Region Growing in GIS, an application for Landscape Character Assessment

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EXTENDED ABSTRACT

Region growing is an image analysis technique that uses the spatial patterns in an image to divide an image into regions or spatially continuous clusters. A region growing process is an iterative bottom-up optimization process, where in each round the most similar neighbouring regions are merged, minimizing the dissimilarity within the regions and maximizing the dissimilarity between the regions. The underlying data structure of a region growing process is the regional adjacency graph (RAG). A RAG = (V,A,W) is a mathematical data format in which the regions are represented by a set nodes $V = \{v_1, v_2,\ldots,v_n\}$, the adjacency between these nodes by a matrix matrix A^{nxn} where a_{kl} ε $\{0,1\}$ and the dissimilarity between the nodes by a matrix of weights W^{nxn}, where w_{kl} ε R^+. In geo-sciences region growing is mainly used for the classification of high resolution satellite imagery and aerial photographs. By representing a spatial database as a RAG the scope of region growing can be broadened to other types of spatial data, including raster and vector data consisting of nominal and continuous data, operationalizing a new tool for the analysis of spatial data patterns in a GIS. This tool can be used for the classification of mosaic patterns on a vegetation map, to detect clusters in point clouds or to aggregate spatial data for map generalization and other applications where the segmentation of spatial data patterns is required.

We have implemented a region growing algorithm in a methodology for landscape character assessment. We define the landscape character as presence, arrangement and variability of different landscape features. A region growing algorithm is used to delineate landscapes in a spatial database of landscape features. Each region represents a distinctive landscape and is characterized by its pattern of data values. The quantitative description of the landscape character can then be used to further analyse the dataset. The methodology proposed consists of 4 steps:

1. Building a spatial database
2. Delineating landscapes
3. Classifying landscape types
4. Evaluation of the analysis result.

We applied this methodology to characterize an agricultural area in the north of the Netherlands called 'the Northern Friesian Woodlands'. In the first step a spatial data base derived from a small scale topographical map was created consisting of 22.723 polygons describing 10 distinctive landscape features. In the second step the region growing algorithm was used to segment the dataset into 132 different regions. In the third step a non spatial clustering algorithm was used to classify the 132 regions into 13 different landscape types. To evaluate this classification we combined the information from 4 expert maps into a reference map. The classification consistency between the two maps varied between 60 and 100%. The differences between the two maps can be explained from lack of information among experts, lack of information in the region growing analysis and the difference between human perception and a digital segmentation algorithm. This last observation provides an interesting handle to study the human perception of landscapes.

It can be concluded that region growing is a powerful tool for landscape character assessment and for the analysis of geographical boundaries in general. Using region growing to analyse data patterns there is no need to assume predefined analysis units. To further develop region growing as spatial database technique there is a need for a systematic comparison of different region growing algorithms in relation to data types and data patterns and for the development of evaluation criteria to assess the quality of a segmentation.

1. INTRODUCTION

Region growing is an image segmentation technique (Pal and Pal, 1993) to divide an image into a set of homogeneous and spatially continuous clusters on the basis of the pixel pattern. Region growing is often applied as the first step in a number of complex image analysis tasks, for example to recognize specific patterns on an image (Wu et al., 2005), to classify an image (Yan et al., 2006), to detect differences between images (Montoliu and Pla, 2005), to analyse structures in 3D images (Jiasheng and Yi, 2006) and to represent images at multiple scales (Bertolino and Montanvert, 1996). In geo-sciences region growing is mainly used for the classification of high resolution satellite imagery and aerial photographs. Examples can be found in Lu and Weng, (2007). This type of classification provides generally better results than the traditional pixel based classification methods (Yan et al., 2006). All applications found we are based on spectral data, but the application of region growing does not need be restricted to this type of data. In geo-information science region growing could be used to classify patterns of data values, such as the vegetation pattern in a vegetation map (Vos and Stortelder 1992) or to define eco-regions in continuous physio-climatic dataset (Fairbanks, 2000). In general region growing can be applied for geographical boundary detection, to classify spatial patterns or to interpret spatial data at a higher scale level when the adjacency between neighbouring data elements is known and the dissimilarity between the data elements can be expressed mathematically.

