Paper-ID: VGI_200209

Automatic differentiation of linear features extracted from remotely sensed imagery

S. J. Wallace [1], M. J. Hatcher [2], R. G. Ley [3], G. Priestnall [4], R. D. Morton [5]

[1] *QinetiQ, Space Department, Cody Technology Park, Farnborough, Hampshire, GU14 OLX UK*
[2] *QinetiQ, Space Department, Cody Technology Park, Farnborough, Hampshire, GU14 OLX UK*
[3] *QinetiQ, Space Department, Cody Technology Park, Farnborough, Hampshire, GU14 OLX UK*
[4] *School of Geography, University of Nottingham, University Park, Nottingham, NG7 2RD UK*
[5] *Laser-Scan Ltd., Cambridge Science Park, Milton Road, Cambridge, CB4 4FY UK*

VGI – Österreichische Zeitschrift für Vermessung und Geoinformation **90** (3–4), S. 87–91

2002

BibTEX:

```
@ARTICLE{Wallace_VGI_200209,
Title = {Automatic differentiation of linear features extracted from remotely
    sensed imagery},
Author = {Wallace, S. J. and Hatcher, M. J. and Ley, R. G. and Priestnall, G.
    and Morton, R. D.},
Journal = {VGI -- {\"O}sterreichische Zeitschrift f{\"u}r Vermessung und
    Geoinformation},
Pages = {87--91},
Number = {3--4},
Year = {2002},
Volume = {90}
}
```

Automatic differentiation of linear features extracted from remotely sensed imagery

S.J. Wallace, M.J. Hatcher and R.G. Ley, Hampshire; G. Priestnall, Nottingham; R.D. Morton, Cambridge

Abstract

An approach to automated feature extraction is presented which uses an object-oriented geodata model as the framework to store contextual knowledge and to use this both to control feature extraction routines and to automatically differentiate between linear feature classes (roads, railways, rivers etc.). The problem of geographic extraction has proved complex and ideally requires the incorporation of contextual clues similar to those used by human interpreters of imagery. The paper describes a proof of principle system developed under UK Ministry of Defence Corporate Research funding. The geodata model comprises a class hierarchy representing the features under study and their likely relationships. Each class of object within this model contains criteria that need to be satisfied in order to strengthen the belief that an instance of that object type has been recognised. The system described has at its core a spatially enabled object oriented database. This enables the extraction of linears to be divorced from the classification process which gives the system the flexibility to build up evidence of class membership from a variety of sources. In this way linears can be tagged with initial probabilities of class membership and refined following further processing, such as network building stages, where classification conflicts are identified and resolved to provide more probable class memberships.

1. Introduction

1.1 Background

Although linear features are recognisable by humans in the majority of medium to high resolution remotely sensed imagery, the task of algorithmically discriminating between the linear features observable in imagery is complex and calls for an approach based upon objects rather than pixels. The properties of objects and their placement within the wider scene may be considered in order to utilise some of the contextual knowledge used by humans. This paper presents an approach to managing the complexity of this recognition problem, which involves the development of a flexible and extensible system set within a spatial object-oriented database environment.

The Automatic Linear Feature Identification and Extraction (ALFIE) project is led by QinetiQ (formerly the UK Defence Evaluation and Research Agency), and involves the School of Geography at the University of Nottingham, and Laser-Scan Limited. It is funded under the UK Ministry of Defence Corporate Research Programme. The project is driven by the need to rapidly populate military Synthetic Natural Environment (SNE) databases. Standard military datasets are typically used to provide the bulk of the data for a SNE database. However, such datasets may not be available for the specific area of interest, they require augmentation and filtering, and may be based on out-of-date mapping. The requirement therefore exists to generate tailored, up-to-date geospatial data in a cost effective manner. The strategy presented also has direct implications for operational automated map production and revision systems.

