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Automated Pattern Detection and Generalization of Building Groups

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Statement of Authorship

Herewith I declare that I am the sole author of the thesis named **"Automated Pattern Detection and Generalization of Building Groups"** which has been submitted to the study commission of geosciences today. I have fully referenced the ideas and work of others, whether published or unpublished. Literal or analogous citations are clearly marked as such.

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Abstract

This dissertation focuses on the topic of building group generalization by considering the detection of building patterns. Generalization is an important research field in cartography, which is part of map production and the basis for the derivation of multiple representation. As one of the most important features on map, buildings occupy large amount of map space and normally have complex shape and spatial distribution, which leads to that the generalization of buildings has long been an important and challenging task.

For social, architectural and geographical reasons, the buildings were built with some special rules which forms different building patterns. Building patterns are crucial structures which should be carefully considered during graphical representation and generalization. Although people can effortlessly perceive these patterns, however, building patterns are not explicitly described in building datasets. Therefore, to better support the subsequent generalization process, it is important to automatically recognize building patterns. The objective of this dissertation is to develop effective methods to detect building patterns from building groups. Based on the identified patterns, some generalization methods are proposed to fulfill the task of building generalization. The main contribution of the dissertation is described as the following five aspects:

(1) The terminology and concept of building pattern has been clearly explained; a detailed and relative complete typology of building patterns has been proposed by summarizing the previous researches as well as extending by the author; (2) A stroke-mesh based method has been developed to group buildings and detect different patterns from the building groups; (3) Through the analogy between line simplification and linear building group typification, a stroke simplification based typification method has been developed aiming at solving the generalization of building groups with linear patterns; (4) A mesh-based typification method has been developed for the generalization of the building groups with grid patterns; (5) A method of extracting hierarchical skeleton structures from discrete buildings have been proposed. The extracted hierarchical skeleton structures are regarded as the representations of the global shape of the entire region, which is used to control the generalization process.

With the above methods, the building patterns are detected from the building groups and the generalization of building groups are executed based on the patterns. In addition, the thesis has also discussed the drawbacks of the methods and gave the potential solutions.

Kurzfassung

Diese Dissertation befasst sich mit dem Thema Gebäudegeneralisierung unter Berücksichtigung der Erkennung von Gebäudemustern. Generalisierung ist ein wichtiges Forschungsgebiet in der Kartographie, das großen Einfluss auf die Kartenproduktion und die Mehrfachdarstellung hat. Als eines der wichtigsten Merkmale in der Karte decken Gebäude einen großen Kartenbereich ab. Auf Grund ihrer komplexen Form und räumlichen Verteilung ist deren Generalisierung seit Langem eine wichtige und herausfordernde Aufgabe.

Aus sozialen, architektonischen und geografischen Gründen werden die Gebäude nach bestimmten Regeln gebaut, die bestimmte Muster bilden. Gebäudemuster sind entscheidende Strukturen, die bei der graphischen Darstellung und Generalisierung sorgfältig berücksichtigt werden sollten. Obwohl Benutzer diese Muster mühelos erkennen können, werden Gebäudemuster in Gebäudedatensätzen nicht explizit beschrieben. Um den nachfolgenden Generalisierungsprozess besser zu unterstützen, ist es daher wichtig, Gebäudemuster automatisch zu erkennen. Ziel dieser Dissertation ist es, effektive Methoden zur Erkennung von Gebäudegruppen und zur Erkennung unterschiedlicher Gebäudemuster zu entwickeln. Basierend auf den identifizierten Mustern werden einige Generalisierungsalgorithmen vorgeschlagen, um die Aufgabe der Gebäudegeneralisierung zu erfüllen. Der Hauptbeitrag dieser Dissertation umfasst die folgenden fünf Aspekte:

(1) Die Terminologie und das Konzept des Gebäudemusters wurden klar erläutert. Eine detaillierte und relativ vollständige Typologie der Gebäudemuster wurde vorgeschlagen, indem die vorherigen Untersuchungen zusammengefasst und vom Autor erweitert wurden. (2) Es wurde eine linien- und gitterbasierte ("stroke-mesh") Methode entwickelt, um Gebäude zu gruppieren und verschiedene Muster aus den Gebäudegruppen zu erkennen. (3) Durch die Analogie zwischen Linienvereinfachung und linearer Gebäudegruppentypisierung wurde eine Typisierungsmethode entwickelt, die darauf abzielt, die Generalisierung von Gebäudegruppen mit linearen Mustern zu lösen. (4) Für die Generalisierung der Gebäudegruppen in Gitteranordnung wurde eine netzbasierte Typisierungsmethode entwickelt; (5) Ein Verfahren zum Extrahieren hierarchischer Skelette aus diskreten Gebäuden wurde vorgeschlagen. Die extrahierten hierarchischen Skelette werden als Repräsentationen der globalen Form der gesamten Region betrachtet, die zur Steuerung des Generalisierungsprozesses verwendet wird.

