Detection and extraction of complex map symbols

Ruedi Boesch
Federal Institute for Forest, Snow and Landscape Research (WSL)
CH–8903 Birmensdorf, Switzerland
e-mail: ruedi.boesch@wsl.ch

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Abstract

The problem of extracting distinct map symbols from raster maps will be addressed in this paper. To enable natural scientists to analyse the nation-wide distribution of natural objects such as avalanche obstructions, dry channels, tree groups, a semi-automatic method has been developed to detect specific symbols from scanned topographic maps. The Swiss Federal Institute of Forest Snow And Landscape Research (WSL) uses the published map scale 1:25‘000 of the Swiss Federal Office of Topography (L+T).
After labelling and tracing the binarised raster data, shape descriptors like area, perimeter, moments, elongation, eccentricity, skeletons, Euler number and Fourier descriptors are calculated and stored in an image symbol database. In an interactive process, the user defines the best fitting discrimination parameters based on the shape descriptor values. A local Hough transformation improves the detection rate for line symbols such as found for avalanche obstacles.
Shape descriptors allow to identify map symbols like single trees, observation towers and triangulation. To detect complex map symbols such as dry channels or avalanche obstacles, a distance-weighted triangulation is used to build a tetrahedron-like data structure called tetra-tree. The tetra-tree allows to analyse and classify the spatial distribution of the primitives found with shape descriptors. Generalised orientation and the convex hull of complex map symbols can be calculated directly from tetra-trees.
Some implementation details and generic limitations will be discussed.

1. Introduction

Landscape ecologists, biologists and geographers need data about the existence, frequency and spatial distribution of specific objects contained on maps or aerial images. Such objects include single trees, bushes, hedges, forest edges, dry channels, tree nurseries, orchards or avalanche obstructions (Figures 1a-1c). The map symbols for these can be defined as aggregations of simple symbols such as points, lines, circles and rectangles and are termed complex map symbols.
Major efforts have been made in the past to detect map symbols [Bähr 1995, Lin 1994, Stengele 1995, Weber 1988]. In most projects the methods of recognition are based on the scanned map as a whole. Different types of lines and their related topology, houses and text labels are of major interest to cartographers.

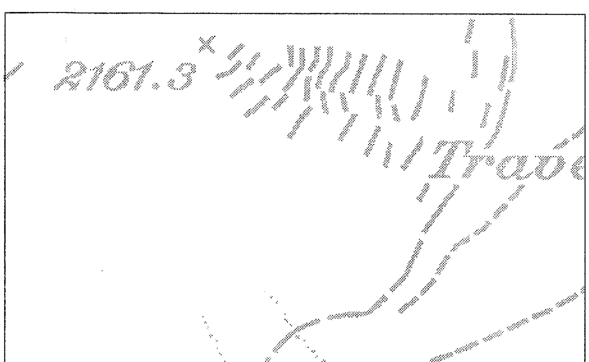


Figure 1a: avalanche obstacles

Natural objects such as forest, bushes or terrain-related map symbols are often neglected or have less priority. Fully automatic map vectorisation remains still to be achieved [Lütjen 1987, Meyer 1993] and general pattern recognition on maps will therefore remain a major research topic for the next years. Currently, methods for the acquisition of complex map symbols are mainly based on interactive definition or manual digitalisation.