In this paper we will elaborate how to implement a region growing process into a GIS using different types of data. In addition we will demonstrate how region growing can be used for landscape character assessment (Swanwick and Consultants, 2002). Landscape character assessment is the process of describing, mapping and evaluating the landscape on the basis of the presence, arrangement and variability of landscape features: such as land use, hedgerows and trees. In this paper we use a region growing algorithm to delineate regions on the basis of the pattern of landscape features in a spatial database. Each region represents a separate landscape characterized by its pattern of data values. In an additional analysis step the regions will be classified into landscape types using a non spatial clustering algorithm and the resulting classification will be evaluated using expert knowledge.

2. REGION GROWING IN GIS

2.1. Region Growing

A region growing process is an iterative bottom-up optimization process, where in each round the most similar neighbouring regions are merged, minimizing the dissimilarity within the regions and maximizing the dissimilarity between the regions.

The underlying data structure of a region growing process is the regional adjacency graph (RAG). A RAG = (V,A,W) is a mathematical data format in which the regions are represented by a set of nodes $V = \{v_1, v_2,\ldots,v_n\}$, the adjacency between these nodes by a matrix A^{nxn} where a_{kl} ε {0,1} and the dissimilarity between the nodes by a matrix of weights W^{nxn}, where w_{kl} ε R^+. As a result of the region growing process a new RAG^{k+1} is defined from the previous RAG^k iteration and the resulting data structure is a graph pyramid, consisting of multiple representations of the dataset (figure 1). The relation between the layers can be expressed by an additional set of edges $F^{k,k+1}$. Each node at level k+1 (parent) is a union of a set of neighbouring nodes at level k (children). This union is the so called contraction kernel (Kropatsch et al., 2005). By using the parent-child relation between the nodes in subsequent layers, the original pixels at the base of the pyramid can be traced from any level of the pyramid. This set of pixels at the base of the pyramid is called the region or the receptive field (Jolion and Montanvert, 1992) and has a conceptual resemblance with the way information from the receptors within the retina is being processed (Kropatsch et al., 2005).

The final segmentation result and the shape of the graph pyramid is determined by the optimization

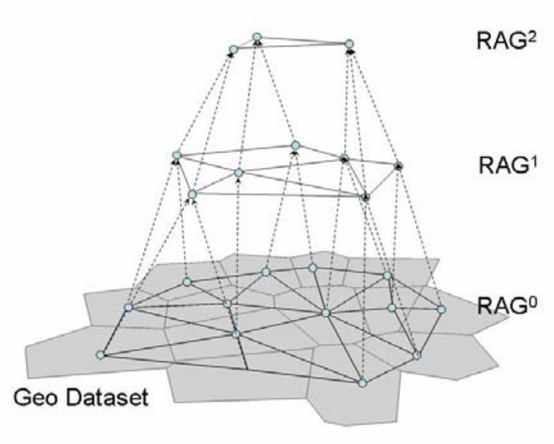

Figure 1: Graph Pyramid consisting of multiple representations of the dataset. RAG^k is the regional adjacency graph for iteration k.

method, the dissimilarity criterion and the stop criterion of the algorithm.
The region growing algorithm applied in this paper is a variation on the Fractal Net Evolution (NFE) algorithm (Baatz and Schape, 2000). In the NFE regions are merged according to the mutual best fit optimization criterion. This is a conservative approach in which two regions A and B can merge if and only if they are each others most similar neighbour. The algorithm is less greedy than other approaches and results therefore in fewer optimization mistakes. In addition the mutual best fit method takes into account local variation in the dataset. In the NFE algorithm the dissimilarity w_{kl} between two regions k and l is expressed as a function of a data dissimilarity value w_{kl}^{data} and a shape dissimilarity value w_{kl}^{shape}:

$$w_{kl} = w_{kl}^{data} + \beta * w_{kl}^{shape} \tag{1}$$

,where β is a scaling factor between the 2 dissimilarity measures. Its value is determined by the user. The data dissimilarity expresses the numerical differences between the data patterns in the regions and is defined as the relative increase in data heterogeneity after cluster merging.