Unter Verwendung der genannten Verfahren werden aus den Gebäudegruppen die Gebäudemuster erkannt und die Generalisierung der Gebäudegruppen unter Berücksichtigung der

Muster durchgeführt. Darüber hinaus wurden in der Arbeit die Nachteile der Methoden diskutiert und mögliche Lösungen aufgezeigt.

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List of Abbreviations

MST	Minimum Spanning Tree
CNNs	Convolutional Neural Networks
OSM	OpenStreetMap
DT	Delaunay Triangulation
CDT	Constrained Delaunay Triangulation
MABR	Minimum Area Bounding Rectangle
SMBR	Smallest Minimum Bounding Rectangle
OBB	Oriented Bounding Box
DAD	*DiagonalAngleDiffer*
RAD	*RightAngleDiffer*
OR	Overlapping Ratio
TM	Triangular Mesh
QM	Quadrangular Mesh
PM	Polygonal Mesh
NNG	Nearest Neighbor Graph
RNG	Relative Neighborhood Graph
GG	Gabriel Graph
DC	Degree Centrality
CC	Closeness Centrality
BC	Betweenness Centrality
EC	Eigenvector Centrality
PGN	Proximity Graph Network
PT	Polarization Transformation

Chapter 1

Introduction

1.1 Background and motivation

1.1.1 Cartographic generalization

Cartography (from Greek "*chartis*=map" and "*graphein*=write") is a study and practice of making maps. Combining science, aesthetics, and techniques, cartography builds on the premise that reality can be modeled in ways that communicate spatial information effectively. A map can abstract the features of the geographical environment into different graphics, which can help people to better cognize the real world. For reasons of the demand of multiple representation and map production, cartographic generalization has been a necessary process in cartography. Cartographic generalization is the core of multiple representation and map production, which aims to represent the geographic reality as faithfully as possible under map scale restrictions. It is a process of deriving smaller-scale maps from larger ones by keeping the essential structures of features on the source dataset and simplifying unimportant details (Weibel 1995). The process of generalization is composed of different operators, such as selection, simplification, displacement, etc. which in sum lead to a simpler and more clear representation of the spatial scene at smaller-scales. Cartographic generalization of spatial data has long been a major research field. Many issues have been addressed, including algorithms for individual generalization operators, the order strategy of operators, and evaluation of the results. The ultimate goal is to perform automated high-quality generalization as much as possible.

1.1.2 Urban building and building patterns

In urban spaces, the building features are fundamental structural elements and serve many activities of human living, working, and recreation. Buildings accommodate most urban activities and act as the crucial origins and destinations of the urban movement, which makes buildings becoming an important aspect of cities and contains crucial information about city organization and evolution (Sevtsuk and Mekonnen 2012). Characterizing and comparing buildings in different regions could then be helpful for a better understanding of urban formation and evolution. On large-scale maps, buildings are important geographical objects, which act as one of the most

common types of artificial objects and occupy large map space. As a result, building generalization has long been an active research field in cartographic generalization.

For social, architectural and geographical reasons, people built their houses following certain rules, and in turn, this leads to the emergence of different urban landscapes. When the houses are drawn on maps, they can create simple or complex, regular or irregular patterns. Gestalt psychologists have argued that human beings naturally perceive objects in organized patterns according to certain laws so that regular patterns formed by neighboring buildings can be easily seen by human eyes (Deng et al., 2017).

Although building patterns can be easily recognized by human eyes, these visually well-perceived patterns are not explicitly described in the dataset. Therefore, it is necessary to reveal the patterns from the building datasets. Map generalization has to take into account spatial objects properties in geometrical, semantic and topological aspects. Building patterns are one of the most important geometrical properties. If the building patterns cannot be recognized precisely, the subsequent generalization process might be affected by losing some important patterns.

