An Adaptive GIS Tool For Image Characterisation

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Abstract. *GIS* systems often rely on low-level, pixel-based representations of satellite scenes. The purpose of this paper is to show the advantages of using an intermediate representation incorporating multiple criteria in scene characterisation, as well as a framework for monitoring changes over time based on features of interest. A *Conceptual Spaces* framework, in conjunction with navigation-based skeletonisation are employed for this purpose. We evaluate our system on satellite images of rivers and lakes.

1 Introduction

The problem of identification of important features with remote sensing methods is a very active research field, with applications ranging from cartography and oceanography to the identification of military targets. This application lies in the general field of *Geographical Information Science* [11]. It goes one step further than being merely a data collection system, since it employs artificial intelligence techniques to represent and characterise the scene. At the same time, the approach followed does not aim to create or use a symbolic representation and ontology of geographical information. The major reason for selecting this application is the quantity of visual information that is included in satellite images, as well as the fact that the depicted objects are all natural. The aim of the system is to collect visual topological and morphological information about river segments, and create an intermediate graph representation containing this information. This graph representation can then be utilised for further high-level processing, such as formal concept analysis [19]. The dataset is deliberately restricted to segmented satellite images, in order to avoid the process of segmentation of complex scenes. The system can be used in conjunction with a supervised or unsupervised GIS scene classification algorithm [17] to identify river segments automatically. The developed system aims to provide a generic and modular visual characterisation platform for inland water features. In this sense, it forms a GIS spatial analysis tool. However, contrary to traditional spatial analysis approaches, spatial information is represented in a *sub-symbolic* intermediate representation. This contrasts the tendency to merely be limited to image coordinates signifying areas or attributes of interest. This distinctive feature enables the reusability of the data produced. The simplification of information exchange is a major issue when attempting to combine collected data from several geographical information systems. Thus, a sub-symbolic representation would provide a platform encouraging GIS *interoperability.* At the same time, this approach does not suffer from the pitfalls of ontology-driven GIS applications. A major potential use of the monitoring of inland water features is the fluctuation of water levels and the erosion of the coastline occurring over a period of time. A direct application of this monitoring is the measurement of the effects of global warming in specific areas of interest. The correlation between descriptive attributes (pollution levels, etc) and position (skeleton of river) is the key to successfully characterising a river [3]. Effective river segment characterisation is the first step to their categorisation and identification. The collection of several descriptive attributes concerning their shape facilitates this categorisation process. Common examples are pollution levels and the development of river bank deterioration. In addition, a structural representation of a river within an image can further facilitate the enrichment of this representation with attributes specific to the application. The proposed graph representation as applied to river networks combines the advantages of both vector and polygon representations in terms of the included spatial information. The method employed in this paper has the potential of acting as a representation framework for such information.

2 Characterisation as Navigation

In [18], the need for a new technique of computing the skeleton of an object is examined. The tight coupling between the generation of the skeletal points and the higher-level representation of the skeletal line is proposed. A novel skeletonisation algorithm is presented that draws on techniques developed for mobile robot mapping and navigation and offers a number of advantages over existing skeletonisation methods. First, because the algorithm works by hopping from one landmark position in the image to another, it has to visit far fewer pixels to find a skeleton compared to conventional algorithms. Second, unlike other techniques, the exploratory nature of the algorithm allows it to identify junctions and endpoints on the fly, which facilitates later high-level symbolic processing. Finally, the method is more generic than others, in the sense that it can be adjusted to compute skeletons containing a variety of different sorts of morphological information. Although much effort has been put into developing skeletonisation algorithms, no attempt up to now has been made to treat skeletonisation as a problem of navigation. However, it turns out that methods for mobile robot mapping and navigation, such as those presented in [10, 9, 8], can be transferred to skeletonisation. The conceptual challenge here is to think of a robot's environment as analogous to an object in a segmented image, with the robot itself located at a pixel inside that object. The problem of skeletonisation is then analogous to that of exploring and mapping the environment by navigating inside it while remaining on the skeletal line. These features of the algorithm make it particularly suitable to object characterisation, based on features or attributes of interest.