$$w_{kl}^{data} = n_{k+l} * std_{k+l} - n_k * std_k - n_l * std_l \tag{2}$$

,where n_k and n_l are the number of data elements in region k and l, and std_k and std_l are the standard deviation of region k and l.
Using this definition regions tend to grow to a similar size and heterogeneous regions can merge as easily as homogeneous regions as long as the increase in heterogeneity after merging is the same. This property facilitates the segmentation of datasets with large differences in local variability.
The shape dissimilarity expresses the improvement of the new region towards the shape of a perfect circle.

$$w_{k+l}^{shape} = n_{k+l}\left(\frac{s_{k+l}}{p_{k+l}} - 1\right) - n_k\left(\frac{s_k}{p_k} - 1\right) - n_l\left(\frac{s_l}{p_l} - 1\right) \tag{3}$$

where s_k and s_l are the perimeter of region k and l, and p_k and p_l are the perimeters of a circle with the same area as regions l and k. As a stop criterion a simple threshold value τ is used, which represents the maximum dissimilarity for merging. If the dissimilarity between two regions exceeds the threshold they can not be merged. If during an iteration no merges are possible the algorithm stops. We implemented the algorithm in such a way that in each iteration all edges matching the mutual best fit criterion are determined and merged simultaneously, i.e. semi-parallel processing (Jolion and Montanvert, 1992).

2.2. Implementation into GIS

To allow a region growing process in a spatial dataset it needs to be converted into a RAG^0 .Each data element (pixel, raster cell, point or polygon) is be represented by a separate node and the neighbourhood relationships between data elements need to be determined. Adjacency in a raster data set is can be derived from the neighbourhood of its cells, in a point data set by Delaunay triangulation and in a polygon data set by determining the neighbouring elements for each polygon.
A GIS can consist of different data types, including nominal, ordinal interval, and ratio data. To be able to include each of these data types into the region growing process we use an alternative way to calculate the standard deviation of a region:

$$std_k = |K|\sqrt{\frac{\sum_{i\in K}\sum_{j\in K} d_{ij}}{2}} \tag{4}$$

,where d_{ij} is the data difference between two continuous values expressed as the Euclidian data distance between data elements i and j, K is the set of data elements in region k and |.| the cardinality of the set. Other data types, such as nominal or ordinal data, are included by replacing data difference d_{ij} by an appropriate measure. The calculated standard deviation is no longer a proper standard deviation in the statistical sense, but is still a valid measure of heterogeneity. When a geo dataset consists of several attribute layers the contribution of each attribute z to the total data difference is normalized.
Two examples of the segmentation of different data structures and data types are given in figure 2 and 3. In figure 2 the segmentation of a point dataset is presented using the point density as the variable of interest. For each data point the density was calculated as the average distance between all neighbouring nodes in the Delaunay neighbourhood. Figure 3 presents the segmentation of a nominal raster with a 6 neighbourhood. The data difference between the raster cells was calculated as the summed difference in relative frequency of occurrence of the classes in the neighbourhoods of the raster cells.

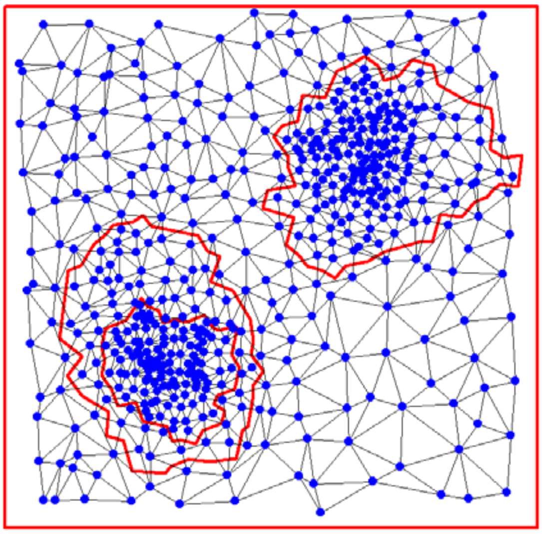

Figure 2: Segmentation of a point data set into 4 regions based on point density using a Delaunay neighbourhood, τ =1.3 and β = 0.

