AGRICULTURAL FIELD EXTRACTION FROM AERIAL IMAGES USING A REGION COMPETITION ALGORITHM

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ABSTRACT

The segmentation of agricultural fields on aerial images is still a manual activity in most Geographic Information Systems, requiring repetitive, tedious and time-consuming work. In this article we address the problem of semiautomatic segmenting of agricultural fields by region competition techniques that integrate region growing and deformable models. The deformable models dynamically adapt their contour, starting from a rough seed, and homogeneous parcels are analyzed in an energy-minimizing framework. The algorithm is integrated into an edition menu that also allows parcels to be drawn from scratch and set operations to be applied between parcels that have already been extracted. To achieve the optimum image segmentation, we study different aspects: user interaction, parameterization and convergence criteria.

1 INTRODUCTION

In this paper we consider the problem of segmenting agricultural fields on digital aerial images by using a generalization of region growing techniques (Hong 84) combined with deformable models (Kass 87). This mixed approach is called Region Competition (Chun 96). The aim of this approach is to alleviate the tasks of digitizing the region contours, in order to obtain the vector representation of these types of features that appear in an aerial photograph. In our experience, this is one of the most time consuming tasks involved in the generation of Geographic Information Systems (GIS). Moreover, parcels are one of the most dynamic features in the course of time, and following their evolution is of interest for a large number of applications.

Our aim is to segment areas that are homogeneous enough to be represented by a Gaussian distribution and are different from the neighboring regions, or areas that are delimited by linear features such as roads or rivers, or by woods. The combination of these characteristics makes the joint approach of region growing and deformable models a reliable extraction technique.

Deformable models (snakes) are defined as elastic curves that dynamically adapt a vector contour to a region of interest by applying energy minimization techniques. For the parcel segmentation, we use region growing techniques to obtain snakes and region competition parameters, and to divide the raster image into homogeneous parcels. Region Competition combines the best features of Snake/Balloon models and Region Growing techniques. In our approach we apply this technique to the case of having only two regions: the parcel to be segmented and its complementary.

The most common approach to agricultural field segmentation is based on pixel grouping (clustering) and subsequent classification (Cees 99). These techniques do not provide information about the number of existing regions and their location, nor do they control the shape of the boundary. The deformable models recover the boundary information by refining a coarse initial curve given by the operator.

Other techniques that preserve the information details (Dellepiane 99) deliver oversegmented results. The growth of the region controlled by the snake constraints helps to generalize in a manner that is similar to manual operation.

This 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. In view of the fact that the existing techniques of Snake/Balloon models, Region Growing and Minimum Description Language (MDL) can address different aspects of the segmentation problem, they are unified within a common statistical framework, so that advantage may be taken of all of them. Applying this strategy, the preservation of topological features of the agricultural fields guides and strengthens the pixel aggregation process of homogeneous regions.

In view of the difficulties inherent in a fully automatic process when extracting geographic information (Ruiz 96), we have implemented a semiautomatic tool for the parcel segmentation. This approach is also reinforced by Tannous et al.[(Gruen 97),(Gülch 97),(Radeva 99)] who note that due to the lack of robustness of automatic extraction tools, the best way of increasing the productivity lies in designing semiautomatic tools. If an automatic process is prone to fail, the best approach is to let the operator gain full control of the process, rather than force this operator to search for the incorrect results in the whole image. Therefore, with our approach, the user provides the initial position of the feature to be extracted and can control and edit the results interactively.

We apply the general region competition algorithm that is presented in (Chun 96) to the agricultural fields. Our contribution is to make it as operative as possible by studying its dependency on the parameterization and the initial conditions, as well as to implement convergence criteria and validate it in a production environment, defining in which type of parcels this approach yields good results.

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

2 UNIFIED FRAMEWORK FOR SNAKES AND REGION GROWING

Our aim is to represent a continuous gray scale image by a vector set representing the parcel boundaries, with the aid of Minimum Description Language (MDL). With this approach we segment the parcels that are mainly characterized by their high homogeneity, or are outlined by linear elements or other areas with different homogeneity. This combination makes it feasible to apply a combination of deformable models guided by region growing criteria.