Building patterns are defined as visually salient structures that are illustrated collectively by building groups (Du et al., 2016). Automated detecting building patterns from datasets is a complex process based on grouped buildings, which aims to describe in a global view whether grouped buildings have a special shape or distribution characteristic. Special building patterns are important local structures that should be well preserved or even enhanced after generalization. In the evaluation of generalization, building patterns are also an important index for measuring how well the characteristics of the original map are preserved. For this reason, normally, detecting building patterns from originally captured data is the first step in building generalization. In general, building patterns can be divided into three types based on their pattern layouts: linear pattern, grid pattern, and irregular pattern (Du et al., 2016). Linear and grid patterns are regularly distributed by buildings that can be easily recognized by human eyes, which should be paid more attention in generalization. These two typical regular building patterns are important local structures that frequently appear on large-scale maps, which should be carefully generalized. Linear building patterns can be frequently found along the streets, particularly in less dense parts of the urban areas, such as the residential areas, suburban and rural areas.

1.1.3 Building generalization

Automated map generalization inevitably involves generalizing building features. Among all map objects, building features are one of the most crucial and essential components of topographic maps and databases. For reasons of geometry and spatial distribution, building generalization is considered more complex than other map objects. In general, there are three levels of concerns among building generalization: the operations on individual buildings, the operations on building

groups, and the operations on constructing database structures to model the relationship of buildings at different representation scales. The strategy for generalizing building groups is usually decomposed into two steps: building grouping and operations executing on different groups (Li et al., 2004; Yan et al, 2008). Building grouping is also called building clustering, which targets arranging individual buildings into appropriate groups. In general, the grouping process is based on the Gestalt theory, that the buildings which are similar in proximity, size, closure, continuity, and common fate would be collected into one group. Existing grouping methods normally determine whether buildings belong to one group by considering the high similarity within groups and the large differences across groups.

After all, map generalization is a process to represent and discern important geographical characteristics and patterns. Different patterns are represented in different groups. Many methods have been developed to detect building group through the decades. These methods normally use the Gestalt principle to calculate the similarities in buildings thereby the building groups are formed (Regnauld 1996; Anders 2003; Ruas and Holzapfel 2003; Yan et al., 2008; Zhang et al., 2012; Zhang et al., 2013; Zhang et al., 2013; Cetinkaya et al., 2015; Wang et al., 2015; Du et al., 2016; Deng et al., 2017; Yu et al., 2017; He et al., 2018).

After group formation, the generalization operators are selected and applied to the building groups. The possible operators for generalizing building groups are aggregation, displacement, exaggeration, and typification (Li et al., 2004). For example, buildings with irregular patterns are simply aggregated into blocks or built-up areas for their high densities. By comparison, the building groups with regular patterns are often preserved or even enhanced after generalization. Therefore, it is important to select suitable operators to generalize building groups with different patterns.

1.1.4 Hierarchical property in geographical objects

Hierarchical structure is one of the predominant principles in nature and human organizations. Humans tend to organize their environment in hierarchical structures (Sester 1999). In the real world, the settlement area of different cities shows various patterns due to the division of street networks, historical reasons, geographic surroundings, social-cultural environments, economic conditions, and so on. With repetitive interactions, people living in urban space can get familiar with the city layout. This layout is stored in people's mental representation which to a large extent is organized hierarchically (Tomko et al., 2008). The effect also occurs during the map usage. When people read maps of the same city with different scales, no matter they want or do not, remember subjectively or passively, once they have seen the map of a city, the image of that city will be embedded into their mind (Jiang 2013). The distribution of the map features has been kept in their brain, even with different scales, people have a chance to recognize which city it is. This

is due to the spatial knowledge that is organized hierarchically. The distribution of the city will be abstracted with a framework and stored in human brains.

The spatial distribution characteristics are rooted in the cognition process, therefore the results of map generalization should suit human's mental representation and keep the similarity in different representation hierarchies. The essence of map generalization is to reorganize features within multiple representations. Multiple representation should be based on keeping similarity in different display levels in which hierarchies play an important role. As the same as streets, human's perception of the building objects also has the hierarchical characteristic from global to local. Therefore, the study of the hierarchical structures of building features is beneficial for the multiple representation and has further functions to building generalization.