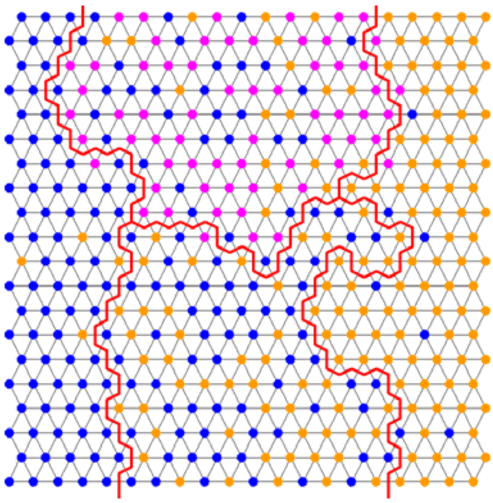

Figure 3: Segmentation of a raster data set with a 6 neighbourhood consisting of 3 classes A,B,C into 4 regions using τ =15 and β = 0.

3. LANDSCAPE CHARACTER ASSESSMENT

The objective of landscape character assessment is to describe, map and evaluate a landscape on the basis of the presence, arrangement and variability of landscape features (Swanwick and Consultants, 2002). The result of such an assessment can be used for landscape planning and management. In this paper a computerized method for landscape character assessment is presented based on the principle of region growing in a spatial data set of landscape features. Each region corresponds to a separate landscape, the landscape character described by its data pattern. The methodology proposed consists of 4 steps:

1. Building a spatial database
2. Delineating landscapes
3. Classifying landscape types
4. Evaluation of the analysis result.

The landscape character assessment methodology will be illustrated using a case study in the Northern Friesian Woodlands. The Northern Friesian Woodlands compromise an area in the north of the Netherlands characterized by small, narrow, long-stretched agricultural fields, reflecting a history of peat reclamation (Renting et al., 2006). Within this area 4 main landscapes types can be distinguished: The '*Dykswal*' landscape consisting of fields divided by hedgerows on wooded banks, the '*Singel*' landscape consisting of fields divided by ditches bordered on both sides by dense alder trees, the '*Tree Lane*' landscape consisting of fields bordered by full grown trees without undergrowth and the '*Open*' landscape consisting of fields bordered by ditches without trees.

3.1. Building a spatial database

The first step in the methodology is to build a spatial database containing the distribution of the landscape features of interest which consists of one or more data layers. The first layer is a spatially continuous layer of data elements (raster or vector) covering the study area. This layer provides the geometrical structure for the region growing process. How smooth the region growing result will be is determined by the size of the data elements compared to the extent of the study area. Data elements which are large or very long disturb the region growing process by interconnecting data elements in different parts of the dataset. The other data layers contain the landscape features, described in continuous, directional or nominal data.
For the Friesian Woodlands a small scale topographical map (Top10 Vector) was used to build a database of landscape features. From this map parcel polygons containing agricultural fields and building plots were used as spatial analysis unit. All linear elements like roads and canals were removed and small topological mistakes were corrected. To recreate a contiguous data set proximity analysis was used on the remaining 22.723 data elements and the neighbouring parcels of each parcel were determined. To characterize the area 10 distinctive landscape features were identified: field size, field shape, field direction, density of wet linear elements such as ditches and canals, density, spatial layout and composition of

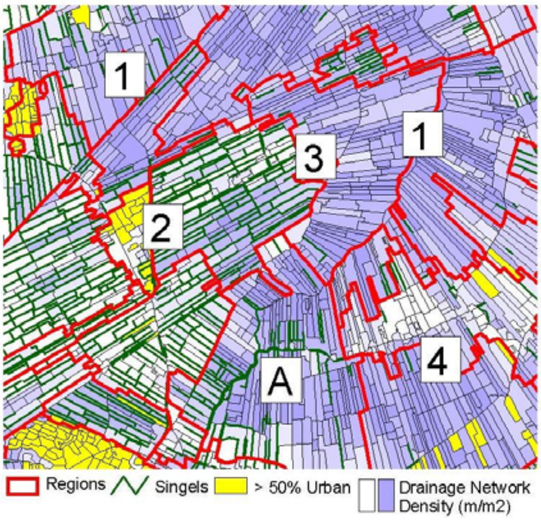

Figure 4: Detail of the region growing result. Characters are explained in the text.

