Agricultural-field extraction on aerial images by region competition algorithm.

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Abstract

The problem of segmenting agricultural fields in aerial images is still a manual work in most Geographic Information System requiring repetitive, tedious and time-consuming human work. Here, we address the problem of semiautomatic segmenting agricultural fields by region competition technique that integrates region growing and deformable models. The deformable model dynamically adapts its contour analyzing homogeneous parcels in an energy-minimizing framework. To assure the optimal image segmentation and practical applicability of the approach, we study different aspects: parameterization, convergence criteria and user interaction. The successful results obtained have allowed introducing the region competition technique in a teledetection environment.

Introduction.

In this work we consider the problem of segmenting agricultural landed-fields in digital aerial images by using a generalization of region growing techniques [7] combined with deformable models [8]. This mixed approach is called Region Competition [3]. The goal of this approach is to alleviate the tasks of digitizing the region contours, to obtain the vector representation of the features that appear in an aerial photo. By our experience, as a center for developing geographic information products, this is one of the most time consuming tasks related to the generation of Geographic Information Systems (GIS).

Our aim is to segment areas that are homogeneous enough to be represented by a Gaussian distribution, and different from the neighbor regions (e.g. woods) or delimited by lineal features like roads or rivers. Due to these characteristics, regions can be segmented by a combination of region growing and deformable models.

Deformable models (snakes) are defined as elastic curves that dynamically adapt a vector contour to a region of interest by applying energy minimization techniques. At the same time, given the problem of agricultural-land segmentation, we need region-growing approach to divide the raster image into homogeneous parcels. Region Competition combines the best features of Snakes/Balloon models and Region Growing techniques. In operation time, these techniques are applied to the case of having only two regions: the parcel to be segmented and its complementary.

Usually, the area segmentation techniques are focused in a pixel grouping approach and its further classification [2]. These techniques do not have information about the region number and location, neither control the boundary shape. The snake contribution consists of recovering the boundary information refining a coarse initial curve.

Other techniques for region segmentation that preserve the information details are presented in [4]; however, often oversegmented results are delivered. The regions growing controlled by the snake constraint generates region boundaries in a similar way as the manual operation does.

The region competition algorithm is based on an energy-minimization approach that actively optimizes the region contours and updates the probabilistic distribution parameters of the region to be segmented. Using the fact that the existing techniques of Snakes/Balloon models, Region Growing and Minimum Description Language (MDL) can address different views of the segmentation problem, they are unified within a common statistical framework to gain the advantage of all of them [3]. Using this strategy the preservation of topological features of the agricultural fields guides and makes more robust the pixel aggregation process of homogeneous regions.

Due to our experiences concluding the difficult full automation of extracting geographic information, like the elevation terrain model [10], we implement a semiautomatic tool for parcel segmentation. This choice is also reinforced by Tannous et al. [5,6] exposing that due to the lack of maturity of automation extraction tools, the best way of increasing the productivity consists of designing semiautomatic tools for image processing. Often the user is required to provide initial position of the feature to be extracted and to perform an adjustment with the information delivered by the image. When the automatic process delivers some imprecise results, the operators feel more comfortable when controlling rather than looking for incorrect results.
We apply the general region competition algorithm [3] to the agricultural field segmentation. Our contribution is to

make it the most operative possible by studying its dependency on the parameterization as well as to implement convergence criteria and to validate it in a practical environment.

The paper is organized as follows: section 2 introduces the region competition approach, section 3 considers its applicability to the agricultural field segmentation, section 4 discusses the results and the article finishes with conclusions.

2. Unified frame for snakes and region growing.

Our aim is to represent a continuos gray scale image by a vector set representing the parcel boundaries by Minimum Description Language (MDL). We start with an homogeneity concept: One region R is considered homogeneous if the intensity values are consistent with being generated by a distribution family of pre-specified probability $P(I:\alpha_i)$, where α_i are the distribution parameters.The next step is to define a function that represents with MDL the image boundaries taking into account the variety of the statistics parameters of each parcel to be segmented:

$$E[\Gamma, \{\alpha_i\}] = \sum_{i=1}^{M} \left\{ \frac{\mu}{2} \int_{\delta R_i} ds - \int \int_{R_i} \log P(I_{(x,y)} : \alpha_i) dx dy \right\}$$

This expression reflects the energy associated to the snake curves. The first term is the internal energy associated to the curve, by minimizing it we force to be the shortest possible one. Where μ is the code length for unit arc length, δR_i is the boundary of region R_i. The second one is the exterior force due to the image information that decreases (considering the negative sign) when the classification is improving. The classification is applied on the intensity value ($I(x,y)$) of pixels (x,y) classified to a homogeneity region R_i, described by a probabilistic density function $P(I:\alpha_i)$, (without loss of generality we consider Gaussian distribution described by its parameters α_i i.e. mean and variance).

