Hierarchical Classification-Based Region Growing (HCBRG): A Collaborative Approach for Object Segmentation and Classification

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Abstract. Object-based image classification approaches heavily rely on the segmentation process. However, the lack of interaction between both segmentation and classification steps is one of the major limits of these approaches. In this paper, we introduce a hierarchical classification based on a region growing approach driven by expert knowledge represented in a concept hierarchy. In order to overcome the region growing's limits, a first classification will associate a confidence score to each region in the image. This score will be used through an iterative step, which allows interaction between segmentation and classification at each iteration. Carried out experiments on a Quickbird image show the benefits of the introduced approach.

Keywords: Collaboration, Expert knowledge, Classification, Segmentation, Region Growing.

1 Introduction

Image segmentation is a crucial process in object-based image analysis (OBIA). Gao et al. [12] have shown the predominant importance of the correlation between the results of the segmentation and the classification. Indeed, they show that image segmentation has a direct effect on the classification accuracy. This can be explained by the nature of OBIA approaches [8],[11] that are composed of two steps; (*i*) the construction of objects which is usually achieved by a segmentation, whereby pixels are aggregated into objects that are homogenous with regard to spatial or spectral characteristics; (*ii*) those objects are classified, but the interaction between both steps is badly missing. Indeed, a poorly segmented region is generally misclassified, since the extracted features of this region will be incorrect. In fact, the OBIA uses semantic high level features such as area and shape to identify regions. It is therefore useful to bridge the gap between

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segmentation and classification. Region segmentation approaches promote the collaboration concept. Indeed, their iterative architecture allows introducing a new knowledge as far as we move through the segmentation process. In this context, we introduce a collaborative approach between the region growing algorithms and supervised object-based classification. In fact, the region growing algorithms have some limitations, mainly the choice of starting seeds and the criterion of growth. These problems can be solved by integrating information from the classification that can provide clues on the membership of objects while assessing the confidence we have on this information. This will provide a semantic aspect to the segmentation and a hierarchy of the choice of seeds and growth according to a confidence criterion. Many hierarchical segmentation was presented in the literature. Marfil et al. [9] compare pyramidal structures proposed to solve segmentation. Deruyver et al. [3] present an adaptive pyramid and show how both the adjacency graph and semantic graph are used to represent homogeneously the low-level content and the semantic content of images. Any type of pyramidal structure can be adapted in our approach. we chose a pyramid of region adjacency graphs because of the speed and the simplicity of its implementation.

This paper is outlined as follows. After having mentioned the related work in section 2, we present in section 3 our HCBRG approach. Experiments and extraction results are given in section 4. Finally we summarize our research and conclude the paper in section 5.

2 Related Work

Region growing algorithms are divided into two steps which are the extraction of seeds and the growing step from those seeds. The seeds extraction step has an important influence on the quality of the segmentation. Indeed, an inappropriate choice of seeds can lead to a bad segmentation. Several approaches have been proposed in the literature to allow better detection of seeds. Fan et al. [6] propose to detect the seeds by extracting the centroids of the regions by applying initially a color edge detection combining an isotropic edge detector with a thresholding isotropic algorithm. The result of extraction is dependent on the edge detection. Shih and Cheng [10] proposed an automatic approach for the seeds' extraction which have to fulfill three criteria; (i) the seed must be a local maxima; (ii) for a candidate region, at least one seed must be generated to produce the region; and (iii) the seeds for the different regions must be disconnected. This approach is dependent on the choice of the mask for selecting the local maxima. The last two criteria are seldom satisfied without a priori knowledge about regions in the image. Cui et al. [2] detect the seeds based on the Harris detector who is invariant to rotations, translations, scale changes and noise in the image. However, it remains dependent on the parameters of this detector. Bendhiaf et al. [4] start from the hypothesis that seeds are the centers of the trees. Then, they use a mask for the detection of local maxima. This maxima is used as a seed for the growing process. The extraction of seeds is dependent on the choice of the mask, which can lead to under or over-segmentation of tree crowns.Athanasiadis et al.[1] use a fuzzy classification to detect seeds. In fact, they select the seeds based on two criteria. First, the seed must have a maximum score of fuzzy membership $h(La)$ above a threshold $Tseed$. Second, this score must be greater than the sum of membership degrees of the other concepts. The major inconvenient of this method is the choice of threshold that is dependent on the image even if the authors propose a method to estimate this threshold by finding the percentage of seed candidates, but this threshold stay an approximate.

