Generalization of geological maps: Aggregation and typification of polygon groups

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Abstract

The automation of the map generalization process has been the focus of much research and investigation, which has repeatedly highlighted the significance of modelling the spatial relationship between map features to understand their meaning and importance for the generalized map. For the case of polygon generalization for reduced-scale geological maps, this research focuses on developing algorithms for aggregation and typification of polygon groups that take into account different spatial structures to support the automated generalization solutions.

The overall approach is divided into three stages: groups analysis, generalization of groups, and evaluation of results. For the first stage, the groups are further divided into subgroups, which opens more room for different aggregation and typification operators and algorithms. The result of this group analysis allows the following generalization stage to informatively select the appropriate algorithms to deal with a group of polygons. In the second stage, two generalization operators are available, aggregation and typification, implemented by different algorithms. The concluding evaluation stage takes two forms, constraint-based and visual assessment.

This research is part of a larger research project devoted to developing an integrated methodology for the generalization of geological maps. In particular, the polygon groups used in this paper were already identified in a preceding step, and hence this short paper focuses primarily on the second stage, that is, generalization of polygon groups.

Keywords: Geological mapping, polygonal maps, map generalization, constraint-based algorithms, typification, aggregation.

1 Introduction

Map generalization is both a crucial and complex process of map-making, responsible for producing legible and useful maps, by making choices about what map features to display, simplify, aggregate or even emphasize for a specific map purpose. Due to the importance of map generalization, its automation has been an active area of research for several decades (Brassel & Weibel 1988, McMaster & Shea 1992, Mackaness et al. 2007, Burghardt et al. 2014). However, rather little research has been devoted to the generalization of thematic maps, and in particular to polygonal maps, with some exceptions (e.g., Galanda 2003; Smirnoff et al. 2012; Mackaness et al. 2008).

Cartographic practice and research has repeatedly and early highlighted the significance of analysing and modelling the spatial relationships between map features to understand their meaning and importance for the generalized map (Brassel & Weibel 1988, McMaster & Shea 1992). Geological maps are among the most complex thematic maps, with various elaborate polygonal shapes and structures, thus requiring in-depth analysis of these structures prior to their generalization. Yet, existing solutions for generalizing geological maps rely on rather simple principles that have little capability of local adaptation, such as cellular automata (Smirnoff et al. 2012).

We deal with a problem that is frequently occurring in polygonal maps, the generalization of groups of polygons. We propose an approach that builds on the analysis of polygon groups in order to make locally adaptive generalization decisions and employs two generalization operators, aggregation and typification. The overall approach is divided into three stages — group analysis, generalization of groups, and evaluation of results — outlined in the following sections.

The methodology presented here is not only suitable for geological maps but could also be applied to other categorical maps such as soil, land use, or land cover maps with little additional effort.

2 Group analysis

2.1 Constraints for group feature generalization

Maintaining the overall shapes and spatial arrangement of the polygon patches, as well as balancing area loss and gain during map generalization requires the informed selection of generalization operators. Informed decision making, in turn, depends on the analysis of cartographic constraints and characteristics of the groups. In this work, we focus on two sets of cartographic constraints.

The first set of constraints relates to the legibility of polygons at a smaller scale, which are defined and applied in

Anonymous, (2019). Two basic legibility constraints, the size of polygons and the separation distance between them, trigger and control the generalization process at the level of individual polygons. If features are too small or too close to be clearly legible, they should be enlarged or removed. As such generalization operations will change the areas of the different polygon classes (rock types in our case), the proper balance of area gain and loss must be ensured by generalization operators with a more contextual perspective, such as aggregation and typification.

The second set of constraints analyse the shape of polygon groups and identify the overall shape characteristics and spatial organization, such as linear, collinear, curvilinear, grid-like, or unstructured alignments (Zhang et al. 2010; Zhang et al. 2013; Wang & Burghardt 2017). As we are employing two generalization operators in this work, aggregation and typification, we seek to classify polygon groups in light of these two operators, separating them based on density and sparseness (Regnauld & Revell 2007).