The minimization of this energy gives the contour positions at each time step. The solution is reached by the steepest descendent method:

$$\frac{d\vec{v}}{dt} = -\sum_{k \in Q(\vec{v})} \left\{ -\frac{\mu}{2} \kappa_{\kappa(\vec{v})} \vec{n}_{k(\vec{v})} + \log P(I_{(\vec{v})} | \alpha_k) \vec{n}_{k(\vec{v})} \right\}$$

In the particular case of having only two regions (the one R_i that is to be segmented and its complementary R_j) the expression is as follows:

$$\frac{d\vec{v}}{dt} = -\mu \kappa_{i(\vec{v})} \vec{n}_{i(\vec{v})} + (\log P(I_{(\vec{v})} | \alpha_i) - \log P(I_{(\vec{v})} | \alpha_j)) \vec{n}_{i(\vec{v})} \quad (1)$$

(1) represents the evolution of a parcel boundary driven by keeping low curvature and moving depending of the similarity between the distribution of one region or the other one. If not additional information is given, the statistical model chosen to describe the homogeneity of the region is the Gaussian distribution. When replacing the probability by the Gaussian we obtain the region competition formulation:

$$\frac{d\vec{v}}{dt} = -\mu \kappa_{i(\vec{v})} \vec{n}_{i(\vec{v})} - \frac{1}{2} \left\{ \log \frac{\sigma_i^2}{\sigma_j^2} + \left(\frac{(I - \mu_i)^2}{\sigma_i^2} - \frac{(I - \mu_j)^2}{\sigma_j^2} \right) + \left(\frac{S^2}{\sigma_i^2} - \frac{S^2}{\sigma_j^2} \right) \right\} \vec{n}_i$$

The position of the contour is driven by the similarity of a small ball around each point to one of both regions, the Fisher test is the used similarity measure. The next section shows the "landed-fields" region growing implementation.

3. From algorithm to application.

3.1 Parameterization of the model

We compared the polygonal representation considered in [3] to a B-spline representation of the snake. Given the discontinuity of curve derivatives in the polygonal representation, the curvature is not introduced. Some results can be seen in figure 1. The irregularity of the curve shape imposes to replace the snake parameterization by B-splines as follows:

$$Q(u) = \sum_{i=0}^{m} V_i B_i(u),$$

where V_i are the m control points and B_i are the blending functions [1]. Using this representation it is very easy to introduce the curvature constraint into the model to achieve smoother boundaries. In figure 2 the boundaries are represented by B-splines, where the difference between both representations can be appreciated.One of the reasons to select the B-spline representation is its easy and compact way to represent the regularity of the landed-field shape. Another B-spline advantage is the fast computation of the spline derivatives, hence the internal forces, controlling curve curvature, can be introduced at a very low cost.

The contours represented by B-splines are smoother and closer to the ones that can be drawn by an operator, although oversmoothing can be obtained. To cope with it,

we introduce a refinement step only used when the delivered result at the first approach does not follows all the details of the boundary that consists of increasing the number of spline control points.
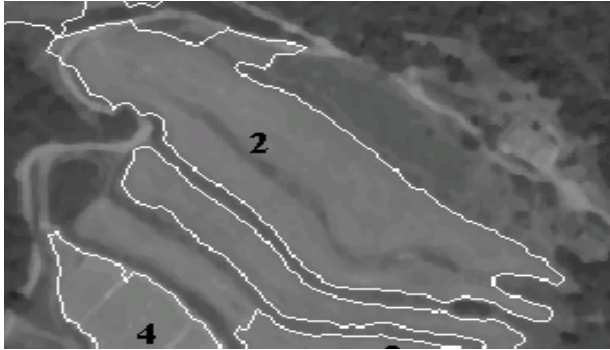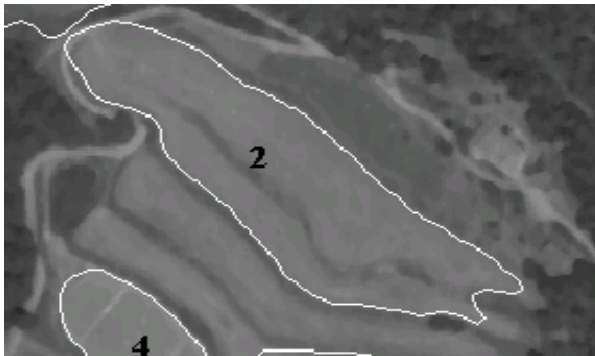

Figure 1. Polygonal snake

Figure 2. B-spline represented snake.

The time spent to segment a parcel in case of recovering the contour by polygonal representation is faster than doing the same by B-splines. However, using the two-step approach necessary only in 8% of all tested parcels, the B-spline segmentation time approximates the polygonal one.