To sum up, most of above mentioned approaches have the same limitations. For the first approaches presented, no knowledge about the nature of the object is extracted which makes the integration of semantic knowledge in the growth process very complicated. The second limitation is the lack of confidence evaluator for seeds. Even the use of filter minimize false positives, it may also prune suitable candidates and does not classify the seeds in order of confidence. The third disadvantage is the sensitivity to noise and its dependence on various parameters. A bad choice of any parameter may cause an over-segmentation or under-segmentation and even omission of objects. To overcome these problems, we introduce an approach that combines a region growing algorithm and a supervised classification.

3 The HCBRG Approach

We propose a Hierarchical Classification-based Region Growing (HCBRG) approach. The classification will allow the association of a semantic label as well as a confidence score to the region extracted in the segmentation step.

This approach is split into two steps, as depicted by Figure 1:

- A first preprocessing step which is a data preparation for the next step. This allows the decomposition of the image into a set of homogeneous objects based on low-level features such as radiometry. After the extraction of homogeneous objects, we classify the image by calculating a score for each region based on low-level features provided by the expert. This score will introduce the notion of confidence that provides a degree of validity of the labeling of each object and allows the creation of a growth hierarchy.
- The second step is the hierarchy of growth which is an iterative step composed of three steps for each iteration. The first step is the selection of seeds based on the scores. This set represents objects not yet processed and that maximize the similarity score. For each object, a set of processing will be done based on spatial constraints if they exist in order to prune it and to re-evaluate the classification. The last phase is the growing step.

3.1 Preprocessing

3.1.1 Segmentation

The choice of the segmentation algorithm is not very important in this approach as long as it fulfills the criterion of over-segmentation. Indeed, given the

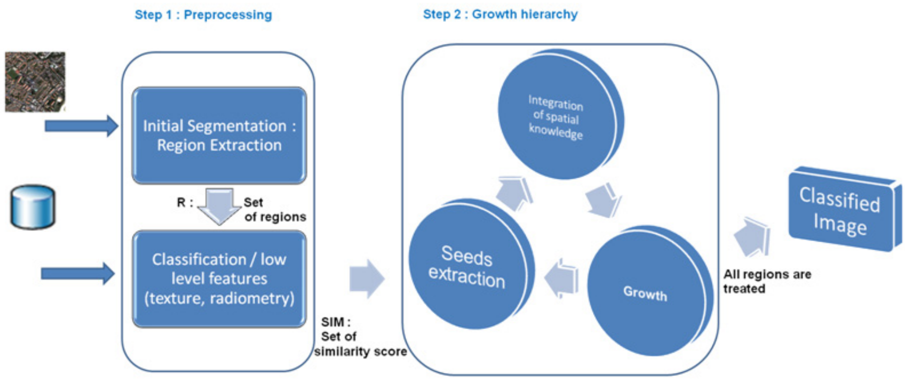

Fig. 1. Workflow of the proposed approach

properties of region growing algorithms, which are based on the fusion of fragments of an object to be detected, it is clear that a sub-segmentation of the image implies a loss of some objects. We have chosen the watershed algorithm that easily allows an over-segmentation of the image.

3.1.2 Classification

We propose a classification based on a confidence score. This classification allows assessing the regions built during the initial segmentation and the possible classes of the image. This score will assess the validity of the regions based on the knowledge provided by the expert. We use the similarity score proposed by Forestier et al.[7,5]. This score is based on an attribute-oriented approach as it uses low-level knowledge of the image that are formalized in the form of low-level descriptors. In [5] authors use the similarity score to propose an object recognition method based on an ontology built by experts. The regions of the segmentation are characterized by features related to spectral, spatial and contextual properties and classified through a matching process between an object and the concepts of the ontology.

The proposed similarity score is used to check the validity of the attribute values of a region with respect to the intervals defined by the expert. The similarity score compares the attributes values of a region with the attributes of the object to classify.

Note 1. **(region)**: Let R be the set of regions obtained from segmentation. $R = \{r_i\}_{i \in [1,N_R]}$ where N_R represents the cardinality of R.

Note 2. **(class)**: Let C be the set of classes in the image. $C = \{c_j\}_{j \in [1,N_C]}$ where N_C denotes the cardinality of C.

Note 3. **(attribute)**: Let A be the set of features identifying a class. $A = \{a_k\}_{k \in [1,N_k]}$ where N_k represents the cardinality of A.

