Map generalization based on a superpixel structure

Yilang Shen
Wuhan University/
School of Resource and
Environmental Sciences
Luoyu Road 129
Wuhan, China
yilangshen@whu.edu.cn

Tinghua Ai
Wuhan University/
School of Resource and
Environmental Sciences
Luoyu Road 129
Wuhan, China
tinghuaai@whu.edu.cn

Abstract

A conceptual model of map generalization based on a superpixel structure is proposed. The basic features of superpixels are analysed and four types of super transformations of geospatial data, super-primary transformation, super-secondary transformation, super-tertiary transformation and super-quaternary transformation, are defined for map generalization according to starting and ending states. Using four different super transformations, various map generalization operations can be realized.

Keywords: Super transformation, map generalization, superpixel segmentation, map data.

1 Superpixels

Ren and Malik (2003) first proposed the concept of superpixel at the 9th IEEE International Conference on Computer Vision. A superpixel consists of some adjacent standard pixels with similar characteristics, such as colours, textures, intensities. Superpixels are usually irregular pixel blocks with homogeneous colour and brightness. The superpixel technology can be used to reduce the redundancy of the original image since the original standard pixels are clustered into different subareas. Many algorithms for generating superpixels were proposed, such as simple linear iterative clustering (SLIC) (Achanta et al. 2012) and superpixels extracted via energy-driven sampling (SEEDS) (Van den Bergh et al. 2012). Superpixel segmentation technology can be effectively applied to different image processing tasks, such as object segmentation, object localization and body model estimation (Shen et al. 2018a, 2018b).

2 A conceptual model of map generalization based on a superpixel structure

In the field of map generalization, Shen et al. (2018b) first used superpixel segmentation for simplification of polygonal and linear features. Subsequently, superpixel technology is applied to the other generalization operators, such as building simplification (Shen et al. 2019b), road centreline extraction (Shen et al. 2019c), polygon aggregation (Shen et al. 2019a). In this paper, we analyse the basic features of superpixels in map space and define four types of super transformations of geospatial data, super-primary transformation, super-secondary transformation super-tertiary transformation and super-quaternary transformation, for map generalization according to starting and ending states. A conceptual model of map generalization based on a superpixel structure is proposed.

2.1 Basic features of superpixels

As shown in Figure 1, the basic features of superpixels include geometry, semantic, neighbourhood and scale features.

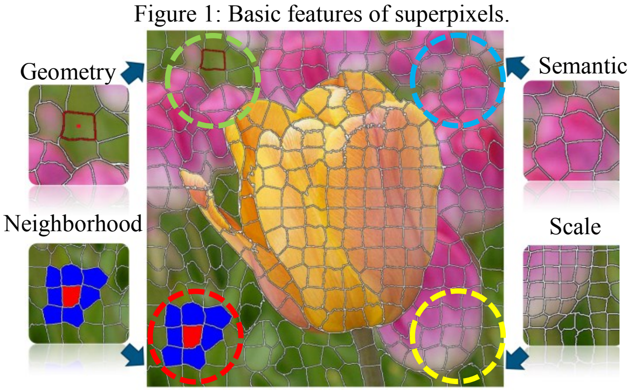
Geometry features: geometric features of superpixels mainly include the area, perimeter, centre of mass and so on.

Semantic features: semantic features of superpixels mainly include colour and brightness.

Neighborhood features: neighborhood features of superpixels are used to describe spatial location relationships between different superpixels. For example, in Figure 1, the blue superpixels are located in the first order neighborhood of a red superpixel.

Scale: under the condition of fixed image size, the sizes of superpixels correspond to different scales in map space. For example, in Figure 1, the same yellow region can be segmeted using the superpixels with different sizes.

Figure 1: Basic features of superpixels.



2.2 Super transformations of map data

Super transformations of map data refer to the multi-scale representation of geospatial data in morphological structures, spatial locations, topological relations, attribute features under the structure of pixels and superpixels. As shown in Figure 2, the input is raster data, according to starting and ending states of map data, super transformations can be divided into the following four types.

(1) Super-primary transformation: the starting state is a pixel structure and the ending state is a superpixel structure.

Function definition: $f_{ps}: Pixel_{In} \rightarrow Superpixel_{Out}$, return the set of superpixels $Superpixel_{Out}$ which satisfies the condition f_{ps}. Namely,

$$Superpixel_{Out} = \{n \mid n \in f_{ps}(Pixel_{In})\}.$$

(2) Super-secondary transformation: the starting state is a pixel structure and the ending state is a pixel structure. Function definition: $\mathrm{f_{pp}}: Pixel_{In} \rightarrow Pixel_{Out}$, return the set of pixels $Pixel_{Out}$ which satisfies the condition f_{pp}. Namely,

$$Pixel_{Out} = \{n \mid n \in f_{pp}(Pixel_{In})\}.$$

(3) Super-tertiary transformation: the starting state is a superpixel structure and the ending state is a superpixel structure. Function definition: $f_{ss}: Superpixel_{\mathrm{In}} \rightarrow Superpixel_{Out}$, return the set of pixels $Superpixel_{Out}$ which satisfies the condition f_{ss}. Namely,

$$Superpixel_{Out} = \{n \mid n \in f_{ss}(Superpixel_{In})\}.$$

(4) Super-quaternary transformation: the starting state is a superpixel structure and the ending state is a pixel structure. Function definition: $\mathrm{f_{sp}}: Superpixel_{\mathrm{In}} \rightarrow Pixel_{Out}$, return the set of pixels $Pixel_{Out}$ that satisfies the condition f_{sp}. Namely,

$$Pixel_{Out} = \{n \mid n \in f_{sp}(Superpixel_{In})\}.$$

In the process of each type of super transformations, various operators, such as superpixel generation (Achanta et al. 2012), Fourier descriptors (Shen et al. 2018b), analysis and comparison of superpixel features (Shen et al. 2019b), superpixel selection (Shen et al. 2019a) and so on, can be applied. Using four different super transformations, various map generalization operations can be realized. For example, as shown in Figure 3, Figure 3a is the input, the SUSS method (Shen et al. 2018b) for simplifying polygonal and linear features is a combination of one super-primary transformation (superpixel generation, from Figure 3a to Figure 3b), one super-quaternary transformation (analysis and comparison of superpixel features, from Figure 3c to Figure 3d) and one super-secondary transformation (Fourier descriptors, from Figure 3d to Figure 3e), Figure 3e is the output.