(lines of alders along ditches), tree lines (rows of trees without undergrowth) and land-use. These features were selected because they are considered characteristic for the Friesian Woodlands (Renting et al., 2006) and because they are clearly visible in the landscape.

3.2. Delineating landscapes

The result of the region growing algorithm depends on two user-defined parameters, weighting parameter β and threshold parameter τ. To determine an appropriate value for these parameters in advance is difficult. By systematically varying these parameters a number of landscape segmentations are created from which the best-fitting result may be selected based on a visual comparison with the original data. As selection criteria we used interpretability of the border between the regions and the homogeneity within regions in terms of the underlying data. The range over which to vary the region growing parameters was determined heuristically.
For the area of the Friesian Woodlands 126 different segmentations of the study area were created, the selected segmentation consisted of 132 regions. The overall match between the data and the segmentation result was good. An example of the segmentation and the some of the underlying data is presented in Figure 4. It is shown that most borders can be explained by transitions in different variables: border 1 by the field pattern, 2 by urban lands cover, 3 by the presence and density of Singels and 4 by the density of the drainage pattern. However all borders between the regions are clear and distinct. Some of these borders may be explained by variables not shown, but not all borders are easily explained. These borders may be the result of the under segmentation or because of the greediness of the algorithm, regions which may seem similar on a local scale may be dissimilar at a higher scale. Also mixed regions occur, for example region A. Mixed regions may represent the heterogeneity of the study area or may be caused by the merging of small distinctive regions to other regions which were too small to survive the region growing process as a separate entity.

3.3. Classification and evaluation

In the following step the regions are classified using a non spatial clustering algorithm. The data patterns of the regions were characterized by their mean values and the dissimilarity between the regions was expressed using Equation 2. Similar to the region growing process a threshold value was used to cut off the resulting dendrogram on the basis of the interpretability of the analysis result. In the Friesian Woodlands 13 different landscape types were distinguished as shown (figure 5).
The evaluation was performed using an external reference created on the basis of information provided by 4 regional experts. We asked each individual expert to create a landscape character map of the Northern Friesian Woodlands focusing on visual landscape features in the area. Each expert map was created by delineating the landscapes in the study area on a paper version of the Top10 Vector map and by describing the main characteristics of these landscapes. The landscapes on the map were delineated in such a way that