Definition 1. ***(Validity degree)**: Let $Valid(a, c_j r_i)$ the degree of validity between a class c_i and a region r_i for a given attribute a_k and let $v(r_i, a_k)$ be the value of the attribute a_k for the region r_i.*

$$Valid(a, c_j r_i) \begin{cases} 1 & if\ v(r_i, a_k) \in [min(c_j, a_k), max(c_j, a_k)] \\ \frac{v(r_i,a_k)}{min(c_j,a_k)} & if\ v(r_i, a_k) < \quad min(c_j, a_k) \\ \frac{max(c_j,a_k)}{v(r_i,a_k)} & if\ v(r_i, a_k) > \quad max(c_j, a_k) \end{cases} \tag{1}$$

Definition 2. ***(Similarity score)**: The similarity score $Sim(r_i, c_j)$ is computed according to the validity between the region r_i and the class c_j of each attribute weighted by a weight $w(k, c_j)$:*

$$Sim(r_i, c_j) = \frac{\sum_{a \in A} w(a_k, c_j) Valid(a_k, c_j, r_i)}{\sum_{a \in A} w(a_k, c_j)} \tag{2}$$

Definition 3. ***(Set of similarity)**: We define the set of similarity as all the similarity scores of any region $r_i \in R$ with respect to any class $c_j \in C$.*

$$SIM = \{Sim(r_i, c_j) | r_i \in R\ et\ c_j \in C\} \tag{3}$$

3.2 Growth Hierarchy

This step is an iterative process. Based on the sets of regions R, the set of classes C and the set of similarity scores SIM, it allows the creation of the growth hierarchy based on the confidence we have for each region.

The creation of the hierarchy is preceded by a calculation based on the similarity scores as we explain in the follows.

Definition 4. *For a region $r_i \in R$, we define the set of classes that maximize the similarity score $(Sim(r_i, c))$ among all the classes $c \in C$. We note $\delta(r_i)$ this set:*

$$\delta(r_i) = \arg\max_{c \in C} Sim(r_i, c) \tag{4}$$

Definition 5. *For each region $r_i \in R$, we define $S_{max}(r_i)$ and $C_{max}(r_i)$ as follows :*

$$C_{max}(r_i) = \begin{cases} random(\delta(r_i)) & if\ |\delta(r_i)| > 1 \\ \delta(r_i) & otherwise \end{cases} \tag{5}$$

$$S_{max}(r_i) = \begin{cases} Sim(r_i, C_{max}(r_i)) & if\ |\delta(r_i)| > 1 \\ 0 & otherwise \end{cases} \tag{6}$$

$(S_{max}(r_i))$ represents the maximum similarity score of the region r_i for all classes of C. In the case where $\delta(r_i)$ has more than one class, we deduce that there is a confusion *(i.e. this region is no longer a trustworthy region but a conflictual region)*. In this case, $C_{max}(r_i)$ will arbitrarily take one of the classes of $\delta(r_i)$ and $S_{max}(r_i)$ will be assigned 0. If $\delta(r_i)$ contains a single value, then it will be assigned to $C_{max}(r_i)$ and $S_{max}(r_i)$ will be the similarity score $Sim(r_i, C_{max}(r_i))$ of the class C_{max} for the region r_i.

The calculation of C_{max} and S_{max} will serve as basis for the iterative algorithm of hierarchical growth. Each iteration of this algorithm is equivalent to a growth level of the hierarchy, and is composed of three steps.

We denote by $candidates_{k-1}$ all the candidate regions for the extraction of seeds at iteration $k(k >= 1)$, and $Seeds_k$ all seeds extracted during this iteration. The set of initial candidates ($candidates_0$) is initialized to all regions R composing the image: $candidates_0 = R$.

The three steps of an iteration k of the algorithm (Fig. 1) are as follows:

- The extraction of all seeds of level k from the set $candidates_{k-1}$ of the regions not yet been processed in previous levels of the hierarchy. The seeds extracted at this level are the regions r_i that maximize $S_{max}(r_i)$ among all candidate regions at this level, *i.e.*,

$$Seeds_k = \arg\max_{r \in candidates_{k-1}} S_{max}(r). \tag{7}$$

- The integration of spatial constraints re-evaluates the remaining regions and prunes the conflict seeds. Having a set of neighborhood constraints for each class, we browse $Seed_k$. For each seed, we check the compatibility between the seed and all those surrounding regions. If a neighbor region is affected to a class that cannot satisfy the adjacency constraint, we re-evaluate the classification.
- The region growing begin from the seeds of level k. This growth is based on a growing algorithm that allows merging each seed with its neighboring regions based on a set of homogeneity criteria. This fusion is constrained by a set of rules specific to the hierarchy and manages the integration of constraints and growth within the hierarchy. Indeed, a seed of level k cannot change the state of a seed of lower level.
  The choice of the growing algorithm remains dependent of knowledge about the image. The use of the hierarchy of growth allows the integration of the semantic notion in the growth process. Knowing the membership of the seed, a specific growth can be used for each seed. The use of growth based on low-level knowledge such as texture and radiometry is also feasible.