Figure 2: Map generalization and super transformations.

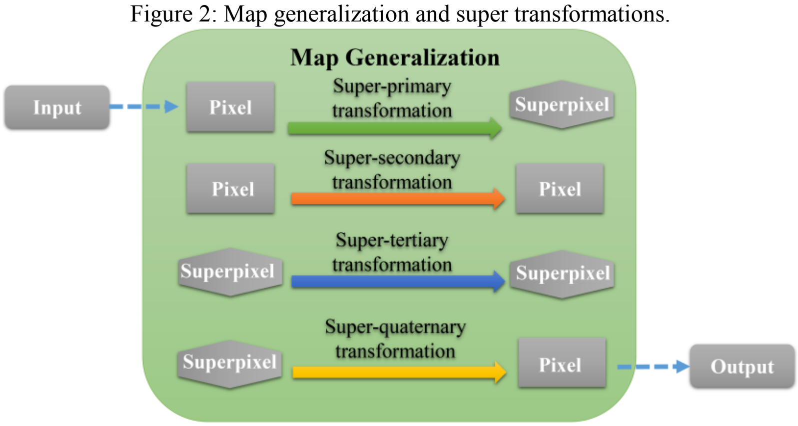
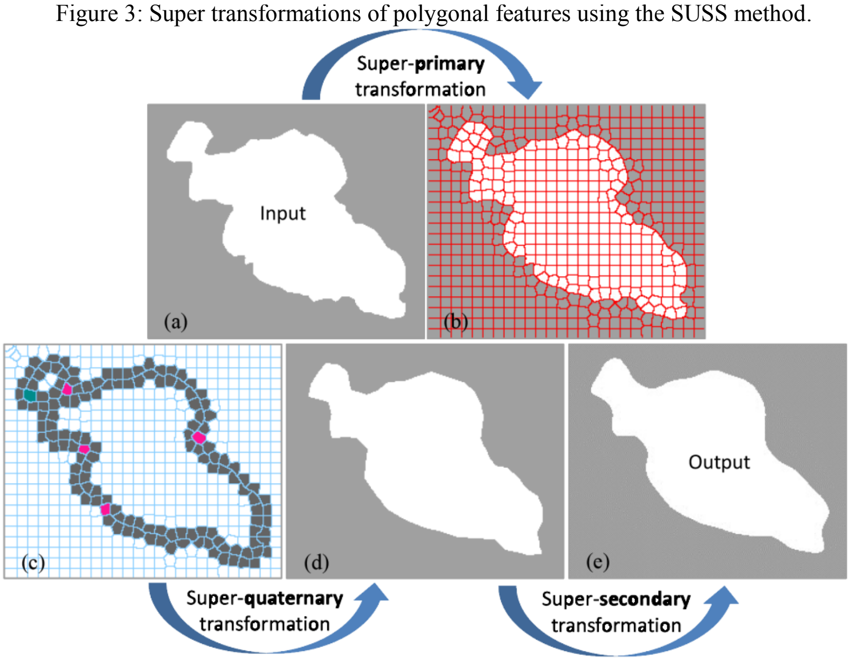


Figure 3: Super transformations of polygonal features using the SUSS method.



References

Achanta R, Shaji A, Smith K, Lucchi A, Fua P, Süsstrunk S. (2012) SLIC superpixels compared to state-of-the-art superpixel methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34 (11), 2274–2282.

Ren X., Malik J. (2003) Learning a classification model for segmentation. In *Proceedings of the Ninth IEEE International Conference on Computer Vision*, 13–16 October 2003, Nice, France, 10–17.

Shen Y., Ai T., He Y. (2018a) A new approach to line simplification based on image processing: A case study of water area boundaries. *ISPRS International Journal of Geo-Information*, 7(2), 41.

Shen Y., Ai T., Li W., Yang M., Feng Y. (2019a) A polygon aggregation method with global feature preservation using superpixel segmentation. *Computers, Environment and Urban Systems*, 75, 117-131.

Shen Y., Ai T., Li C. (2019b) A simplification of urban buildings to preserve geometric properties using superpixel segmentation. *International Journal of Applied Earth Observation and Geoinformation*, 79, 162-174.

Shen Y., Ai T., Wang L., Zhou J. (2018b) A new approach to simplifying polygonal and linear features using superpixel segmentation. *International Journal of Geographical Information Science*, 32(10), 2023-2054.

Shen Y., Ai T., Yang M. (2019c) Extracting centrelines from dual-line roads using superpixel segmentation. *IEEE Access*, 7, 15967-15979.

Van den Bergh, M., Boix, X., Roig, G., de Capitani, B., Van Gool, L. Seeds: Superpixels extracted via energy-driven sampling. In *European conference on computer vision*, Springer, Berlin, Heidelberg, 2012, pp. 13–26.