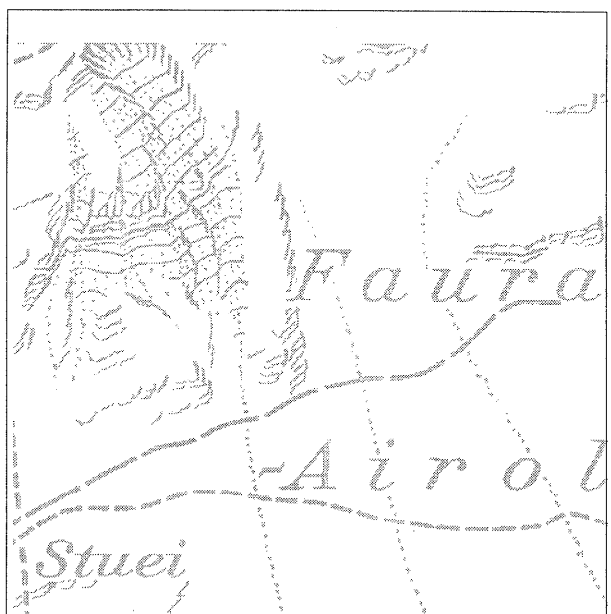


Figure 1b: dry channels

Topographic maps and aerial images are available covering extended regions of Switzerland. Since 1995, the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) has used a complete set of scanned topographic map sheets. Maps with scales 1:25'000, 1:50'000, 1:100'000, 1:200'000 and 1:500'000 [L+T 1994] and with a maximum resolution of 508 dpi have been published by the Swiss Federal Office of Topography (L+T).
Specifically-tuned methods for the automatic detection of specific map symbols have been developed for the L+T maps, in order to shorten the data collection process.

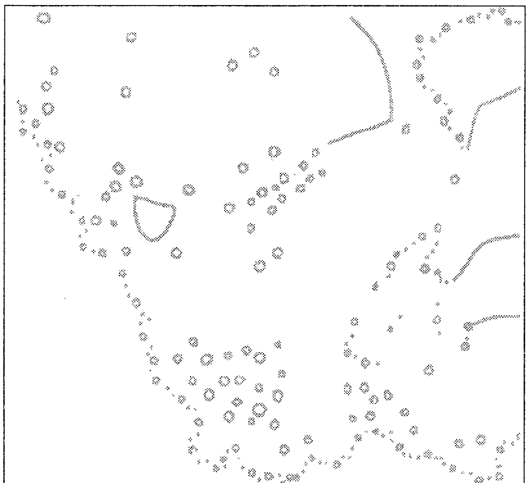


Figure 1c: tree symbols

2. Shape descriptors

Instead of trying to resolve the map pattern recognition process as a whole, the methods that are applied here are focused on the detection of one specific symbol at a time, following the „divide-and-conquer" principle. Due to this simplification and also reasons of efficiency, the recognition process does not rely on any operator interaction.
As individual map symbols are drawn by hand at L+T, their geometric properties are non-rigid (Figure 2). In practice they vary considerably in shape and quality and therefore cannot be described with a single geometric shape measure.
Complex symbols such as forest boundaries, dry channels and avalanche obstructions differ even more from symbol to symbol (Figures 1a-1c), due to the local surface properties, and do not have salient features such as key-points or an object centre.
A suitable recognition method therefore needs to be sufficiently robust and scale-, rotation- and „distortion"-invariant. Although distortion is an inexact terminology, it has been used for any kind of non-linear distortion.
Shape descriptors such as area, perimeter, moments, elongation, eccentricity, skeletons, Euler number and Fourier descriptors fulfil the requirements fairly well and have been chosen as low-level feature descriptors. Many different shape descriptors have been reported and applied in different research areas [Ballard 1981, Marshall 1989, Pavlidis 1976, Rauber 1994, Reeves 1981, Zahn 1972].
Despite its wide use, template matching, either in the spatial or frequency domain, has been shown to be an inappropriate detection method [Ballard 1982, Stengele 1995]. Map symbols are often distorted due to the limited resolution of the scanning process and therefore the missing rotation and scale invariance is a severe limitation. Tree symbols contain less than 10-15 pixels and are highly sensitive to filtering by image processing. Some experiments have been made with a rotation-dependent set of templates but the computational requirements are so large as to make the process impractical.
Deformable templates have been applied successfully using weak models such as „snakes" [Henricsson 1994, Kass 1987, Lee 1989], but gray-level data are needed to calculate potential surfaces.
Morphological operators such as erosion and dilatation are inadequate [Pitas 1992, Trahanias 1992] because of the limited object dimension, and the resulting deviation from the „original" object form makes even a weakened rule definition unpredictable.