2.1 Including Morphological and Structural Information

Skeletonisation on its own is not sufficient to describe a shape in a satisfactory way. The reason for this is that similar shapes can have very different skeletons, while very different shapes can have similar skeletons. Hence, additional information is included, with the intention of capturing the morphology of the object contour. Various techniques have been proposed for accomplishing this. The two most important influences on the author's work have been Blum's Medial Axis Transform [2] and the Shock Graph [22]. In [2], the shortest distance from every point belonging to the skeleton to the object contour is encoded. The reconstruction of the original shape from its skeleton is possible in this manner. Shock graphs [22] go one step further and keep a record of the rate of change of the minimum distance to the contour along the skeleton. In this fashion, each segment of the skeleton is assigned a status. By creating these categories, a symbolic representation of the shape can be formed. The development of the algorithm took place with the aim of using the data it yields for high-level representation. In pursuit of this, it features two major advantages. First, the navigation process is not continuous. It consists of hops from one skeletal point to another. The data produced will therefore be more easily processed by high-level representation frameworks, such as those proposed in [20, 5, 13]. Second, this technique allows for the computation of any kind of morphological information, including those presented in [2, 22], since the data encoded on the skeletal points is being added on the fly. Finally, unlike other related work [24], structural information of vital importance for logical reasoning in object recognition, such as junctions and end points, is extracted with no post-processing.

2.2 The Algorithm in Detail

As mentioned in Section 2, the crucial issue is to think of an analogy between the movement of a pixel inside an object with the motion of a robot inside a room. The aim for the pixel is to explore and navigate inside the object whilst staying on a path corresponding to the skeletal line. In order to achieve this, the pixel-robot has virtual sensors, which yield information about the distance to the boundaries. The sensors are emulated by checking a circular area around the pixel-robot for points that belong to the boundary. In this way, touch-points on the boundary can be extracted. The aim of the pixel-robot is to maintain a path along which there are only two touch-points. If there are fewer than two, the robot adjusts its position, the radius of the circular area, or both. If there are more than two touch-points, that means there is a junction and the robot explores all the possible branches. The real-world equivalent of this topic has already been studied in the context of Kuipers' *Spatial Semantic Hierarchy* [8]. What is more, the close connection between mapping and the skeleton has been explored in [10, 9]. In the present author's work, an attempt is made to adapt these ideas to the context of a digitised image. The roaming pixel checks a circle around it for touch points with the contour. If two touch points are found, then the pixel jumps a distance equal to the normal distance between the current

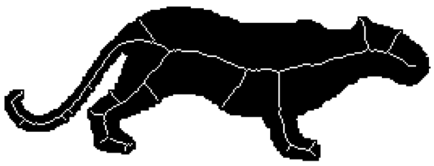

Fig. 1. Divergence-based skeleton

Fig. 2. Navigation-based skeleton

centre and the cord connecting those two touch points. For object segments whose width remains constant, the algorithm performs no hops and the output is similar to that of standard skeletonisation algorithms. However, the more the object's width varies along the skeletal line, the greater these hops will be. Hence, the algorithm is better suited to naturalistic shapes. Special mention should be made of the sub-cases of the two touch-point case. At every stage, the algorithm retains a memory of the last skeletal pixel traversed, and calculates the angle formed by that pixel, the current pixel, and the next pixel. This in turn affects the decision of whether the pixel-robot is going to move forwards or backwards. There is also a special provision for the cases where the movement of the pixel-robot makes the sensors lose touch with one of the surfaces, and confuse it with a newly seen surface. This would clearly yield an incorrect skeleton, since only two of the total of three touch points would be sensed.

A very common problem among skeletonisation algorithms, and one that is not straightforwardly overcome, is the generation of many spurious branches. Moreover, small variations in the contour of an object can have rather drastic consequences in the shape of its skeleton. Consequently, branch pruning is often used as a method of deleting these branches [4]. The advantage of navigation-based skeletonisation is that by adjusting sensitivity parameters these spurious branches can be limited to a minimum, or completely eliminated. In effect, this feature of the algorithm renders it more suitable for the skeletonisation of complex shapes, where these branches become a source of great confusion and usually have no structural significance. This comparative advantage is illustrated in figures 1 and 2. The navigation-based skeleton (figure 2) produces no spurious branches at all. In contrast, the divergence-based thinning algorithm [4] generates several of them (figure 1).

3 Characterising River Networks

Characterisation involves monitoring specific characteristics of the scene that are important to the user. In the particular case of river characterisation [23, 16], both structure and shape are indispensable elements in the description of different river segments. Rivers are structured shapes, with branches and forks, but nonetheless exhibit considerable variation in the morphology of different segments. For this work, the *Conceptual Spaces* framework [5] is used. A Conceptual Space is a *metric* space in which entities are characterised by a number of quality dimensions. Quality dimensions can be closely tied to the raw input or defined in more abstract terms. In this respect, the goal of our system is to not just consider a single descriptor, but several of them.

