A GENETIC PROGRAMMING APPROACH FOR COFFEE CROP RECOGNITION

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1. INTRODUCTION

The use of Remote Sensing Images (RSIs) as a source of information in agrobusiness applications is very common. In these applications, it is fundamental to know how the space occupation is. However, some crop type regions recognition in remote sensing images is not a trivial task yet. The place or the age of the crops, for example, may hinder the recognition process. In these cases the spectral response and the texture patterns to the same kind of crop can be different. A crop can be planted in different ways and this factor, allied to the different phases of the plants, tends to create a distinction between regions of the same class.

Problems in land use survey works on mountain relief have being reported a long time. On the other hand, at the same time, efforts have been made to solve these problems. Holben and Justice [1], for example, have examined the spectral band rationing to reduce the topographic effect on remote sensing images. Peddle and Franklin [2] used textural aspects and integration of data for discrimination of surface different patterns. Baban and Yusof [3] used remote sensing and ancillary for the mapping of land use/cover distribution on a mountainous tropical island as well as Dorren et. al. [4] have studied forest in mapping in same relief conditions that Baban and Yusof using object-based classification and both reached good results. Other works taking into account prior probabilities such as Pedroni [5] improved the accuracy of forest types classification, but we can observe that results settle specific problems not adaptable to other conditions. Coffee mapping is inserted in later context because it is planted in mountain relief and generaly very close to forest areas. There is a lack of works with focus on this theme as state Cordero-Sancho and Sader [6]. Further, the authors studying accuracy classification in coffee crops just achieved a better classification when have considered the use of Landsat Tm bands and ancillary data rather than the classification using just red, near-infrared and mid-infrared TM bands. In this case the accuracy reached 56% and it agrees with Langford and Bell (1997) that reported a maximum 58% of overall accuracy showing most mixing between coffee plantation and young/mature woodland.

This work aims to present a new approach and evaluate the contribution of using successful information retrieval techniques to automatic recognition of coffee crops in RSIs. This method applies an approach based on Genetic Programming (GP) to combine texture and spectral information by using image descriptors. A descriptor can be characterized by two functions: *feature vector extraction* and *similarity computation*. The feature vectors encode image properties, like color, texture, and shape. Therefore, the similarity between two images is computed as a function of their feature vectors distance. Genetic programming (GP) [7] is a machine learning technique based on the theory of evolution and is used in various applications. This strategy was motivated by recent works in content-based image retrieval that achieved good results applying GP to combine successful image descriptors.

2. THE GP-BASED CLASSIFICATION APPROACH

The proposed approach can be divided into two main phases: (i) the image description and (ii) image vectorization. The image description concerns the image content characterization and is performed off-line. First of all, images are selected and inserted into the system (step 1 in Figure 1). Next, this image is partitioned into several tiles (rectangular subimages) – step 2. Finally, descriptors are used to extract texture and spectral image properties (step 3).

The image classification process includes steps 4, 5, 6 and 7 in Figure 1. The process of identifying relevant partitions is performed by using GP to combine the similarities provided by descriptors. Each tile is considered as an independent image and this process starts by the indication of relevant samples (step 4). These samples are assumed to present the same texture and spectral properties as the RSI regions which are of interest. A pattern recognition using GP is performed and all subimages are

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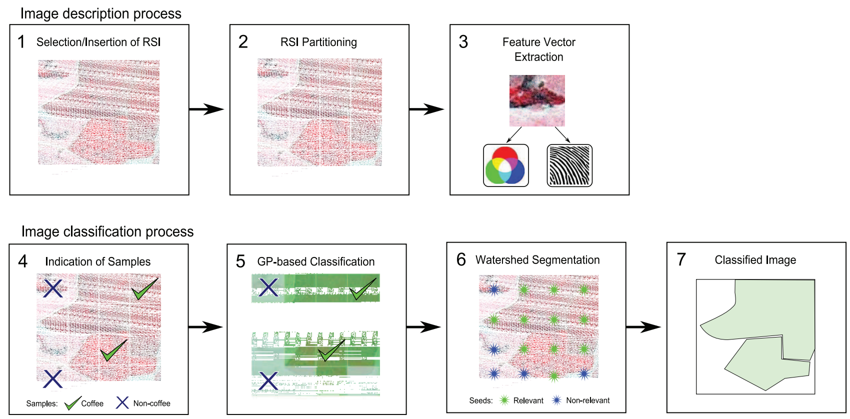