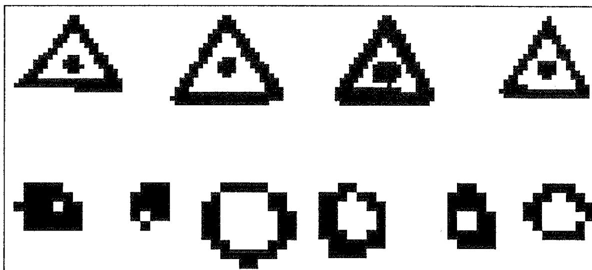


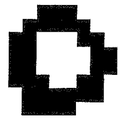
Figure 2: distorted tree and triangulation point symbols

3. Discrimination

Shape descriptors enable classification according to the values of the different descriptors. Contrary to classification methods for remote sensing data, different shape features are often correlated among each other and build a non-orthogonal n-dimensional feature space, which is not appropriate for the required statistical independence. Dimension reduction methods such as the Karhunen-Loève transformation are not applicable due to the inconsistent feature measuring units.
Each symbol discriminator is defined by a set of rules based on the basic shape descriptors. The definition process is the only interactive part of the method, whereby the user iteratively solves the complex discrimination problem.

	ID 63	SX 408	SY 605		
Area 12		Perimeter 9		Holes 0	
Eccentricity	1.05	Circularity		1.86	
Elongation	0.12	Alpha		32.07	
Spreadness	0.02	M11		2.8	
M20	12.9	M02		10.3	

	ID 64	SX 410	SY 627		
Area 35		Perimeter 20		Holes 1	
Eccentricity	-0.12	Circularity		1.10	
Elongation	0.03	Alpha		10.58	
Spreadness	0.01	M11		-1.9	
M20	165.5	M02		175.1	



	ID 74	SX 419	SY 488		
Area 47		Perimeter 30		Holes 1	
Eccentricity	1.16	Circularity		0.66	
Elongation	0.09	Alpha		6.72	
Spreadness	0.04	M11		11.2	
M20	493.3	M02		587.0	