2.2 Legibility constraints

The legibility constraints ensure that the map will be readable by a human map user at the target scale of the generalized map. First, the minimum size constraint indicates the minimum area of colored polygons such that they can be unequivocally be perceived by the human eye, and should not be less than 0.5 mm^2 (Regnauld 2001; Galanda 2003; Sayidov & Weibel 2016).

The separation threshold defines the minimum distance between two features and should not be less than 0.15 mm (Regnauld 2001; Galanda 2003; Sayidov & Weibel 2016).

Maximum density is the number of objects per unit area and is the point at which the map becomes locally unreadable due to visual clutter and thus may trigger a removal or a displacement operator (Mackaness 1994), or in our case an aggregation or typification operator.

2.3 Spatial organization

Apart from the properties of individual features, map-makers should also consider collective characteristics of compound map features (i.e. polygon groups in our case), which denote the spatial and semantic relationships of individual map features relating to principles of Gestalt theory (Wertheimer, 1923, 1938; Steiniger & Weibel 2007). Properties of spatial organization include the proximity between features, the similarity in size, shape, and orientation, as well as class of the polygons participating in a group. Groups should only be formed between similar polygons. Spatial organization also includes visual continuity that identifies groups of objects based on their arrangement and alignments (Regnauld 2001; Zhang et al. 2010; Zhang et al. 2013; Wang & Burghardt 2017).

2.4 Group formation

The polygon groups used in this paper were identified in the preceding part of this research (not reported here in detail), which takes two steps: pattern identification and group identification. In the first step proximity patterns are identified by building a Delaunay triangulation from representative polygons and removing global as well as local long edges of the network (Deng et al. 2011). The second step is dedicated to identifying polygon groups using similarity measures such as the size of the polygons, distance between them, shape, orientation, and category of the polygons.

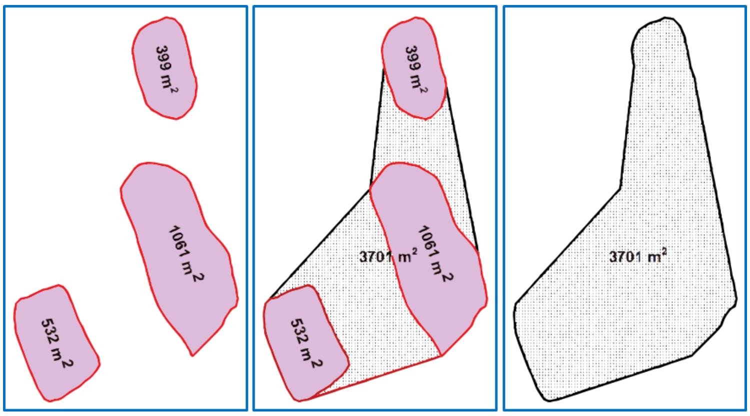
3 Generalization

The second stage of this research focuses on developing generalization algorithms that adequately aggregate and typify the polygons that represent the geological features portrayed on the map. This stage can build on the rich set of measures and data structures made available by the group analysis stage.

3.1 Aggregation

Aggregation (also referred to as amalgamation; McMaster & Shea 1992) involves the fusing together of free-standing polygonal features — such as a series of lakes, islands, or in our case polygons representing rock types — due to scale reduction. In Figure 1, the aggregation resulted in the fusion of three polygons and a corresponding area gain. The area of the three individuals polygons sums to 1992 m^2 (smaller than the minimum area limit of 2500m^2, which is the minimum area limit for the 1:50 000 scale); after aggregation, the area is 3701 m^2, clearly above the minimum area limit. Thus, after

Figure 1. Aggregation of polygons. Left: Original polygons. Middle: Merged pairwise convex hulls of the polygons. Right: Fused, aggregated polygon area.



aggregation, the resulting polygon may see some amount of shrinkage in size.