1.2 Research objectives

This thesis aims at proposing methods to detect building patterns and then developing corresponding methods for the generalization operators to generalize the building groups with different patterns. This research has four objectives that are related to this aim.

(1) The first objective is to compare various typologies of building patterns and find common and different parts. This objective tries to unify the terminology in the research field of building patterns and building grouping.

(2) Various simple and complex patterns can be easily observed with eyes, however, it is relatively hard to be detected and modeled in the building datasets. Therefore, the second objective is to develop methods to group buildings and detect the specific patterns from the building groups.

(3) The third objective is to develop different algorithms to generalize the detected building groups with different patterns. Specifically, two algorithms for the typification operator are developed for the generalization of building groups with linear and grid patterns.

(4) The fourth objective is to extract the hierarchical structures from the building datasets, which will be used for the building generalization.

1.3 Study area

In this thesis, the study is mainly carried out in the suburban and rural areas where buildings have the discrete distribution. Urban morphology normally classifies urban areas into the inner-city areas, suburban areas, and rural areas (Figure 1.1). The buildings were built with different distributed characteristics in different areas, which results in different characteristics of building patterns in these three areas. In the inner-city areas, the density of building is the highest, and the intervals between buildings are extremely narrow or even neighboring with each other. It is also pervasive to find buildings with large sizes or complex footprints (shopping malls, churches, museums, etc.). By comparison, buildings in the suburban and rural areas are mainly filled with

residential houses that have a reasonable distance from each other and simple outline shapes. The density of building in suburban and rural areas is also much lower than the inner-city areas. The patterns summarized in the existing hierarchical pattern typology are normally presented by the discrete buildings. By observing the building's structural organization in different urban areas, it is found that in the dense inner-city area, there are fewer regular patterns. In suburban and rural areas, most buildings are discretely located along the roads so that it is more frequent to form regular linear and grid patterns. From the above descriptions, our study selects discrete buildings in suburban and rural areas as research objects.

(a) (b) (c)

Figure 1.1 Building distribution in different urban areas. (a) Inner-city; (b) suburban areas; (c) rural areas.

1.4 Thesis structure

This thesis is based on four journal research papers. Three papers have already been published in different journals, and the other one is submitted and under review. The four research papers are:

Research paper 1:

Wang, X., and Burghardt, D. (2019): Using stroke and mesh to recognize building group patterns. *International Journal of Cartography*. DOI:10.1080/23729333.2019.1574371

Research paper 2:

Wang, X. and Burghardt, D. A typification method for linear building groups based on stroke simplification. *Geocarto International*. DOI: 10.1080/10106049.2019.1669725

Research paper 3:

Wang, X.; Burghardt, D. A Mesh-Based Typification Method for Building Groups with Grid Patterns. *ISPRS Int. J. Geo-Inf.* 2019, 8, 168.

Research paper 4:

Wang, X. and Burghardt, D (Submitted): Hierarchical extraction of skeleton structures from discrete buildings. *The Cartographic Journal*.

This thesis is divided into eight chapters. The main structure of the thesis is organized as shown in Figure 1.2, and the main content of each chapter is described below:

Chapter 1 gives the general introduction of the research topic of this thesis. It firstly introduces the background and the motivation of the research. Next, the objective of this research is proposed with an explanation of the study area.

Chapter 2 reviews the previous work of building generalization and building pattern detection. The research work of the past decades is summarized and analyzed. Then, the problems and potential improvements are described.

Chapter 3 proposes the stroke and mesh-based methods for building pattern detection. This chapter belongs to Research Paper 1.

The next two chapters focus on a very specific generalization operator: typification. Chapter 4 presents a stroke simplification based typification method for building groups with linear patterns. Chapter 5 develops a mesh-based method to typify building groups with grid patterns. These two chapters belong to Research Paper 2 and Research Paper 3, respectively.

Chapter 6 proposes a centrality-based method for extracting hierarchical skeleton structures from the discrete buildings, which provides the support to the building generalization. This chapter belongs to Research Paper 4.

Chapter 7 evaluates the methods by discussing the strengths and limitations of the proposed pattern detection and generalization methods. The potential further steps are also given.

Chapter 8 summarizes the findings and contributions of this research as well as the insights and makes an outlook about further study.