1.2 Aims

The prime requirement of the research is the investigation and design of a methodology which supports rapid database generation for any part of the world. Timeliness and universality are fundamental considerations. The aim is to investigate the development of a fully automated extraction process which is capable of extracting more than one type of linear feature. The output of the research is a prototype system which aims to ingest a variety of remotely sensed imagery, extract all (as yet unknown) linear features, and automatically assign each linear object to the appropriate object class (in this case railways, rivers, and different classes of road). As part of the process, the aim is to capture some of the contextual knowledge used by humans to characterise each linear object and enable the discrimination between each object class.

1.3 Related work

In disciplines where the object or pattern under investigation has quite a predictable shape, size and type, then reliable total automation can be achieved. However, the problems of developing transferable rules for automated object extraction to geographical features have been recognised for many years (McKeown et al, 1985). Due to geographical objects being so variable, attempts to extract them in a totally automated fashion have been largely unsuccessful unless restrictions are placed upon the source image type or the characteristics of the target object.

Semi-automated approaches often involve the manual identification and seeding of a certain type of object, the geometry of which is then extracted (e.g. Vosselman and de Knecht, 1995). An alternative approach is to reduce the search space for objects by using existing map data to guide the extraction process (Bordes et al, 1997). Such approaches must address issues of cartographic generalisation and in particular the degree to which positional information can be relied upon (Abramovich & Krupnik, 2000). Attempts to increase the level of automation may utilise some of the contextual information which humans effortlessly employ when interpreting an image. The placement of an object within the wider scene and its inter-relationships with other objects at a range of scales would constitute general contextual knowledge (Priestnall and Wallace, 2000). When putting these broad concepts into practice more specific mechanisms for representing contextual clues are described. Contextual regions and local rule-based 'sketches' (Baumgartner et al, 1997) represent different levels of spatial context. Containment within broad land use regions influences the type of object patterns observed, and at the local level certain rules can describe commonly observed inter-relationships between objects of different types. Local relationships between roads and linear groupings of buildings are presented by Stilla and Michaelson (1997). In addition to knowledge contained within one scene, collateral evidence from other imagery can be used (Tonjes and Growe, 1998).

2. Methodology

2.1 Overview

The attributes of a feature may vary depending on the region of interest. For example, the nature of a road may differ for rural and urban areas (called context regions). For this reason ALFIE has the ability to treat these areas separately. ALFIE aims to use context by deriving a number of attributes associated with a linear object within different context regions. Object orientation (O-O) is fundamental in the approach taken. Extracted linear features are maintained as objects within Laser-Scan Ltd's O-O spatial database. By defining suitable methods it becomes possible to interrogate primitive linear objects for contextual information that can be used in their classification. 'Value methods' dynamically extract attributes from both source image and extracted linear primitives. As this information is derived on the fly by the method, rather than being stored as a static attribute, the information can be guaranteed to be up-to-date, honouring automatically any changes made to the database. A total of eighteen methods were devised with five proving particularly successful at differentiating between feature classes. These are: width; variation in width; sinuosity; dominant spectral value; and variation in spectral value.

A full description of the ALFIE processes can be found in Priestnall and Wallace (2000), Wallace et al (2001), and Priestnall et al (2003, in preparation). The salient features of the process are described here to provide the context for the results reported. ALFIE uses a toolkit of extraction algorithms to cater for the variation in image types and resolutions used. For a fully automated system the most appropriate algorithm has to be automatically selected for the given input image. A control strategy is therefore required which initiates and tracks each stage of the extraction and classification process. The research is addressing these issues in a modular fashion in an attempt to provide a flexible framework which facilitates the incorporation of new algorithms and provides the capability to extend the system to extract features other than linears.

2.2 Process flow

Table 1 details the processing undertaken during each stage of the processing under the control of a control interface.