We will begin with a homogeneity concept: a region R is considered homogeneous if the intensity values are consistent with being generated by a distribution family of a pre-specified probability $P(I : \alpha_i)$, where α_i are the distribution parameters.

The next step is to define a function with MDL that represents the image by 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 with the snake curves. The first term is the interior energy associated with the curve, and forces it to be the shortest possible. The parameter μ is the code length for unit arc length and δR_i is the boundary of the region R_i. The second term is the exterior force due to the image radiometry that inversely decreases with the degree of similarity of the intensity value at (x, y) $(I(x, y))$ to a homogeneity region described by $P(I : \alpha_i)$. Because we do not have any additional information relating to the parcel characteristics, we assume that the region homogeneity can be described by a Gaussian distribution, parameterized by α_i, which expresses the mean and the variance.

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

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

In our case we handle only two regions, because we apply this reasoning to a parcel that grows and competes with neighboring areas. The expression is as follows:

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

Formula (1) represents the evolution of a parcel boundary driven by keeping the curvature low, and modifies the contour depending on the similarity to the intensity distribution of one region or the other. When replacing the probability by Gaussian, we obtain the region competition formula:

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

The position of the contour is driven by the constraint of keeping the curvature as low as possible. The pixels are then tested in order to decide to which of the two regions they belong: for each point of the contour a small ball (circle) is taken and its statistical parameters computed. The likelihood ratio is then computed to decide whether the region parameters fit better into the distribution describing region i or j. Thus two adjacent regions are competing for pixel ownership *(region competition)*.

3 FROM ALGORITHM TO APPLICATION

Apart from implementing the region competition algorithm, we divide its design into three parts: parameterization, convergence criteria and user interaction.

3.1 Parameterization of the model

Two possible model parameterizations are the polygonal representation and the B-splines.

In the polygonal representation considered in (Chun 96), some features of the curve are not introduced due to the discontinuity of curve derivatives in this representation. Some results can be seen in figure 1. The irregularity of the curve shape forces the snake parameterization to be replaced 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 (Barsky 87). Using this representation it is very easy to introduce the curvature constraint into the model to achieve smoother boundaries. In figure 1 the boundaries represented by B-splines are shown on the right, at this figure the difference between both representations can be appreciated.

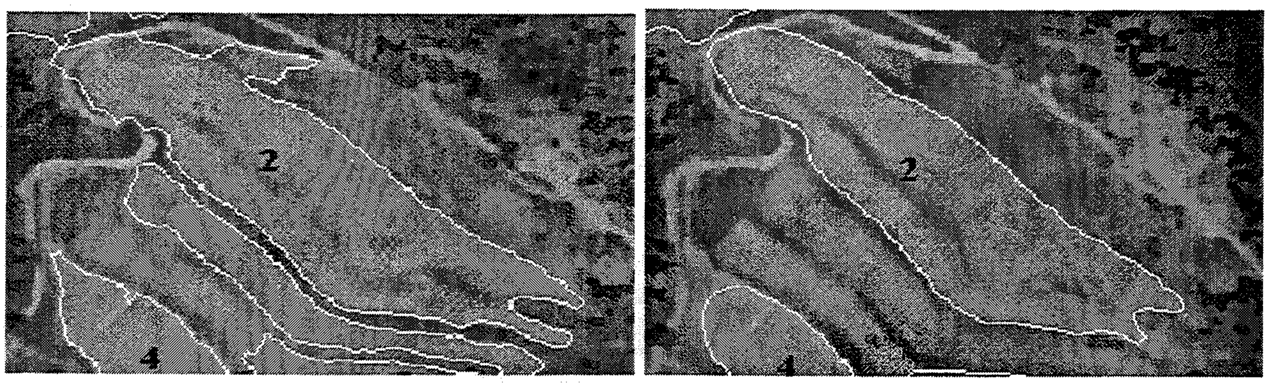

Figure 1: Polygonal snake vs. B-spline representing snake.

One of the reasons for selecting the B-spline representation is the easy and compact way in which it represents the regularity of the parcel shapes. Another advantage of the B-spline is the fast computation of its derivatives, and thus the internal forces controlling curvature can be introduced at a very low cost. The contours represented by B-splines are smoother and closer to the ones drawn by an operator, although oversmoothing may be obtained. To solve this problem, we apply a refinement step when the result delivered by the first approach does not fit the details of the boundary, although this step doubles the number of spline control points. Practical experience shows that this two-step approach is only necessary for 8 % of the parcels.