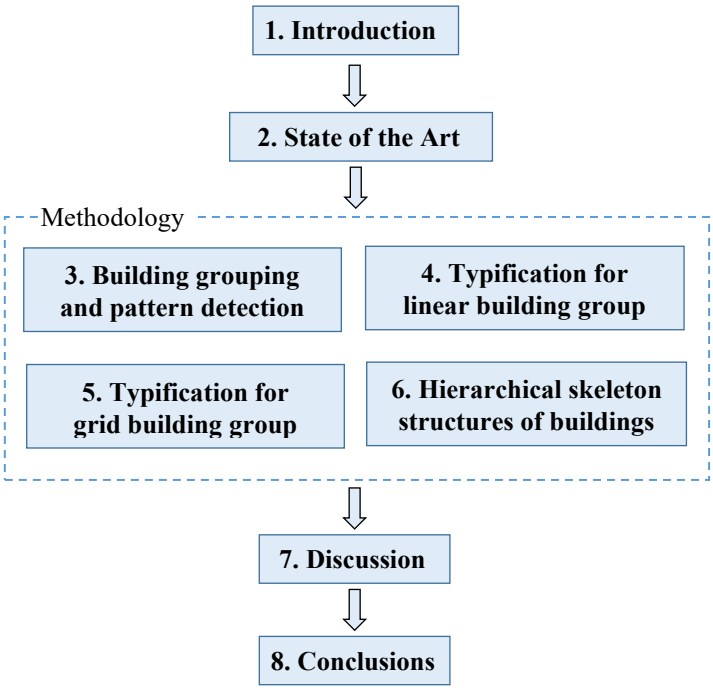


Figure 1.2 Thesis structures.

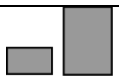
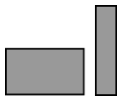
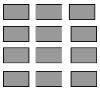
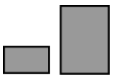
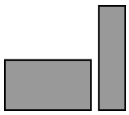
Chapter 2

State of the Art

2.1 Operators for building generalization

Over past decades, many studies have been carried out on building generalization. Some studies focused on the overall process of generalization while others were devoted to developing strategies on specific generalization operators. The frequently used operators for building generalization include selection, aggregation, simplification, displacement, and typification (McMaster and Shea 1992; Li et al., 2004; Roth et al., 2011). Table 2.1 lists the graphic instructions of the operators deriving from the work by McMaster and Shea with occasional modifications. These generalization operators can be categorized into two classes: non-contextual operators for an individual building (such as simplification, exaggeration) and contextual operators for building groups (such as aggregation, typification).

Table 2.1 Operators for building generalization.

Generalization operators	Original	Simply reduced	Generalized
Selection / Elimination			
Aggregation			
Simplification			
Displacement			
Typification			
Collapse			
Exaggeration			

In the past decades, a lot of work has been done into developing different algorithms for these building generalization operators. The following paragraphs are the overview of the previous

work about building generalization operators. As an important generalization operator for building groups, the review of the previous researches about building typification will be given in chapter 2.3.

2.1.1 Selection

Selection is to eliminate small and unimportant buildings, which can be also referred as building elimination. Under the cartographic specifications, the number of buildings is reduced. Mostly, in the process of building selection, buildings are abstracted into point features so that most selection methods have been developed for point features. The selection should consider the distribution density and patterns of the original building dataset. Bjørke (1996) proposed an entropy-based method for feature elimination. In the point cluster generalization method of Yan and Weibel (2008), four types of information, i.e. statistical, thematic, topological, and metric information are considered. Wang et al. (2017) designed an improved genetic algorithm for building selection which can incorporate cartographic constraints related to the building selection problem.

2.1.2 Aggregation

In building generalization, aggregation is one of the most important and difficult operators, which aims to combine the separated buildings by filling the space. The combination is executed on the close and adjacent buildings which are not visually separable after the scale reduction. The Delaunay triangulation skeleton is usually used to the aggregation of vector building data. For instance, Ai and Zhang (2007) presented a progressive algorithm for building cluster aggregation based on the skeleton partitioning of gap space. He et al. (2018) developed a method that can amalgamate clustered buildings gradually without significant modification of geometry while preserving the map details as much as possible under cartographic constraints. By identify an optimal aggregation sequence based on land cover data, Peng and Touya (2017) proposed a method to continuously generalize buildings from a given start map to a smaller-scale goal map by aggregating the buildings into built-up area polygons. The above researches are vector-based methods, by comparison, there are also raster-based aggregation strategies. Morphologic operators are often applied to raster data, such as Su et al. (1997) decomposed the aggregation process into two components, combination and shape refinement, and algebraic models for both components are developed. There exists also other strategies to aggregate buildings at the raster level. For example, Shen et al. (2019) applied superpixel segmentation into area aggregation which achieved good performance in raster datasets. To make the aggregation process more intelligent, Cheng et al. (2015) proposed a local perception-based intelligent approach to aggregate building outlines.