Operation	***Control Module***
Selection of imagery	**Preparation**
Choice of algorithm	
Selection of parameters	
Pre-processing of imagery	**Pre-processing**
Derive contextual information	**Collateral Extraction**
Extraction of linear primitives	**Linear Extraction**
Classification/identification of extracted linears	**Classification**
Construction of topology	
Network building	
Validation	**Validation**
Final editing	*Manual*

Table 1. Operations undertaken by each control module

In essence, the control strategy selects the most appropriate algorithm for the given input image. The results of the extraction are populated to the O-O database as 'unclassified'. The value methods are run to derive the contextual information for each linear and the unclassified lines attributed with the results. A Cluster-Weighted Model (CWM) classifier is used to determine the initial probabilities of class membership. The output from the CWM is a straightforward probability table, which has as many columns as there are discrete valued dimensions. These discrete dimensions correspond to the database methods determined to be significant discriminators. The CWM is trained using a manually created truth dataset representing a typical set of features where class membership is known. Following classification the linear features are populated to the relevant feature class. At this stage the lines are still fragmented and therefore a network building stage is initiated with the aim of creating a topologically correct network for each feature class. Junctions are determined either with comparison to existing coarse resolution mapping (e.g. VMap) or by pattern matching techniques. Corridors are built between these junctions taking into account the classification of extracted lines between the junctions and the underlying image characteristics.

3. Results

3.1 Extraction of linear primitives

Table 2 provides details of metrics derived for the initial linear feature extraction phase. Results are provided which compare fully automatic extractions made for both urban and rural context regions with reference datasets for an area around Worcester, UK. Figure 1 shows an example extraction for a subset area showing a major dual carriageway junction within the urban area. The urban reference dataset for this area is given in Figure 2 with the area of extraction shown in the top right of the figure. (Note: minor roads are not indicated in the Figure 2 for clarity but were included in the metrics). The metrics quoted are for extractions made by the selected algorithm (which may be different) for both rural and urban areas operating on a Russian KVR image with GSD ~2m. The metrics are those used by Harvey (1997) as a means of quantifying extraction results.

At this stage in the processing no filtering of the extraction result has been made and therefore a significant number of false positives are

Figure 1. Example initial extraction result

likely. Further refinement occurs after this stage. The extraction is characterised by fragmented lines although the major features such as the junction slip roads and the railway running north-south have largely been delineated. A significant number of false positives in the form of short linears can be seen and these typically represent building edges. In Table 2 the percentage complete figure is a measure of the reference model that is covered by the extraction result. The percentage correct is the inverse. The rank distance is a normalised distance measure between the extraction and reference data, ranging from 0 to 100, while the branching factor indicates the degree to which the extraction „over extracts". With a perfect result this factor would

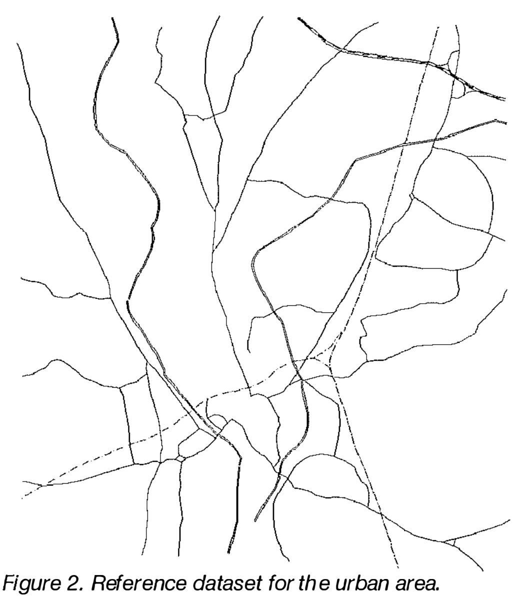

Figure 2. Reference dataset for the urban area.

be 0 while a factor of 1 indicates that for every correctly extracted line a false line has also been extracted. Therefore the higher the number the greater the number of false extractions.

Intersecting the extractions with the reference datasets show that 72% of linears in the rural areas have been extracted while this figure falls to 37% for the urban areas.