On the other hand, the spline representation makes the process slower. Although very little time is needed to segment a parcel, using the B-spline representation increases the time in which the same region is obtained by 20. Due to this considerable difference the combined approach based on a first approximation by using polygonal and refining by B-Splines is the most efficient solution.

3.2 Convergence criteria

The iterative approach makes it necessary to define when a solution is reached. We work with two convergence criteria, whose application depends on the parameterization that has been chosen.

For the polynomial interpolation, it is possible to follow the evolution of each point at the different steps in the iterative approach. In this case a vertex remaining in the same position is considered as a stable point, and a stable contour is defined when all its vertices have this property.

This strategy is necessary due to the fact that the B-spline representation is not an interpolation: the control points at a given iteration step are different from those of the previous iteration, so it is impossible to monitor their history. The convergence criteria must change to another dimension. We have developed two different strategies to stop the process when a solution is reached. One of these is based on shape correlation between two successive iterations. The other is based on the stabilization of the area by computing the number of pixels inside the region. This second method is slightly faster than the first one, but the shape correlation is more reliable, because it detects balanced contour oscillations.

3.3 User interaction

On the basis of our past experience, a semiautomatic tool was chosen because:

1. It gives a better approach to the initial position of the starting curve.
2. It increases the reliability of the initial statistical model describing the area.
3. It makes it possible to detect the problems relating to automation by validating the results.

Apart from accepting/refusing the results, since the operator interaction is to give a point or a seed region from which the initial approximations are computed, the knowledge as well as the experience of the operators assure "better" initial conditions. The seed is an initial snake that defines a small circular area used for computing the first approximation of the statistical parameters of the region.

We studied the dependency on the initial conditions and detected that in most cases it is very difficult to obtain a reliable homogeneity description of the area by simply giving a seed point and taking a small area around it, as proposed in (Chun 96) and shown in figure 2.

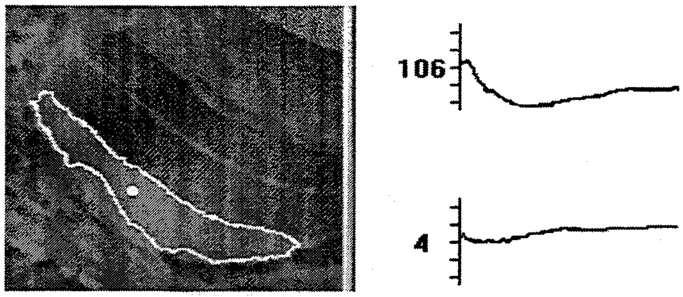

Figure 2: Point seed result and the mean and deviation progression.

As can be observed, the standard deviation is large enough to consider the selection of only one point inside the region that is sufficiently representative.

In these cases it is necessary to define a region in order to compute the probabilistic distribution describing the parcel. The operator defines an area that is representative of the region homogeneity. Furthermore, this region is the first approximation to the parcel boundary. By means of this approach a better performance is achieved in terms of reducing the time needed to obtain a solution, because the statistical parameters that describe the parcel are not updated at each step. In this case, the first approximation is considered sufficiently representative of this distribution. The same parcel with a seed area can be seen in figure 5.

The importance of the seed size may be observed in figure 3. The image on the left contains a small seed, so the variability of the pixel tones in the area cannot be obtained, and thus the boundary is not accurately detected. This is solved in the

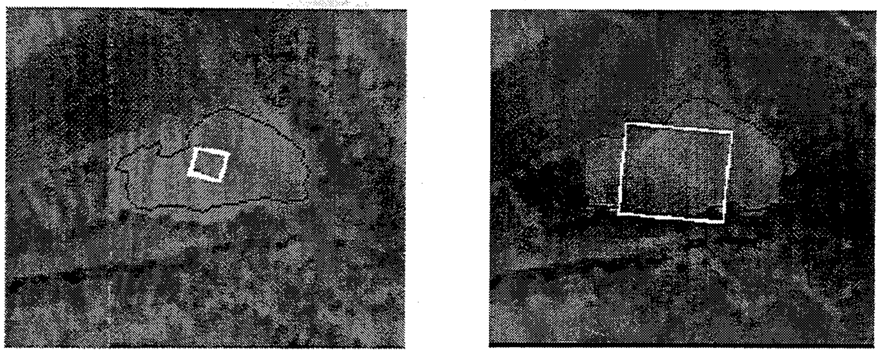

Figure 3: Seed selection effect.