We have implemented the aggregation operator by three basic algorithms. The first aggregation algorithm simply relies on buffering and merging polygons (Perikleous 2006; Mackaness et al. 2008; Lui et al. 2014). The second algorithm builds a bounding geometry (convex hull, concave hull, or alpha shapes), while the third one is builds a constrained triangulation from the polygon outline vertices, followed by merging the connecting triangles (Jones et al. 1995; Galanda 2003; Regnauld 2005; Wang & Doihara 2004; Li et al. 2017). Most aggregation algorithms in the literature have been developed for building generalization and other algorithms exist in building generalization, such as triangulation and drawing rectangles around the groups of polygons (Regnauld & Revell 2007), graph partitioning (He, 2018), or raster building polygon aggregation (Li et al. 2017), but these are not relevant for the purposes of this work, where we focus on aggregating arbitrarily shaped polygons.

3.2 Typification

Typification is a generalization operator presents a set of objects by a subset of representatives, or placeholders. Hence, a collection of objects can be represented by fewer objects in a symbolic representation (Figure 2, c and d). An important requirement of this generalization operator is that the *typical* spatial structure and arrangement of the original set of map features is preserved (McMaster & Shea 1992, Anders & Sester 2000). Hence the name *typi*fication. A number of typification algorithms have been proposed in the literature, though almost exclusively for the purposes of building generalization (i.e. the situation is similar to that of aggregation algorithms).

Anders & Sester (2000) propose cluster detection and its application to typification using graph analysis. The approach first finds dense areas and selectively removes some features from the polygon cluster and uses the PUSH displacement framework (Sester 2000) to rearrange the cluster. The challenge here to select which building to remove, which is selected arbitrarily in the approach. Although the position of clusters slightly varies, still the cluster shape is preserved.

Regnauld (2001) used three steps to tackle the typification of buildings. First, partitioning building sets into groups using alignments to roads or proximity to roads; second, ‘global’ typification, enlarging, removing or displacing feature in the groups; and third, evaluating the groups with regards to initial constraints.

Burghardt & Cecconi (2007) present a two-step approach for the typification of buildings. The ‘positioning’ step identifies the number and position of the objects based on a Delaunay triangulation; the ‘representation’ step calculates size and orientation for the replacement buildings.

Building typification at medium scales was carried out by Bildirici & Aslan (2010), using so-called ‘length and angle’ methods, however, also enlarging buildings and removing some due to space limitations and building overlaps.

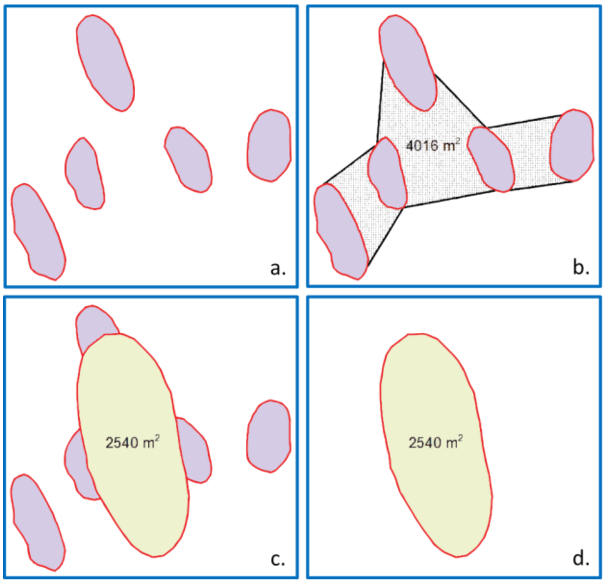
Wang et al. (2017) proposed an improved genetic algorithm to automate building selection. The approach succeeds in removing intra-feature conflicts, but misses inter-feature conflicts among buildings.

3.3 Approach and initial results

Building on the rich information and triangulated data structures of the group analysis stage (Anonymous, 2019), we propose an approach that proceeds through polygon groups and applies aggregation operations and placeholder replacements, resulting in overall typification.

