRF and other two methods to classify roads with a hyperspectral dataset and also found better results with OCSVM. In spite of this, according to the authors, it is difficult to set suitable parameters for OCSVM. Désir et al. [23] compared the OCRF with OCSVM and another OCC. The authors mentioned that the performance of the methods varied according to the dataset used: none of them reached the best accuracy for all situations. Hempstalk et al. [16] compared the same OCC technique of this study, however associated with the bagging algorithm instead of RF, with the OCSVM. As well as Désir et al. [23], the authors also mentioned that the results varied according to the dataset. Baldeck and Asner [9] compared three SVM methods designed for single-class detection—binary (one against all) SVM, OCSVM, and biased SVM—in detecting five focal tree and shrub species using airborne hyperspectral data over an African savanna. Among the different single-class methods, binary SVM showed the best overall performance (average F-scores of 0.43–0.78 among species), similar to biased SVM (F-scores of 0.40– 0.72), whereas OCSVM showed a very poor performance (F-scores of 0.09–0.46). However, our study involved only one focal tree species, which can be easily identified as a single conifer in the study area. Thus, in such a situation, a simpler solution as OCC may be feasible, since this kind of method can detect tree species with less training data requirements, allowing the species of interest to be mapped with reduced costs.

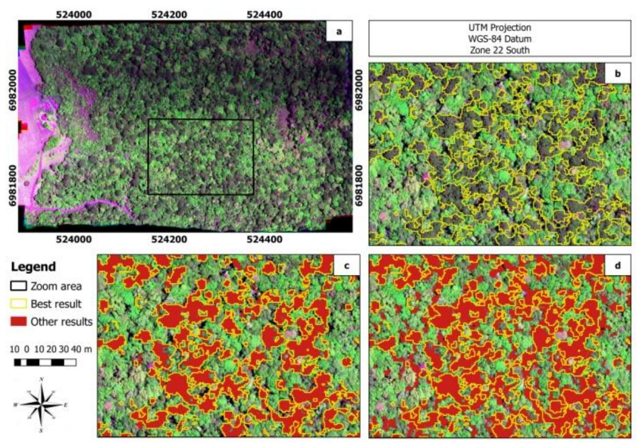

Figure 3. Hyperspectral UAV image of the study area: R(535 nm) G(769 nm) B(679 nm) composition (a); classification result of OCSVM and PCA dataset (b); classification result of OCSVM and MNF dataset (c); classification result of OCRF and SB dataset (d).

4. CONCLUSION

In this work, two OCC methods, OCSVM and OCRF, were employed to classify an endangered tree species of a subtropical forest. Both algorithms and all the datasets reached good results, with F-scores varying from 0.81 for OCRF and SB datasets, to 1 for OCSVM associated with the PCA dataset.

The use of transformed components data, such as PCA and MNF, led to a higher accuracy in the classification performance of both classifiers when compared to the SB. This latter dataset was more susceptible to differences in lighting conditions of the scene, leading to misclassification of the focal class with shaded areas.

The main advantage of the OCC methods over the multi-class ones is that they need training samples only of the class of interest. This facilitates its application in forests with high diversity of species, reducing costs and efforts demanded for collecting training samples of a lot of species.

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