image on the right, in which the seed area has been enlarged. Moreover, to obtain the unsatisfactory contour requires twice as much time as in the correct case, where a bigger sample gives a better approximation of the statistical distribution.

The seed location is also very important. Since the contour of the seed is the first approximation of the deformable model contour, the more intersections with the parcel image boundary the contour has, the faster the process convergence is.

In this case the smooth curvature condition makes the seed become circular and reduces its area in the first iteration, but the reliability of the statistical parameters pushes as an internal force and recovers the boundary in few iterations.

As mentioned before, past experiences with other photogrammetric tasks have led us towards a semiautomatic tool. Any automatic tool that cannot assure the correctness of the results in almost all the cases and whose errors cannot be discovered and labeled, forces the operator to make an exhaustive check of all the information. This makes the automatic tools hard to use and the time spent on quality control could cancel out the expected advantage of automation.

To improve interaction the semiautomatic tool has been integrated into an editing menu. It is useful in the case of small editing actions, such as point modifications or insertions. With this utility it is also possible to draw the parcel boundaries from scratch, when it is impossible to obtain them by automatic means (e.g. when there is lack of homogeneity, or the parcels can only be extracted by complementary perception).

The different actions that can be performed with the editing menu are grouped into three sets. The first group includes the actions applied to one whole element, such as moving, simplifying, and deleting. The second contains the partial actions affecting one element, such as modifying, inserting or eliminating vertices, or cutting and redrawing parts of the element. The last group contains commands that affect several elements at once, for example union of boundaries, which is useful because the semiautomatic algorithm can over-split some areas that the user's interpretation would have put together. In the third group it is important to observe that both the input and the output elements are in vector format, although the operations are performed in a raster environment (it is a particular case of the region growing algorithm applied to a bitmap set). Therefore, union, intersection and subtraction of contours, as well as any combination of these operations are available.

The set operations between parcel contours are useful in the event of over or undersegmentation. The example shown in figure 4 unifies two parcels that the automatic process splits into two parts on account of their radiometric difference. In the second image a single contour is shown as a result of the union of the previous ones.

4 RESULTS

The results presented in figure 5 have been obtained with the rectangular seeds that appear there and the parameterization used has been B-splines. In this figure it can be observed that parcel 6 invaded the neighboring parcel above it. This is due to the seed size, which in this case takes a piece of the parcel below, and the statistical parameters are diverted to the dark part, whereby it becomes impossible to distinguish them from the parameters of parcel 5.

The time needed to obtain these results varies from $40''$ in the case of parcel 5 to $1'10'$ in the case of parcel 7. The computer used for this test is a 300 MHz Pentium-Pro with 32Mb RAM. Use of a 300 MHz Pentium-II processor reduced these times approximately fourfold.

