Digital Image Classification of Land Cover

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Abstract

Classification of land cover represents a quite standard example of natural fuzzy boundaries between phenomena: many classes show in nature internal gradual differences in species, health, age, moisture, as well other factors. It is unrealistic to establish a line between different classes, assuming homogeneous different phenomena in each side. In this paper we consider the unsupervised algorithm presented in Amo *et al.* [2], applied to a real image in Sevilla province (south Spain). As expected, image is easier to be understood taking into account few fuzzy classes and all their transition zones, rather than assuming a large family of crisp classes showing no structure between those classes.

Keywords: Fuzzy classification, Remote Sensing.

1 Introduction

Classification of land cover by means of remote sensing (see, e.g., [9]) implies a search for formal definition of what a class is. From a traditional remote sensing point of view, our theoretical aim is a partition of the image in *homogeneous* sectors, each one of them hopefully corresponding to a class (see [8]). As long as our precision increases, we are able to realize that a given class is not so homogeneous, and therefore new classes should be defined. In this sense, the number of classes should be as big as possible, but we still should be able to interpret and manage them. In fact, quite often we realize that an image is based upon a few *natural* classes, with the picture full of transition zones (see, e.g., [10]). This is a typical situation in resource classification (see also [7, 13] and [11]). In this paper we consider a fuzzy classification algorithm, already introduced in a previous paper [2] based upon an basic *outranking* model [12, 14]. Such an algorithm is now applied to a real image, and results are discussed. The image here chosen is an orthoimage of Sevilla province (south Spain) that was taken on August 18, 1987, by the LANDSAT 5 satellite (*Worldwide Reference System (WRS)* image $202-34-4$). This image was taken with the Thematic Mapper sensor, which has a spatial resolution of 30 meters.

2 Image classification

The goal of our digital image classification is to identify the different land-cover types, which are specified as classes, and to distinguish the different zones within the image. In our case, we intend to identify the different elements of a particular image in Sevilla (see [3] for details). On one hand, we are going to consider the algorithm initially proposed in Amo *et al.* [2]. On the other hand, in order to test its effectiveness, we shall perform an alternative classic methodology based on a crisp unsupervised classification. Both approaches will be finally compared and discussed.

Lets show first a crisp approach. A crisp classification was developed here by means of the $ERDAS^{TM}$ program, which uses the crisp Isodata algorithm developed in the *Stanford Research Institute* by G. H. Ball y D. J. Hall (see [4, 5, 6]). In first place we considered a standard crisp classification allowing two crisp classes with the $ERDAS^{TM}$ program, but it was clear that a classification using only two crisp classes was not enough for our classification purposes. Next, we successively took three classes, four classes, five and so on. But it was not until we considered ten crisp classes, that the structure of the image could be distinguished accurately. But none of the previous crisp classifications were able to show the expected spectral variations.

Then we applied the fuzzy approach proposed in [2]. When two fuzzy classes were considered, our algorithm showed not good enough results. But when three fuzzy classes where considered, it showed to be good enough for our purposes (information seemed to be equivalent to that classification taking into account ten crisp classes).

3 Comparative study

First of all, we have to remark that in the case of the above crisp classification, ten classes were necessary to distinguish key details in our image, while our fuzzy classification reached the goal with only three classes. In fact, our fuzzy classification using two classes gave us as much information as the crisp classification using five classes and even more in some aspects. Both classifications discriminate between vegetation and land use.

Besides that, both classifications distinguish sprinkler irrigation zones, although the spectral variation between them can be better appreciated in the crisp classification using five classes than in the fuzzy one using two classes. On the contrary, the fuzzy classification differentiates the spectral variation in ricefields, while that does not happen in the crisp classification, unless we take ten crisp classes.

From a global point of view, if we compare the fuzzy classification using three classes with the crisp one, it is necessary to take ten classes to reach a similar level. And even in some aspects the fuzzy classification gives more information than the crisp one.

As shown in this paper, our fuzzy classification retains more accurate information about the image we are analyzing, using a small number of classes. In fact, fuzzy methodologies will better suit real world problems, whenever gradual transition between classes exists. Natural earth surface borders usually are not crisp.

4 Final comments

As already pointed out, results obtained by means of a few fuzzy classes, when applied to our particular image, needed quite a number of crisp classes in order to get equivalent results. This was indeed an expected result, since a fuzzy class allows a continuous gradation meanwhile any finite family of crisp classes will capture differences between at most a finite number of stages. The lower number of classes can not be argued as an advantage of fuzzy classification. But notice that a naive look at our real image shows up that there exist three main concepts explaining such a picture, and this is what our fuzzy classification is telling us. Fuzzy classification is much more natural and accurate than a corresponding crisp classification.

The key issue is the conceptual accuracy given by fuzzy classes. Increasing the number of crisp classes increases the possibilities of distinguishing different situations, but such a family of crisp classes are not structured. We can confirm that one object belongs to a class which is different from other two classes, but we shall not be able to realize that such a class is *in between* those two classes.

If reality shows natural fuzzy classes, with no crisp borders but gradation between classes, fuzzy approaches will be more accurate, and easier to understand and explain, and therefore easier to be managed (see a first proposal in [1]). We expect only a few classes in a remotely sensed image to be crisp. Most of the image requires fuzzy classes to capture gradations between classes.

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