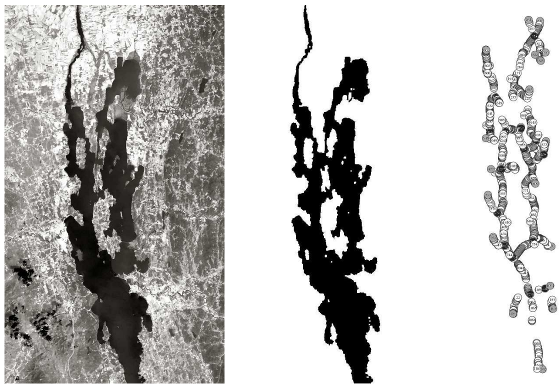

Fig. 3. Near Toronto, Canada

The local topology of a river system plays a prime role in the successful characterisation of that region. Structural information can be highly informative to the end of identifying segments and sources. Once the topology of the river network has been determined, a more detailed characterisation of the river segments can be accomplished by bringing morphology into the picture. Lastly, in addition to the morphological attributes that can potentially be recorded by navigation-based skeletonisation, graphs based on navigational skeleton representations allow for other non-morphological attributes to be considered. These could include sediment, nutrients, toxicants, and heat. Such a characterisation technique can also be used to classify water features. The most significant advantage of having an adaptable skeletonisation system is the capability to vary the collected attributes to best describe or identify a given feature. The best case scenario is where the variation of one single attribute is sufficient to distinguish between features of interest. Even though this is usually not the case, the mere fact that the attributes can be adapted facilitates the classification process. In figure 3 to figure 5, examples of the application of the algorithm to real satellite images can be seen. The topology is recorded on the fly, while morphology or additional thematic data can be included or added according to the specific application. In the skeletons extracted from these examples, nodes corresponding to junctions appear as black, while nodes corresponding to end-points appear as grey.

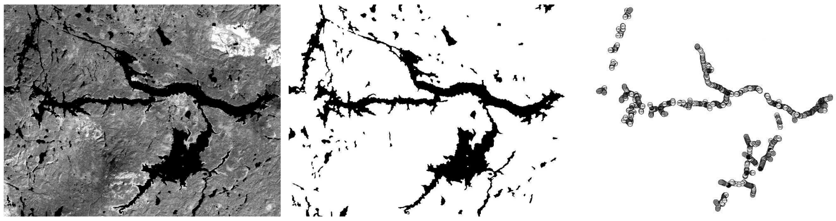

Fig. 4. Near Toronto, Canada

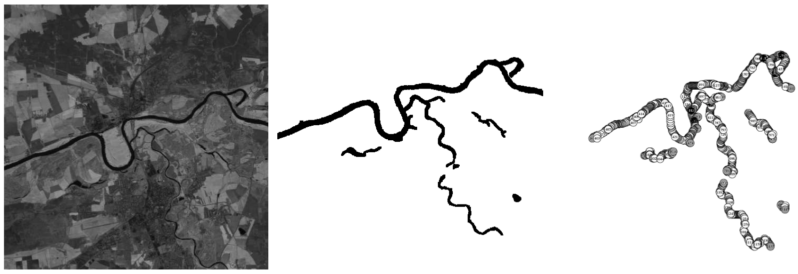

Fig. 5. Dessau, Germany

4 Monitoring Change

Measuring and quantifying changes in time series images is a topic of considerable importance in the GIS community [15, 6, 12]. The developed representation system is applied to a series of satellite images depicting the same area, taken over large time intervals. We claim that an attributed graph representation is sufficient to successfully describe the changes that have taken effect to the water features present in the images. In turn, this method can potentially be used to measure the consequences of global warming to lakes, ponds and rivers around the world. Time intervals could range from a few months or days in the case of e.g. floods, to decades in the case of the effects of global warming.

4.1 Quantifying Change

Conceptual Spaces can prove very powerful when one attempts to describe similarity [7, 1] . To each conceptual space corresponds a *similarity metric*. In this way, a degree of similarity can be determined when comparing *knoxels* - or points in the n-dimensional metric space - belonging to different objects. This metric is tailored to the nature of the conceptual space itself. Since our low-level representation yields skeletons, we selected graph matching as the similarity metric of choice. When it comes to the problem of inexact graph matching, one must ask what kind of application this matching will serve, in order to find the most suitable approach. Probably the first inexact graph matching algorihm is the one proposed by [14], an improvement of which is also used in the widely popular *SubDue* software. In our case, the *Approximate Graph Matcher* [21] seemed an appropriate choice. The original motivation for the development of the algorithm was various biology-related applications. Two features of the algorithm render it most suitable for classification in the context of conceptual spaces. First, the matcher allows for attributes to be included in the graph representations. Since we are pursuing the comparison of attributed graphs, a matcher allowing attributes (or weights) is imperative. Second, the nature of its input enables comparisons and identifications of matches between many different graphs in one go. The graphs that need to be classified are encoded in a text file. The program then compares every graph to every other graph in the file, which effectively acts much like a database. Hence, even when comparing a large number of graphs, the process of classification is uncomplicated. At the same time, the fact that the software has been written in the K language, which was developed to process large amounts of data for financial applications, ensures that execution will be very fast.