	% Complete	% Correct	Rank Distance	Branching Factor
Rural	52.72	9.77	37.91	9.24
Urban	30.88	8.75	22.69	10.43

Table 2. Initial extraction metrics

This reduction is due mainly to the increased complexity of the scene in the urban areas with a significant proportion of the lines extracted representing building edges rather than the linear network features of interest. The figures in Table 2 quantify what is evident in the extraction – that a significant number of false positives, (or "noise") have been extracted. It is these false positives that lead to the smaller percentage correct figures. Clearly the requirement exists to reduce the "noise" in the extractions. This is achieved through the generation and analysis of context information and these pieces of evidence are used to generate initial assessments of the feature class into which each line falls.

3.2 Classification

Table 3 details the result of the classifier in determining the most probable feature class for each true positive extracted line (combined for both urban and rural areas) when compared to the reference datasets. It can be seen that dual carriageways have a high correct classification percentage. Although spectrally similar to other roads, with which there is some misclassification, the key discriminant here is width. Differentiating between single carriageway roads and railways has proved more problematic. These tend to be spectrally similar and of similar width. If fine resolution imagery is available, texture can provide some degree of discrimination since road surfaces tend to be more homogeneous than the elements comprising a railway feature.

Rivers are the most straightforward to classify since water is more spectrally distinct than the elements comprising other linear features. Thus a water mask is created from a multi-spectral image as part of the collateral extraction phase. This can then be intersected with the extraction result to provide high classification probabilities for the intersecting features.

3.3 Network building

The ideal output from the ALFIE system is a complete network of linear features, topologically correct, and correctly classified. Clearly a number of intermediate outputs can be generated from the ALFIE system which facilitates manual correction or completion as appropriate. Space precludes a full description of the results but Figure 3 shows the final output to the system

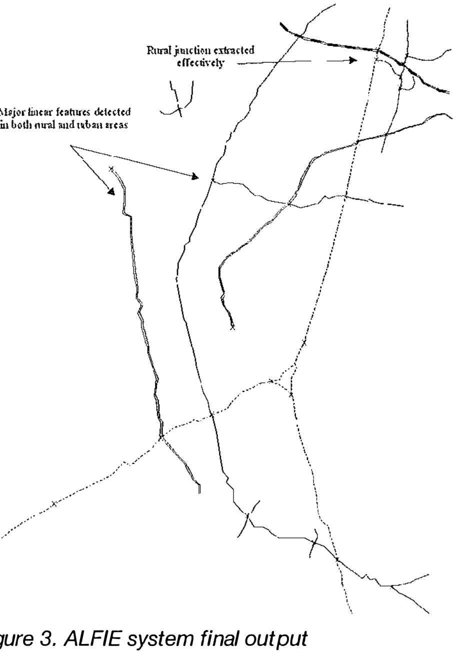

Figure 3. ALFIE system final output

	Road – Dual Carriageway	Road – Single Carriageway	Railways	Rivers
Road – Dual Carriageway	80%	0%	0%	0%
Road – Single Carriageway	15%	56%	31%	0%
Railways	5%	31%	68%	3%
Rivers	0%	12%	1%	97%

Table 3. Classification confusion matrix

for the urban test area. This represents all those features that were (1) correctly extracted, (2) correctly classified, and (3) topologically correct following the completion of the network between identified junctions.

Prior to the network building stage, analysis with the reference datasets show that the lines extracted correctly represented 18% and 16% of the overall network for the rural and urban areas respectively. Following the network building stage to join extracted lines of the same feature class, these percentages increased to 70% and 21% respectively. Comparison with the reference dataset in Figure 2 shows that the dual carriageway in the top right corner has been particularly well delineated and the railways have been classified correctly following refinement of the classification probabilities during the network building stage. Geometric inaccuracies are apparent particularly where the railway passes through a station where a number of parallel tracks exist. The river feature running north-east to south-west has also been successfully delineated although the second river channel running mainly north-south shows gross geometric inaccuracies due to an error in the network building stage. Where the network building has been possible, major single carriageway roads have also been delineated successfully. A more rigorous network building algorithm should improve on the overall connectivity since many of the roads not evident in the final result were successfully extracted.