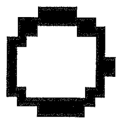


Figure 3: image symbol database

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Show (every Record whose Cell "Holes" = 1 ¬
    and Cell "Area" > 100 and Cell "Area" < 200¬
    and Cell "Circularity" < 0.45 ¬
    and Cell "Spreadness" < 0.1¬
    and Cell "Compactness" > 30.0 ¬
    and Cell "FP0" > 2.8 and Cell "FP0" < 2.9 ¬
    and Cell "FP1" > 0.01 and Cell "FP1" < 0.2 ¬
    and Cell "FP2" > 0.9 and Cell "FP2" < 1.0 ¬
    and Cell "Absm11" < 200)
```

FP0-FP2: Power spectrum values of fourier descriptors

Absm11: $| M_{11} |$ where $M_{ij} = \Sigma (x - x_0)^i (y - y_0)^j$

x_0, y_0 = center of gravity

Table 1: Discrimination parameters for observation towers

In an interactive training phase helped by an image symbol database (Figure 3), the symbol being sought is characterised by defining selection rules based on the identified shape descriptors. The user identifies parts belonging to a composed map symbol and sets up the different discrimination values for the symbol:In an interactive training phase helped by an image symbol database (Figure 3), the symbol being sought is characterised by defining selection rules based on the identified shape descriptors. The user identifies parts belonging to a composed map symbol and sets up the different discrimination values for the symbol:
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The objects are then classified either as candidate objects or rejected according to specific characteristics.
Depending on their complexity, certain symbols (e.g. triangulation points) can be detected in one pass, whereas aggregated symbols such as tree groups or avalanche obstructions need multiple passes. Fourier descriptors of the contour line have been proven to be very powerful [Lai 1994, Staib 1992, Udomkesmalee 1991]. For the multi-pass case, the rules do not need to produce a „perfect" match because the matched objects represent only candidate symbols and the subsequent triangulation enables a better discrimination than at the single object level.

After the shape discrimination, point or line symbols remain difficult to distinguish from similar background objects (see Figure 1b). To ensure to detect „true" line symbols, a local Hough transformation will be applied for every line symbol candidate [Chang 1994, Palmer 1993]. Because only the enclosing boundary box of each symbol will be used for the Hough detection, potential performance problems are minimised [Han 1994].

4. Triangulation

To model the spatial distribution of complex map symbols, all candidate objects will be Delaunay-triangulated [Sedgewick 1992] according to the minimum distance criteria and build the base triangle level (Figure 4). Starting from the seed triangle (typically the three nearest candidate points), each triangle side is the basis for the next possible triangle. The triangulation stops when no more points are found within a specified distance. Using the centre of gravity of the identified triangles, the next higher degree of triangulation are built until less than three centre points remain (Figures 4 and 5). The triangulation levels build a data structure called a tetra-tree (the full structure is similar to a tetrahedron). The top triangle (level 3 in Figure 4) defines the generalised direction and centre of gravity of the whole object. The convex hull of the base level triangles models the surrounding polygon.