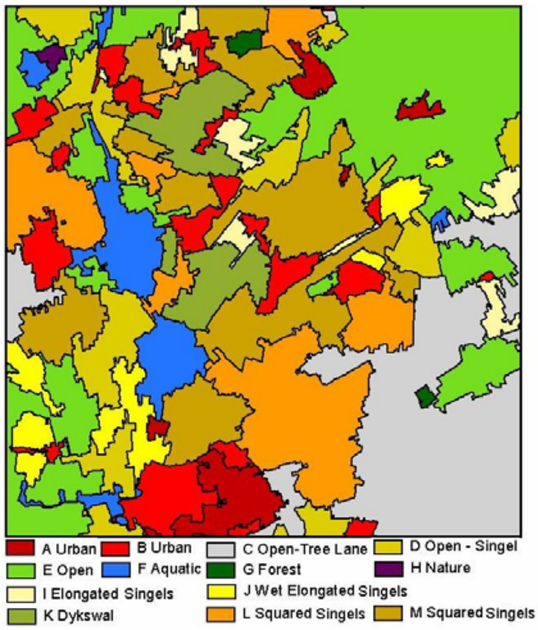

Figure 5: Landscape Classification of the Friesian Woodlands

together they covered the entire study area, similar to the end result of the region growing process. No predefined landscape types were provided, the interpretation of which landscapes to delineate on the map and how to characterize these landscapes was left to the expert, as long as the result was based on the presence of visual landscape features. This resulted in 4 different maps which were consistent in some parts of the study area but very different in other parts. The maps differed in the number of landscapes, their delineation and their characterization. The expert maps were simplified by a reclassification to 6 landscape types which allowed comparisons among the four maps. The expert landscape types distinguished were: *Urban, Open, Aquatic, Nature, 'Singel' and 'Dykswal'* landscape. To create the final reference map, we only took into account those areas, which were identified consistently by at least 3 of the 4 experts. We denote these as core areas and identified them by intersecting the 4 expert maps. For comparison we simplified the computerized classification by grouping all '*Singel*' landscapes into one landscape type and the resemblance between the segmentation result and the external reference was described using a consistency table.

The consistency with which the segmentation landscape types were represented in the expert landscape types was high and varied between 70% and 100%; the consistency with which the expert landscape types were represented in the segmentation classes was lower and varied between 60% and 85%. The difference between these two consistency measures can be partly explained by the fact that the classification of the region growing result consists of more classes than the expert classification. In addition 3 other reasons for the differences between the two classifications can be identified: Lack of information among experts, lack of information in the region growing analysis and the effect of human perception. The effect of missing information can be best illustrated, considering the *Tree lane landscape*. None of the experts made a distinction between 'Singels' and 'Tree lanes', apparently they were not aware of this difference, however this difference can be found in the field as well as in the database. As a result *Tree lane landscape* was classified by the experts for 91% as '*Singel' landscape*. Conversely, the spatial database had no information about the protective status of grasslands. As a result 65% of the expert *Nature landscape* is classified as *Open landscape* in the region growing result, although the protected status of the grass land has an effect on the visual appearance of the area due to differences in management. A comparison of the expert and the region growing landscape type '*Dykswal' landscape* illustrates how human perception of the landscape influences the classification. According to the consistency table, the computerized landscape type '*Dykswal'* falls for 100% within the boundaries of expert landscape type '*Dykswal'*. On the other hand expert class landscape type '*Dykswal'* matches only for 60 % with analysis landscape type '*Dykswal'*. Overlaying the original data shows that the experts used the description '*Dykswal' landscape* already when only a few hedgerows were present, whereas the clustering algorithm only classifies regions which were dominated by hedgerows as '*Dykswal' landscape*. Apparently for the experts only the presence of a few hedgerows in the area was decisive for the characterization of the landscape. This is different for other landscape features, like singles or housing which need to be abundant.

4. CONCLUSIONS AND RECOMMENDATIONS

As shown in this paper region growing is a powerful tool for landscape character assessment. It allows the delineation and analysis landscapes based on the spatial pattern of landscape features, rather then analysing the pattern of landscape features based on predefined analysis units such as raster cells, system boundaries or administrative boundaries as commonly applied in other studies. While using region growing there is no need to make assumptions about the boundaries of analysis units in advance. Region growing also opens the possibility to study the human perception of landscapes. As shown in this paper the results of the region growing analysis and the expert classification of the study area differs. Interesting insights about the perception of landscape can be obtained when the underlying reasons for these differences are being investigated. In our case it showed the importance of the presence of only a few hedgerows for the characterization of the landscape by the experts. The application of region growing in GIS does not need to be restricted to landscape character analysis. Region growing can be applied as a general tool for geographical boundary detection and spatial pattern analysis (Jacquez et al 2000). For example it can be used for ecological network analysis, using a threshold distance to define spatial clusters of habitat (Urban and Keitt, 2001), to interpret point patterns, such as settlement structures or laser altimetry data (Anders, 2003) and for map generalization or the multiple scale representation of a geo-dataset using the parent-child characteristics of the graph pyramid (Regnauld, 2001). To further adopt region growing and other segmentation techniques, such as the normalized cut (Shi and Malik, 2000) or the SWA algorithm (Sharon et al., 2006) into GIS, the applicability of the different algorithms need to be investigated within this specific domain. Different region growing algorithms, varying in: decimation schemes, dissimilarity criteria and stop criteria, will react differently to different data types and different data patterns. In addition there is a need for evaluation criteria suitable for all GIS data types to assess the quality of a segmentation consistently.

5. ACKNOWLEDGMENTS

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