In this paper, we focus on the hierarchical aspect of growth and not the way that it has been made.

Definition 6. ($fusion_k$) *denotes all the regions that have been merged in the level k with one of the seeds of* $Seed_k$.

$$fusion_k = \{r \in candidates_{k-1} | r \text{ has been merged in the level } k\}. \tag{8}$$

All candidates regions in the level $k+1$*, denoted* $candidates_k$*, will be the set of candidates of the level k after the removal of parts merged regions and seeds of the level k.*

$$candidates_k = candidates_{k-1} \backslash \{fusion_k \cup Seed_k\}. \tag{9}$$

Then from this set, we reiterate in the same manner until exhaustion of all the candidates. The pseudo-code of algorithm of the hierarchical growth is given by algorithm 1:

Algorithm 1. Hierarchical growth

Input: R the set of regions of the image obtained by segmentation, SIM the set of similarity scores for the regions of the image.

Output: candidates the set of candidates to be seed for each level of the hierarchy, Seed the set of seeds selected for each level k of the hierarchy and fusion the set of regions merged for each level of the hierarchy.

Begin
  $candidates_0 = R, k = 1$;
  while $candidates_{k-1} \neq \emptyset$ **do**
    $Seed_k = \arg\max_{r \in candidates_{k-1}} S_{max}(r)$
    $fusion_k = \{r \in candidates_{k-1} \backslash Seed_k | r \textit{ has been merged in the level } k\}$
    $candidates_k = \{candidates_{k-1} \backslash fusion_k \cup Seed_k\}$
    $k = k + 1$;
  endw
End

3.3 Integration of Spatial Knowledge

The spatial knowledge is usually adjacency knowledge that can be modeled by all classes with which it may be close or not. In each level of the hierarchy, and before starting the growth phase, the seeds will inject adjacency constraints on their respective neighborhoods. The initial classification will be re-evaluated in cases of conflict. In the case where two seeds of the same hierarchy have an ambiguity due to the constraints of adjacency, then there is confusion and these seeds lose their confidence and become conflict regions. They will lose their places in the hierarchy and the similarity score of these classes will be given to zero and will be reassigned in the set of candidate regions. So, we will have $Sim(r_j, C_{max(r_j)}) = 0$ and $Sim(r_i, C_{max}(r_i)) = 0$. Otherwise, we keep the class that maximizes the similarity score and which validates the adjacency constraint.

Definition 7. ***(Neighbors)****: Let neighbors(r_i) the set of regions r_j that are adjacent to r_i.*

$$neighbors(r_i) = \{r_j \in R | r_i \textit{ and } r_j \textit{ are adjacent}\} \tag{10}$$

Definition 8. ***(Spatial constraints)****: Let $SC(c_i)$ the set of classes c_j that represent the spatial constraints of the classe c_i.*

$$SC(ci) = \{c_j \in C | c_i \textit{ and } c_j \textit{ can not be neighbors}\} \tag{11}$$

Algorithm 2 illustrates the integration of spatial constraints in the hierarchy.

Algorithm 2. Integration of spatial knowledge

Input: $Seed_k$,SIM and $candidates_{k-1}$.
Output: $Seed_k$,SIM and $candidates_{k-1}$.

Begin
    forall the $r_i \in Seed_k$ **do**
        if $S_{max}(\arg\max_{r \in (neighbors(r_i) \cup candidates_{k-1})} S_{max}(r)) < S_{max}(r_i)$ **then**
            //If r_i have the maximal confidence compared with his neighbors
            forall the $r_j \in neighbors(r_i)$ **do**
                while $C_{max}(r_j) \in SC(C_{max}(r_i))$ **do**
                    $Sim(r_j, C_{max}(r_j)) = 0$
                endw
            endfall
        else
            $Flag = 0$ //to verify if r_i is a region of conflict
            forall the $r_j \in neighbors(r_i)$ **do**
                if $C_{max}(r_j) \in SC(C_{max}(r_i))$ **then**
                    $Sim(r_j, C_{max}(r_j)) = 0$
                    $Seed_k = \{Seed_k \backslash (r_j)\}$
                    $candidates_{k-1} = candidates_{k-1} \cup (r_j)$
                    if $S_{max}(r_i) = S_{max}(r_j)$ **then**
                        $Flag = 1$
                    endif
                endif
            endfall
            if *Flag==1* **then**
                $Sim(r_i, C_{max}(r_i)) = 0$
                $Seed_k = Seed_k \backslash (r_i)$
                $candidates_{k-1} = candidates_{k-1} \cup (r_i)$
            endif
        endif
    endfall
End

4 Experiments

We tested our approach on a Quickbird image covering urban areas of Strasbourg, taken in 2008, having four bands, each band with a resolution of 2.44m/px.