2.1.3 Simplification

The objective of building simplification is to reduce the number of nodes on the outline while preserving the main shape characteristic. It can eliminate unnecessary details of the building without the distortion of its original shape. After the simplification, only the shape of the building becomes simpler, for the other description of the building, like orientation, convexity, they must be preserved as much as possible. Considering the above rule, researchers have developed algorithms for building generalization. Based on the recursive approach, Bayer (2009) presented a new generalization algorithm for building simplification. Haunert and Wolff (2010) simplified the building footprint by selecting a subsequence of its original edges; the vertices of the simplified footprint are defined by intersections of consecutive edges in the selected sequence. Cheng et al. (2013) proposed a novel approach for building simplification with raster-based local perception using a backpropagation neural network model for learning cartographers' knowledge. Yan (2017) proposed a template matching simplification method from the perspective of shape cognition based on the typical template characteristics of building distributions and representations. Wu et al. (2018) presented an efficient polygonal data visualization method by organizing the simplification, tessellation and rendering operations into a single mesh generalization process.

2.1.4 Displacement

Displacement can resolve the problems that arise from conflict among two or more map objects. In general, the current displacement approaches in map generalization can be classified into two types: sequential and optimization approaches (Bader et al., 2005).

The sequential approaches normally use auxiliary data structures and enhanced data models (such as Delaunay triangulation, Voronoi diagram) to support the displacement operation. The related works can be found as follows: Ruas (1998) described a methodology that encompasses detection, resolution through displacement, and evaluation. Ai (2003) presented a field-based method to deal with the displacement of the building clusters. Liu et al. (2014) proposed a combined approach based on constraint Delaunay triangulation skeleton and improved elastic beam algorithm for automated building displacement. Ai et al. (2015) borrowed the idea of vector fields from physics discipline and established a vector field model to handle the displacement of multiple conflicts in building generalization. Sun et al. (2016) applied the immune genetic algorithm for buildings displacement to solve conflicts. Huang et al. (2017) applied the immune genetic algorithm and improved particle swarm optimization to building displacement to solve conflicts.

The optimization approaches are normally realized based on the heuristic algorithms, like simulated annealing, tabu search, and genetic algorithm. The example of using optimization

approaches are: Burghardt and Meier (1997) proposed a snake model to displace linear features. Højholt (2000) developed a finite element method to handle conflicts during the generalization of maps. This method is holistic and can solve conflict problems for the entire map surface simultaneously. Lonergan and Jones (2001) put forward a displacement measure combined with an iterative improvement technique, based on maximizing nearest neighbor distances, which attempts to find an acceptable solution where conflicts can be solved by displacement alone. Mackaness and Purves (2001) presented an algorithm for displacement based on Dewdney's "unhappiness" algorithm for optimizing the position of people at a social gathering. Bader et al. (2005) presented an algorithm for building displacement on the basis of optimization by forming a truss of elastic beams to capture important preserve the patterns during displacement. Sun et al. (2014) used an optimization algorithm, the snake algorithm to displace multiple objects aiming to resolve the spatial conflicts and maintain important spatial relationships between objects during displacement. The above-mentioned displacement methods mainly focus on the individual buildings, currently, to the author's knowledge, there is no algorithm aiming at holistically displacing building groups.

2.2 Researches of building grouping and pattern detection

The integrated building generalization strategy normally involves two steps: building grouping and generalization execution. Building grouping and pattern detection have been popular topics in recent decades. Many studies have been carried out to detect building groups and recognize specific patterns.

2.2.1 Building grouping

The indices in Gestalt principle are widely used in building grouping, for instance, Li et al. (2004) and Yan et al. (2008) used Gestalt principle as guidelines to group buildings. Zhang et al. (2013) detected the urban building clusters based on urban morphology and Gestalt principle by using spatial cognition analysis techniques. Wang et al. (2014) presented an efficient method to discover clustering patterns of polygons by incorporating spatial cognition principles and multilevel graph partition.