Figure 3 shows the result of the group analysis process for a sample map where 678 groups were identified, ranging from 2 to 15 polygons per group. The majority of groups comprise only two or three polygons, accounting for 445 and 130 groups, respectively, or 85 percent of all groups. In these small-group cases the polygons are directly subjected to generalization by aggregation or placeholder typification.

Figure 2. Typification of a group of polygons. a. Original polygons. b. Original polygons and an aggregated polygon. c. Original polygons and a placeholder polygon. d. Final generalization of a group as a single polygon.



For all other cases, the polygon groups are further subdivided into meaningful subgroups, based on the criterion of proximity of polygons, as polygons should be in close vicinity to each other to be considered for the grouping. From the Delaunay triangulation of polygon centroids, the global and local long edges are removed successively. Figure 4 shows the process of network building and edge removal for a group of 15 polygons (the largest group initially found in the data set of Figure 3), akin to divide-and-conquer algorithms. Figure 4d shows how the original group of 15 polygons has been subdivided into 6 groups that are small and compact enough to be amenable generalization. Which operator — aggregation or typification — and which algorithm is used depends again on the shape and spatial organization properties of each individual small subgroup.

4 Evaluation

The evaluation of the results will be carried out in two stages, constraint-based evaluation and visual assessment. The constraint-based approach will take place continuously during the generalization process. Thus, after each step of generalization, the legibility, as well as spatial relationships, are assessed accordingly and compared to target values for relevant constraints. Visual assessment of results will be performed in a qualitative way by experts (cartographers, geologists) to ensure that the cartographic essence and geological properties of the map are maintained.

5 Summary

We have presented an approach for the automated generalization of groups of polygons, as they frequently appear in geological maps (and more generally in polygonal maps). The approach consists of three stages: group analysis, generalization of groups, and evaluation of results. Information gained in the group analysis stage allows informed decision making in the next, generalization, stage as to which operator to choose — aggregation and typification in our case — and it also helps selecting the appropriate generalization algorithm among several algorithms available for aggregation and typification.

As at this stage our research is still in progress. Thus, the proposed approach and the algorithms used will be further reviewed and fine-tuned. In future work, we will process large map samples and subject the results to the evaluation stage described above.

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Figure 3. Number of polygons used in the process of grouping and number of groups formed from them: polygon groups (blue) formed; number of polygons used to group (red).

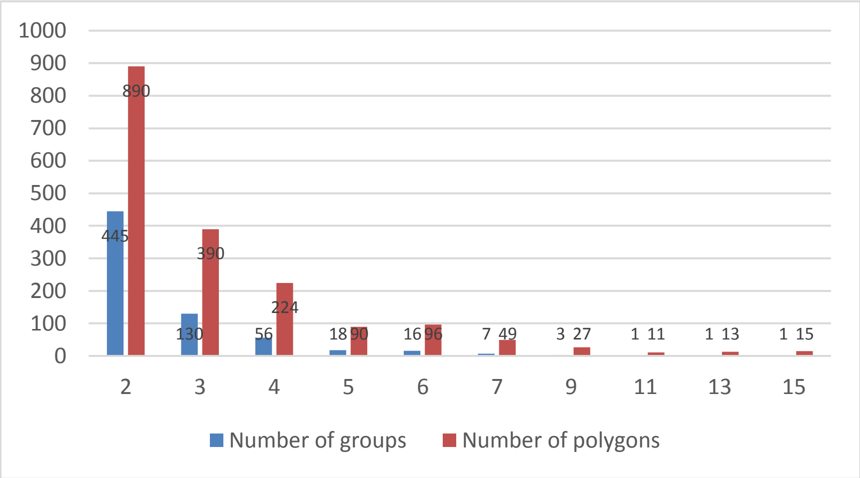

Figure 4. Example of identification of subgroups in a group. a. Original polygons. b. Building a polygon network using a Delaunay triangulation of polygon centroids. c. and d. Removing global and local long edges, respectively.