Fig. 1. Steps of the proposed classification process.

labeled (step 5). This process is described in details in subsection 2.1. After the subimages are classified, the next step concerns the segmentation of relevant regions (step 7). The segmentation process of the image is performed by using a watershed-based algorithm. This algorithm segmentates images using seeds. The seeds are based on areas of interest identified in the last step.

This paper has to do with the first 5 steps depicted in Figure 1, that is, the partition/extraction of image features and classification of the sub-images of coffee.

2.1. GP-based Classifier

As mentioned before, the GP framework is used to determine new similarity functions based on the combination of previously defined image descriptors. For the image classification problem, a good similarity function, i.e., a similarity function with a high accuracy value F, is one that, when applied to an tile I_i of class C, ranks images from class C as the most similar to I_i. The overall classification framework is as Algorithm 1.

Algorithm 1 The GP-based classification algorithm.

1 For each class, generate the initial population of random *similarity functions (GP trees)*
2 For each class, perform the following sub-steps on training subimages for N_{gen} generations
3   Calculate the accuracy of each similarity
4   Record the top N_{top} similarity trees
5   Create new population by: *Reproduction*, *Crossover* and *Mutation*
6 Apply the *best similarity function* of each class on a set of testing images to a kNN algorithm
7 Combine the output of each classifier through a simple majority voting

Steps 1 and 2 concern the training process within GP which intend to discover good similarity functions for each class. However, the discovered functions can only be used to calculate the similarity between any two images. In order to evaluate the performance of those functions in the classification task, we used a strategy based on a nearest neighbor classifier. This classifier assigns a category label to a test image, based on the categories of the k most similar images in the training set. The most widely used algorithm was introduced by Yang [8] and is referred to, in this work, as *kNN*. The *kNN* was chosen since it is simple and makes a direct use of similarity information.

In the *kNN*, to a given test image d is assigned a relevance score $s_{c_i,d}$ associating d to each candidate category c_i. This score is defined as:

$$s_{c_i,d} = \sum_{d' \in \mathcal{N}_k(d)} similarity(d, d') f(c_i, d') \tag{1}$$

where $\mathcal{N}_k(d)$ are the k most similar images of d in the training set and $f(c_i, d')$ is a function that returns 1 if image d' belongs to category c_i and 0 otherwise. In Step 3 the generic similarity function of kNN is substituted by the functions discovered for each class.

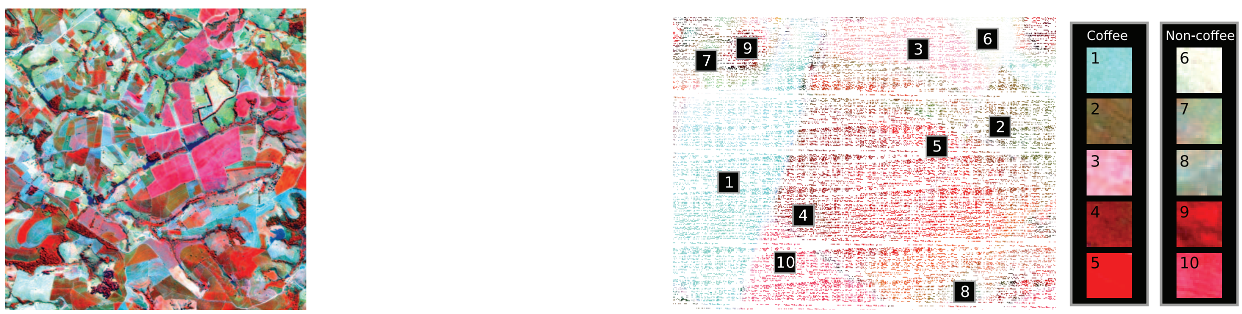
In multi-classification problems with n classes using the described framework, we effectively end up with n *kNN* classifiers . In order to produce a final classification result, we combine the output of all n classifiers using a simple *majority voting* scheme, whereby the class of a image d_i is decided by the most common class assigned by all the n classifiers.