Figure 2(a) presents the extract of the image to interpret whereas figure 2(b) depicts the classification of this extract by the HCBRG. Figures 2 (c) (d) and (e) present the mask of the three classes in the image. We observe that the majority of the objects are identified but the quality of the road identification is the worst and this is reflected by the false positive extracted regions. To validate these results, we have evaluated the quality of the classification obtained. These evaluations are done on geographic objects built and labeled by an expert using Precision and Recall measures . Precision can be seen as a measure of exactness or fidelity, whereas Recall is a completeness measure.

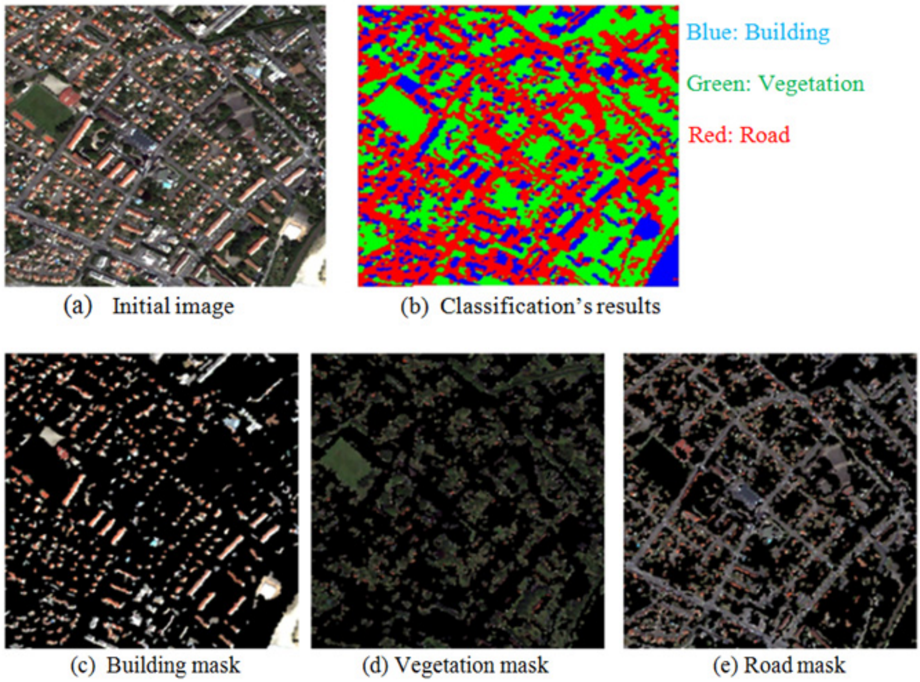

Fig. 2. Classification's results

In order to evaluate the performances of our approach (Fig.1), Recall and Precision have been calculated using the following formulas:

$$recall = \frac{(\ Number\ of\ correctly\ identified\ class\ regions\ )}{(\ Number\ of\ class\ regions\ in\ the\ image\ )} \tag{12}$$

$$precision = \frac{(\ Number\ of\ correctly\ identified\ class\ regions\ )}{(\ Number\ of\ identified\ class\ regions\ in\ the\ image\ )} \tag{13}$$

Table 1 shows the results obtained by the three classes we deal which are building, road and vegetation. We note that the recall accuracy results have a good

Table 1. HCBRG's evaluation results

Classes/Mesures	Road	Building	Vegetation
Recall	0.8064	0.9462	0.9259
Precision	0.6465	0.9047	0.8771

quality between 0.80 and 0.94. The precision gives lower results especially for the class road (0.64). This limit can be explained by the noise in the image due to the sensors, shadows, etc. Another cause is that road extraction needs a tracking step.

5 Conclusion

In this paper, we have presented a new collaborative approach between segmentation and classification. The initial classification of the image allows ordering the regions according to a similarity score. The hierarchical aspect of this approach allows to treat the regions and to introduce the knowledge in an iterative way. The experimental results have shown the robustness of the proposed approach but it can be emphasized by using a specific semantic growing for each class. In future works, in order to deal with these problems, we will add to each class specific semantic growth process based on expert knowledge.

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