3.2 Convergence criteria

By studying the convergence of the process in the different cases of parameterization, we study different strategies to stop the process when a solution is reached. The first approach computes the number of pixels inside the growing polygon. The deformation is stopped when this number becomes constant. A second approach is based on shape correlation between two followed iterations applied to the case of representing the contour by a B-spline. This strategy is recommendable due to the fact that the shape correlation can be computed directly from the analytical B-spline representation. Shape correlation allows detecting converged active contours as well as balanced contour oscillations.

3.3 User interaction

Since the operator interaction is to give a point or a seed region from which the initial approximations are computed as well as to validate the results, his (her) knowledge as well as experience assure "better" initial conditions. A seed, given by the operator, determines the initial snake as a small circular area that is also taken to have the first approximation of the parcel statistical parameters. We study the dependency of the initial conditions and detect that most of the cases it is very difficult to obtain a reliable homogeneity description of the area only by giving a point (fig. 3) as proposed in [3]. In fig. 3 the mean varies considerably and the deviation is large to consider a small ball a good initial approach.
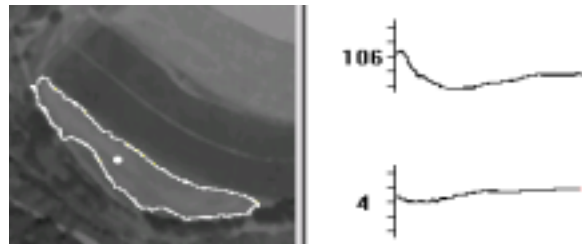

Figure 3. Point seed result and the mean and deviation progression.

In these cases it is necessary to deliver a region to take the sample of the probabilistic distribution used to describe the region. The operator defines an area that represents the region homogeneity. Also this region is the first approximation to the parcel boundary. With this approach a better process performance is achieved in terms of reducing the time needed to deliver a solution, because the stability of the distribution parameters comes faster and the system does not need to compute them any more. The same parcel of fig.3 with a seed area can be seen in fig. 5.
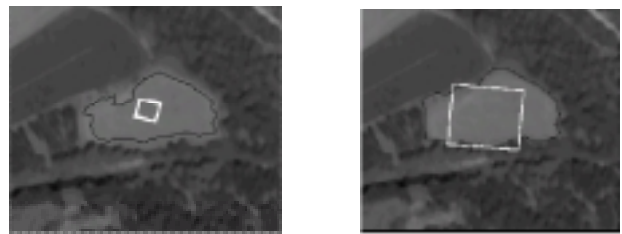

Figure 4. Seed selection effect.

The first seed in figure 4 is small and can not reflect enough the gray-scale gradation. The time needed to obtain the semi-correct solution is twice than in the second image of the same figure, where a bigger sample gives a better approximation of the statistical distribution.

The semiautomatic tool has been integrated into an edition menu, useful in case of necessity of small edition actions, like point modification or insertion. With this utility it is also possible to draw from scratch the parcels boundaries when it is impossible to obtain them by automatic means (e.g. in case of lack of homogeneity, or parcels with radiometry similarity). The different actions that can be done with the edition menu are grouped into three sets. The first group encloses the actions applied to one element, like moving, simplifying, and deleting. The second contains the partial actions affecting to one element as modifying, inserting or eliminating vertices. The last set contains commands that groups several elements at once, for example union of boundaries, useful since the semiautomatic algorithm can over-split some areas that the user interpretation could have put together.

5. Results.

The algorithm has been tested over twenty different aerial images, on the average with 30 parcels per image. We detected that the 70% of the cases are completely successfully recovered and only few of them needs small edition tasks. In these cases the time reduction compared to the manual design is 60% that justifies the use of the algorithm in a productive environment. Some results are shown in fig. 5.
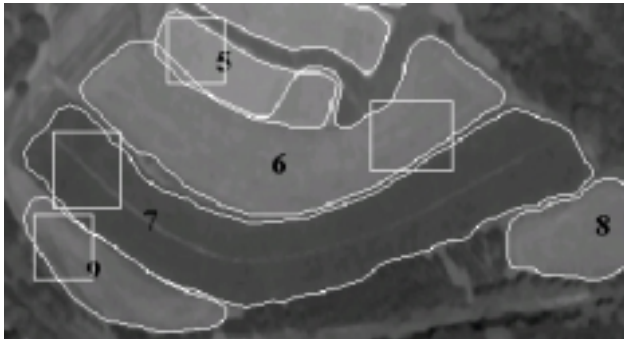

Figure 5. Seeds and boundaries result obtained 60% faster than manual drawn and with a sub-pixel accuracy.

The operator can not reach the sub-pixel accuracy achieved by the semiautomatic approach; however, its interpretation delivers less number of points to the system to build a contour.

6. Conclusions

In this paper we show the applicability of the region competition technique in a teledetection environment to obtain parcel boundaries changing the role of the operator from being the principal delineating "mean" to being a supervisor of the agricultural field segmentation.

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