4. Conclusions

A framework for automated linear feature extraction has been presented. The aim has been to automatically extract lines of different linear feature classes. To investigate this, a number of elements have had to be included within the prototype system. This has required less emphasis on the extraction algorithms per se and more on the overall methodology of automating the extraction and classification process. The framework is modular providing a flexible system and ensuring that improved algorithms can be incorporated as and when required. A control strategy has helped to manage the complexity of the problem and has allowed contextual information to be incorporated in various ways throughout the process flow. The adoption of an object-oriented geospatial database has facilitated complex discriminating characteristics of objects to be dynamically extracted. This enables the extraction process to be divorced from the classification stages, allowing evidence of feature class membership to be gathered from a number of image sources.

Follow on work is already underway to incorporate 3D information into the process flow. This not only allows 3D objects to be extracted but also allows another critical piece of evidence to be used as part of the classification process.

References

[1] *Abramovich, T., and Krupnik, A.,* 2000. In: International Archives of Photogrammetry and Remote Sensing, Amsterdam, Vol XXXIII, Part B3. pp. 17–23.

[2] *Baumgartner, A., Eckstein, W., Meyer, H., Heipke, C. & Ebner, H.* 1997. Context-Supported Road Extraction. In: Gruen, A., Baltsavias, E.P. and Henricsson, O. (eds) Automatic Extraction of Man-Made Objects from Aerial and Space Images (II). Birkhauser Verlag, Basel, pp. 299–308.

[3] *Bordes, G., Giraudon, G., Jamet, 0.,* 1997. Road Modelling based on a cartographic database for aerial image interpretation. In: Semantic Modelling for acquisition of topographic information from images and maps (FÖrstner, W. and PlÜmer, eds.), Birhauser, Verlag, Basel, pp. 123–139.

[4] *Harvey, W.,* 1997. CMU Road extraction test results. (Slides presented at Terrain Week '97 in San Antonio, Texas). http://www.maps.cs.cmu.edu/rcvw/terrainweek97/roads/tw97-roadeval.ROOT.html (accessed 20 July 2002).

[5] *McKeown, D., Harvey, W., and McDermott, J.,* 1985. Rule-based interpretation of aerial images IEEE Transactions on Pattern and Machine Intelligence. PAMI-7 (5) pp. 570–585.

[6] *Priestnall, G.,* et al. A framework for automated extraction and classification of linear networks. In: Photogrammetric Engineering and Remote Sensing. Special Edition on Automatic Feature Extraction, April 2003. (In preparation).

[7] *Priestnall, G., and Wallace, S.* 2000. Semi-automated linear feature extraction using a knowledge rich object data model. In: International Archives of Photogrammetry and Remote Sensing, Amsterdam, Vol. XXXIII, Part B3/2, pp. 740–747.

[8] *Stilla, U., and Michaelsen, E.,* 1997. Semantic modelling of man-made objects by production nets. In: Gruen, A., Baltsavias, E.P. and Henricsson, O. (eds) Automatic Extraction of Man-Made Objects from Aerial and Space Images (II). Birkhauser Verlag, Basel, pp. 43–52.

[9] *Tonjes, R., and Growe, S.* 1998. Knowledge Based Road Extraction from Multisensor Imagery. In: International Archives of Photogrammetry and Remote Sensing, Vol. 32, part 3/1, pp. 387–393.

[10] *Vosselman, G. and de Knecht, J.* 1995. Road tracing by profile matching and Kalman filtering. In: Automatic Extraction of Man-Made objects from Aerial and Space Images, Birkhauser Verlag, pp. 265–274.

Adress of the authors:

S.J.Wallace, M.J.Hatcher, R.G.Ley: QinetiQ, Space Department, Cody Technology Park, Farnborough, Hampshire, GU14 0LX UK. mailto: (sjwallace, mjhatcher, rgley)@QinetiQ.com

G. Priestnall: School of Geography, University of Nottingham, University Park, Nottingham, NG7 2RD UK. mailto: gary.priestnall@nottingham.ac.uk

R. D. Morton: Laser-Scan Ltd., Cambridge Science Park, Milton Road, Cambridge, CB4 4FY UK. mailto: danielm@lsl.co.uk