Besides its simplicity, we chose to use the majority voting in our framework (Step 4) to: help alleviate the common problem of overfitting found in GP training and; help boost performance by allowing *kNN* classifiers to apply different similarity functions which explore and optimize the characteristics of each particular class.

3. EXPERIMENTS

This section describes the experiments performed to validate the method. The configuration of the experiments is described as follows:

- **Remote Sensing Data**: The used image (Figure 2(a)) was captured by the SPOT satellite and corresponds to the Monte Santo de Minas county, in the State of Minas Gerais, a traditional place of coffee cultivation. The region where this image was captured is mountainous. To evaluate the accuracy, we use a mask (Figure 2(b)) that indicates (in white) all coffee crops in the image. Coffee crops presented in the mask was done manually in the whole county using the original image and visits to the place to compose the final result. The image has several targets that may be confused with the types of coffee crops such as bare soil, native vegetation and sugar cane crops. Figure 2 (c) illustrates examples of coffee and not-coffee crops. Note the difference among samples of coffee and the similarities with non-coffee samples.



(a) (b) (c)

Fig. 2. Remote Sensing Data used in the experiments: (a) original image, (b) the mask indicating the regions of coffee and (c) example of coffee samples.

- **Descriptors**: We use 3 color descriptors (JAC, BIC and GCH) and 2 texture descriptors (SID and QCCH) chosed based on previous study [9].
- **Baseline**: We compare our method against *Maximum Likelihood (MaxVer) Classification* [10]. It is the most common supervised classification method used with remote sensing image data.
- **Effectiveness Measure**: To analyze the results we calculate the kappa index for the classified images. Kappa [11] is an effective index to compare classified images, commonly used in the RSI classification.

In our experiments we have fixed the subimage size according to the common extension value of a *region of interest*. In the region of study, coffee crops are normally located in to small parcels on the same farm. We defined that 75×75 meters is a good value to the size of the partition. The dimension of partitions are fixed. We used 30×30 pixels to partition the image generating 6400 subimages to classify. A subimage could belong to one of 2 classes in the experiments: coffee-crops (with more than 50% pixels of coffee) and non-coffee (with less than 50% pixels of coffee) The proposed method is compared to *MaxVer* classification with probability threshold 0.98 and using 43.630 points of the coffee sample. Kappa accuracy for *MaxVer* was 66.0.

The GP-based classification requires the definition of several GP. In the experiments we use crossover rate equals 0.8 and reprodution equals 0.3. We also applyed k equals 13 and 5 in kNN (based on previous studies). In the experiments, we tested variations of population of GP individuals (30 and 50) and maximum of generations (15 and 30). We selected 20% of the tiles (samples) as training set. The results (Table 1) are the mean of 2 diferents training (we called folds) sets randomly selectd proportional to the class sizes.

Table 1. Kappa coeficient for Coffee recognition applying the proposed GP-based classifier.

EXP	POP_N	GEN_N	FOLD 1	FOLD 2	MEAN
1	30	15	65.92	66.04	65.98
2	30	30	64.88	66.51	65.70
3	50	15	65.90	66.46	66.18
4	50	30	66.37	66.29	66.33

According Table 1, it is possible notice that the best configuration for the population of GP individuals were 50 and 30, respectivily. This configurations obtained 66.33 of Kappa accuracy that is slightly better than MaxVer accuracy (66.0). It is important pointed out that we just performed a small set of tests and other configuration paramenters can improve the classification accuracy of our method. Moreover, we just evaluate partially the method. The segmentation process can increase the classification effectiveness.

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