For avalanche obstacles (Figure 4), at least two levels of higher aggregation must be reached, so that a potential obstacle can be defined as a recognised map symbol.

In Figure 5, the triangulations for tree groups reflect the generalisation effect of the higher triangulation levels. The triangles marked by „X" in both figures show triangles which were rejected because

- at least one point is too far away
- the smallest angle is below the minimal angle value

Triangulation can also be used to detect dry channels (see Figure 6), but instead of rejecting thin triangles, only extremely elongated or even collinear triangles are admitted. In fact, we are looking for the reverse of the avalanche obstacles or tree groups.
Within noisy background (see Figure 1b), the triangulation yields too many „proper" triangles and the hidden dry-channel symbol cannot be detected.

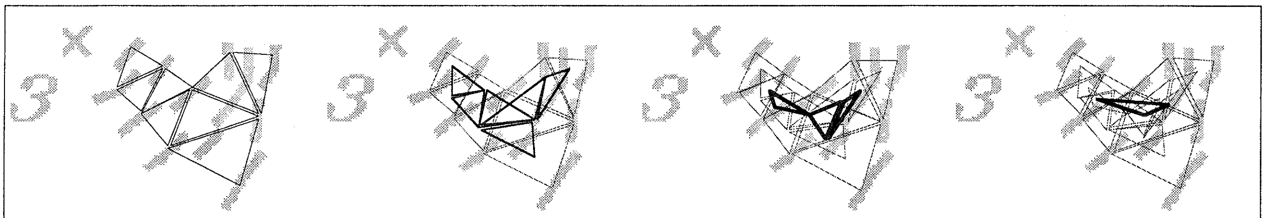

Figure 4: triangulation levels for avalanche obstacles

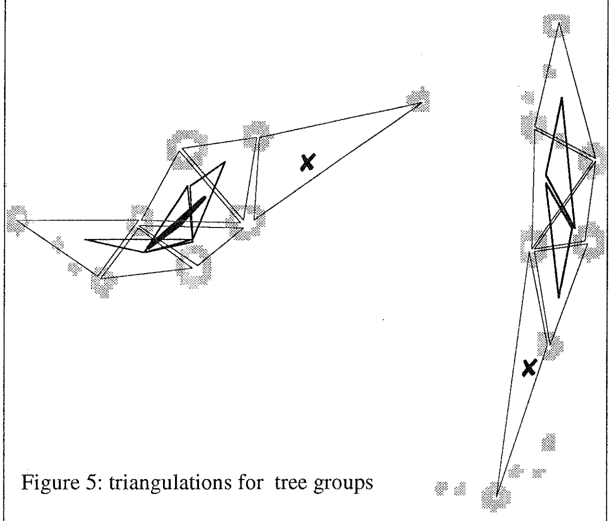

Figure 5: triangulations for tree groups

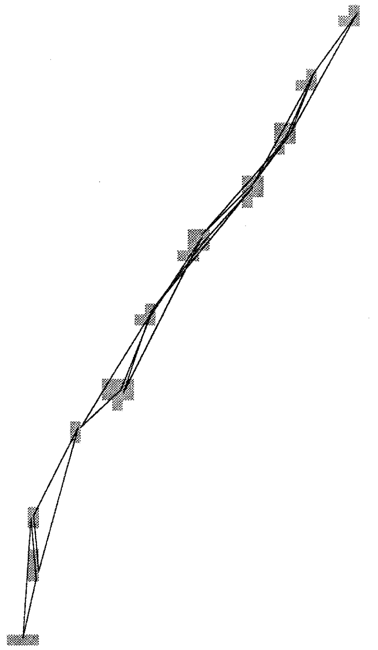

Figure 6: triangulation for dry channels

5. Implementation

The topographic map at 1:25'000 scale is composed of 6 separately scanned layers of forests, forest boundaries, height lines, buildings/streets, lakes and waters. Due to the size of each layer (≈ 200'000 lines x 300'000 columns), an image catalogue with an efficient tiling structure has been chosen for the organisation of the data [Boesch 1995]. Each layer represents a binary image of the original map layer.
In a first step, a tile of an image layer is vectorised by labelling all connected components, allowing the calculation of different shape descriptors (Figure 7).
Discrimination rule interpreters can lead to a serious reduction in performance. Therefore, completed discrimination rules (e.g. Table 1) have been implemented as dynamically loadable libraries (often called plug-ins). Two or more plug-ins can be grouped together to formulate abstract discrimination criteria (e.g. the aggregate of all triangulation points and observation towers) without considerable performance penalty.
The current implementation allows to process about 1MPixels per minute, depending on the complexity of the applied discrimination rules.

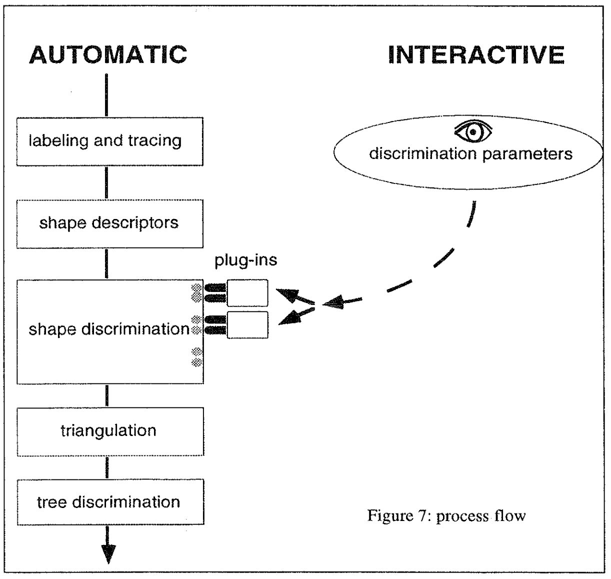

Figure 7: process flow

6. Conclusions

Shape descriptors and distance-weighted triangulation are powerful methods to detect very efficiently non-rigid symbols from scanned topographic maps. Further developments to detect other symbols (e.g. curved text labels, orchards) seem to be promising. It is also planned to use orthophotos from aerial photography as raster input to detect natural objects like single trees and tree groups.

Nevertheless, several drawbacks of the chosen „bottom-up" approach have to be kept in mind:

- trying to recognise all map symbols at once needs a top-down approach
- using shape discriminators to detect line symbols is very inefficient and lacks topology
- discrimination task needs image processing knowledge and user interaction
- detectability varies with drawing quality and scanning resolution

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