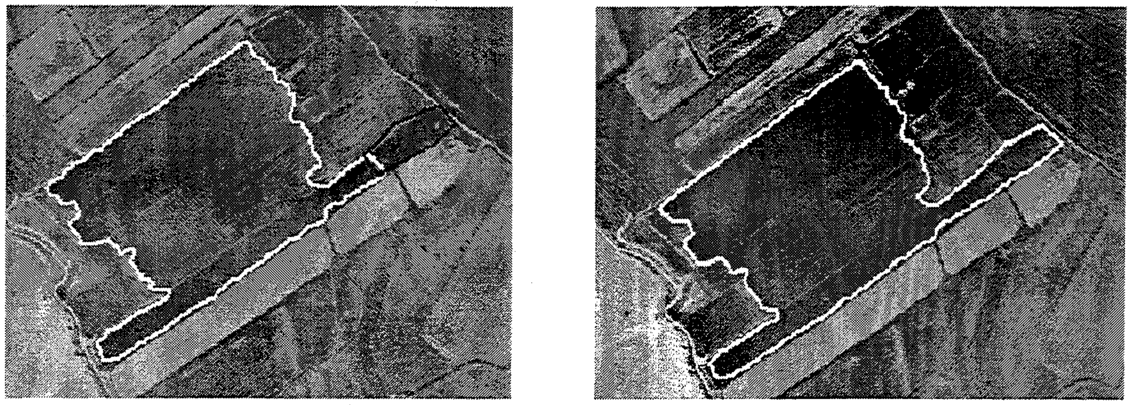

Figure 4: Set operations between parcel boundaries.

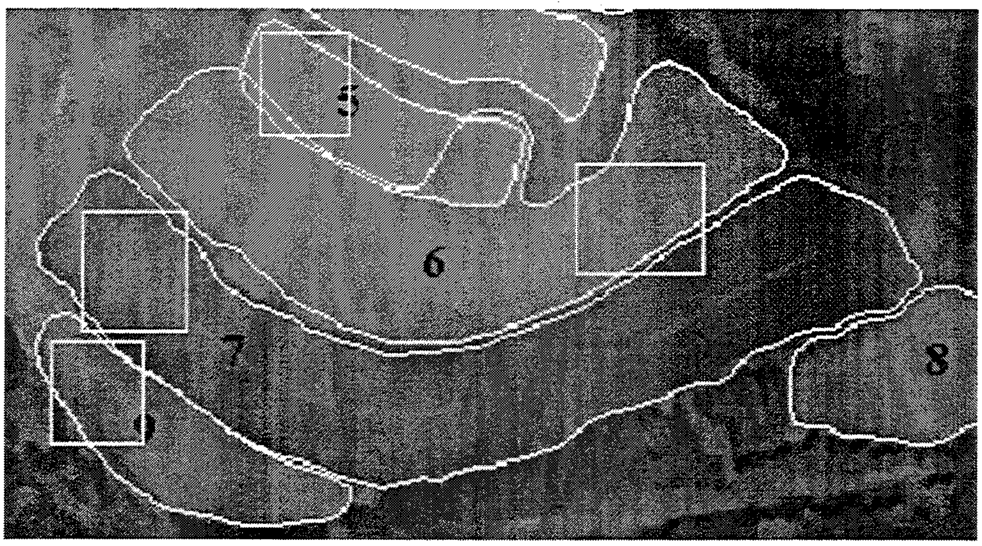

Figure 5: Seeds and resultant boundaries applying parameterization by B-splines.

The degree of homogeneity of all the parcels is high enough to be modeled by a Gaussian distribution. There are other examples shown in figure 6, in which the presence of texture makes it impossible to apply the region growing approach to recover the area. This example also shows the difference between the two parameterizations, since the polynomial parameterization produces more irregular contours than when working with B-splines, which smooth their shape by construction.

To date, the algorithm has been tested on twenty different aerial images, and on average we have worked with 30 parcels per image. We have detected that 70 % of the cases are successfully recovered and only a few of them require small editing tasks. In these cases the time is reduced to half that of the manual procedure, which is good enough to consider the introduction of this algorithm into a productive environment.

Compared with the results outlined manually, the operator cannot achieve the sub-pixel accuracy, but is able to draw the outline with fewer points.

5 CONCLUSIONS

In this paper we have presented the applicability of the region competition technique to the extraction of parcel boundaries by changing the role of the operator from that of a principal delineating agent to a supervisor of the segmentation. The automation can mainly be applied to two kinds of parcel types: firstly, parcels that are characterized by their high degree of homogeneity, and secondly, parcels surrounded by linear elements that can be recovered with a high degree of certainty by deformable models. In these cases a high proportion of parcels can be segmented, and in case of failure the edition required is very simple. The next step is to add texture characteristics to the model, in order to increase the number of parcels recovered, and a further step would be to combine strategies to provide the system with more cross-information, such as pre-existing GIS data used as initial conditions.

Figure 6: Parcels obtained 60 % faster than when manually drawn and with sub-pixel accuracy.

6 ACKNOWLEDGEMENTS

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