4.2 Water Level Changes over Time

In contrast to sea levels, inland water levels tend to decrease as average temperatures rise. Evaporation is the primary cause of this phenomenon. The quantification of the effect of these changes and their consequences on the local landscape have been the motivation for being involved with satellite images in the first place. By altering the measured and compared attributes, conclusions can be drawn regarding the nature of the alterations that have taken place over a period of time. For example, the length of the branches in a drying river changes much more than the angles that are formed between these branches and the main stream. In that respect, the capability of the developed characterisation method to record multiple attributes enables a more thorough monitoring of the changes that are taking effect. Table 1 shows the quantitative measures of change to water features, as computed from images of places taken over 10 year time intervals. Snapshots of the same area taken between 1970 and 1990 (figure 6) have been used for this purpose. The framework has been used with two

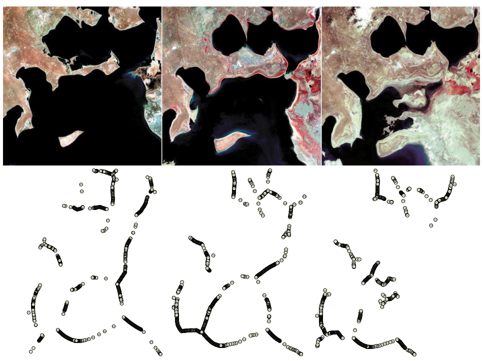

Fig. 6. Change of lake water levels

	Change over time (Sample 1)	
Dimension	average r	angle
1970-1980	59%	28%
1980-1990	75%	84%
1970-1990	85%	87%
	Change over time (Sample 2)	
Dimension	average r	angle
1970-1990	30%	13%
	Change over time (Sample 3)	
Dimension	average r	angle
1970-1980	81%	80%
1980-1990	22%	13%
1970-1990	83%	81%

Table 1. Measuring change over time: 3 time series image samples

attributes, average radius along the skeleton, and branch angle. In the images depicting a lake in Kazakhstan (figure 6), we can see that the greatest structural changes have taken effect during the past 10 years. This can be corroborated by an inspection of the time series images. The recession of water levels during the decade 1980-1990 has caused greater alterations to the shape of the lake, and hence the landscape. In the case of two attributes, a two-dimensional conceptual space containing the results of table 1, can be used in conjunction with *Principal Components Analysis* (PCA)to produce maps of change. The presented data were collected from three sets of time series images over identical time intervals.

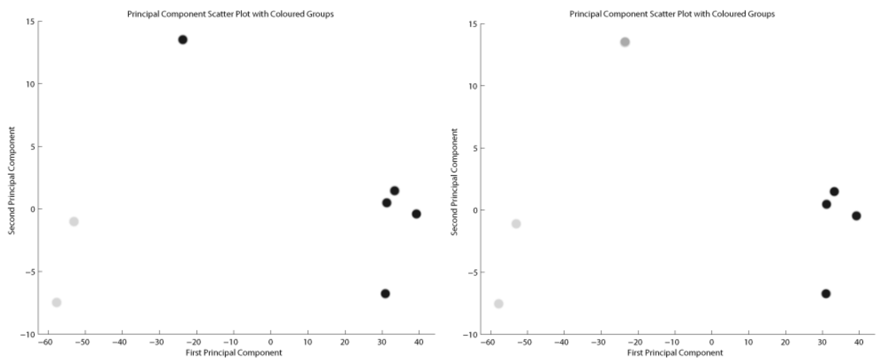

Fig. 7. Analysis of change

Figure 7 shows what this analysis can show for the three time series, similar to the one in figure 6 depicting a lake in Kazakhstan. In figure 7 (left), points corresponding to change between 1970 to 1980 have been highlighted as grey, while the rest as black. Figure 7 (right) indicates how PCA assists in forming groups of points (depicted as different shades of grey). In this example, three groups can be separated by the two principal components. In cases with large numbers of measured attributes, and hence many dimensions, such grouping of data can be useful in extracting patterns of change.

5 Conclusion

This paper demonstrated the applicability of the system presented in previous chapters to the challenging problem of river characterisation based on real satellite images. By providing an intermediate representation of river networks, the system contributes to the field of GIS, where lower level representations are the norm. The advantages of this higher-level representation are adaptability and interoperability. Second, the capabilities of the conceptual space framework employed in this paper are more evidently utilised by measuring and classifying changes in time series satellite images. The multi-attribute approach to river characterisation provides a platform that can successfully describe morphological as well as topological changes to river networks. Moreover, PCA is able to classify these changes and provides the user with an informative measure of monitored alterations. These two functions render the system a useful GIS tool that can be used to characterise river networks or classify water feature alterations over a period of time. In addition, this paper showed that the design choices made can produce an adaptable and versatile GIS tool.

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