There are also other strategies to group buildings or to find building clusters, which can be found in the following works: Regnauld (1996) used Minimum Spanning Tree to detect building clusters. Anders et al. (1999) analyzed the settlement structures by graph-based clustering. Anders and Sester (2000) presented a parameter-free graph-based clustering approach and he also compared the efficiency of different neighborhood graphs in detecting building clusters. Anders (2003) described a new unsupervised clustering approach called Hierarchical Parameter-free Graph Clustering for the automatic interpretation of spatial data. Ai and Zhang (2007) applied skeletons to build a Voronoi diagram to cluster buildings. Based on the analysis of the manual

building grouping process, Qi and Li (2008) proposed a grouping approach by considering the contextual features. Zhang et al. (2009) presented a computational model based on a Voronoi-like auxiliary structure to cluster polygons. Arbelaitz et al. (2013) showed the results of an experimental work that compares 30 cluster validity indices in many different environments with different characteristics. Wei et al. (2018) proposed an approach that combined building classification and clustering to enable the detection of class differences within a pattern. Yu et al. (2019) proposed a framework to generalize the cluttered building clusters that allow for multi-scale mapping, which firstly adopted a heuristic method to group adjacent buildings based on the Delaunay triangulation model.

Some researchers also make comparison tests based on the above different grouping ideas. For example, Arbelaitz et al. (2013) made a comparative study of thirty clustering or grouping indices in many different environments with different characteristics. Cetinkaya et al. (2015) presented a comparison of grouping algorithms for polygonal buildings in urban blocks; four clustering algorithms, Minimum Spanning Tree (MST), Density-Based Spatial Clustering Application with Noise (DBSCAN), CHAMELEON and Adaptive Spatial Clustering based on Delaunay Triangulation (ASCDT) were reviewed and analyzed to detect building groups. Deng et al. (2017) presented a comparative analysis of nine typical building grouping methods, including three methods that only consider the proximity principle and six methods that consider multiple grouping principles.

2.2.2 Pattern detection

From the previous work of pattern detection, the identification of linear patterns and grid patterns received more attention. In this process, proximity graph, graph-theoretic and minimum spanning tree (MST) are the three widely used tools, for example, in the detection of linear patterns, Boffet et al. (2001) identified building alignments by creating neighbor vectors, triplets and grouping triplets into structures. Christophe and Ruas (2002) projected the buildings into a line to detect linear building alignments and characterized the alignments qualitatively. Ruas and Holzapfel (2003) focused on the qualitative characterization of the building alignments. Yang (2008) designed different pattern templates to identify building patterns based on user specifications. Zhang et al. (2009) presented a computational model of spatial autocorrelation based on a Voronoi-like auxiliary structure, which can be used to discern spatial patterns of geographic phenomena. Zhang et al. (2012) concentrated on two specific building structures: align-along-road alignment and unstructured clusters, and two graph-theoretic algorithms were presented to detect these two types of building patterns. By integrating computational geometry, graph-theoretic concepts and visual perception theories, Zhang et al. (2013) also proposed a framework and several algorithms to recognize collinear and curvilinear alignments, which can recognize

alignment-of-center and alignment-of-side patterns. Wang et al. (2015) presented an efficient method to discover clustering patterns of polygons by incorporating spatial cognition principles and multilevel graph partition. Du et al. (2016) presented four integrated strategies for extracting building patterns with the help of a multilevel graph partition method. For grid pattern detection, Wu et al. (2017a) used a graph-theoretic and extended minimum spanning tree to characterize the local urban patterns. Wu et al. (2018) presented a simple and novel graph-theoretic approach, Extended Minimum Spanning Tree (EMST), to describe and characterize local building patterns at the building-unit level for large urban areas. Pilehforooshha and Karimi (2018) presented an integrated framework for extracting building linear patterns.

Other strategies of group buildings and recognize patterns are listed as follow: by using syntax and grammar, Du et al. (2016) presented a three-level relation-based approach to formalize and discover arbitrary building patterns. Yu et al. (2017) developed several building pattern metrics and offered a texton co-occurrence matrix (TCM)-based method to evaluate the features of building patterns. He et al. (2018) identified building group patterns from potential building clusters based on a machine-learning algorithm and further partitions the building clusters with no recognized patterns based on the graph partitioning method. Yan et al. (2019) introduced the machine learning methods, specifically, convolutional neural networks (CNNs) into the classifications of building patterns; in their study, a novel graph convolution was applied by converting it from the vertex domain into a point-wise product in the Fourier domain using the graph Fourier transform and convolution theorem.

For the evaluation of the recognized patterns, Zhang et al. (2010) aimed at a methodology in which the preservation of building patterns can be evaluated automatically. Zhang et al. (2013) focused on three constraints, i.e. on existence, the orientation of alignments, and the spatial distribution of composing buildings to evaluate the building alignments in generalized datasets. Yu et al. (2017) developed several building pattern metrics and offered a texton co-occurrence matrix (TCM)-based method to quantitatively evaluate the features of building patterns.

2.2.3 Problem analysis

Based on the above literature review, it can summarize that the Gestalt principle plays an important role in the grouping process, and the proximity graph is widely used in the pattern detection process. Previous work has largely developed the skills in building grouping and pattern detection, which contributes considerably to building generalization. However, there are still several aspects to be further studied or improved:

(1) The usage of terminology about building groupings and pattern detection should be more normative so that the issues in this research field can be described more precisely and clearly;

there are several existing typologies of building patterns that have similarities and differences, and it is necessary to form an integrated and more completed typology.

(2) Building grouping and pattern detection are relatively separated processes; because they relate to each other, it is useful to develop a more integrated method. Although Regnauld (2001) has tried methods to combine the two processes, further study is still needed.

(3) To the knowledge of the author, there are few methods for detecting grid patterns from building datasets. It would be helpful to develop a novel grid pattern detection method.

To fill the above-mentioned gaps, in this dissertation, the author proposes a relative complete hierarchical typology of building patterns and develop an integrated method that can combine the processes of building grouping and pattern detection.

2.3 Researches of building typification

Among the contextual generalization operators, typification is a discrete process, in which a set of objects is replaced by another set containing a smaller number of objects (Sester and Brenner 2005). In the work of Burghardt (2007), he modeled the typification procedure as a two-stage process, with the steps of "positioning" and "representation". The positioning step determines the number and the position of the newly typified buildings while the representation step considers calculating the size, shape, and orientation of the newly typified buildings. Comparing with other generalization operators, the specificity of typification implies that it is compulsory to create new buildings by considering their numbers, relocations, and representations, which increases the complexity and difficulty in the generalization process. Therefore, typification becomes a challenging topic in map generalization.

Typification denotes using a relatively smaller number of new objects to represent a group of larger number objects, while preserving the similarities of the initial position, spatial characteristics and structures as much as possible, such as distribution patterns and density, spatial coverage and order, orientation and specific arrangements (Foerster et al., 2007; Sandro and Massimo 2011). Accordingly, based on its definition, typification is normally considered as an appropriate operator to generalize building groups with regular patterns, such as linear and grid pattern. To date, several strategies have been proposed for building typification. From the previous work of building typification, three aspects must be considered to determine the typified buildings: (1) the number of preserved buildings; (2) the positions of the preserved buildings; and (3) the alternate representations of generalized buildings (regarding size, shape, and orientation) (Burghardt and Cecconi 2007).

To date, many strategies have been created for building typification. Regnauld (2001) proposed the idea of "global typification", which processes the entire region as the typification objects instead of just processing one group of buildings. According to his terminology of "global

typification", by contrast, the opposite terminology "local typification" is proposed herein because building groups are mainly considered in this dissertation.

2.3.1 Global typification

Global typification regards the buildings in the whole test area as inputs, which considers less about structural knowledge. The aim of global typification is to maintain the overall distribution and structure as much as possible and preserve the similarities and differences between the groups with regard to density, size, and orientation of buildings (Bildirici and Aslan 2010). Global typification idea is often adopted in medium or small scales. For example, Bildirici (2010 & 2011) developed "length and angle" methods to typify buildings with point geometries (Bildirici and Aslan 2010; Bildirici, et al., 2011). Sester (2005) selected optimization approaches for generalization and used self-organizing maps (SOM) for building typification. Burghardt and Cecconi (2007) used a mesh simplification technique which is adapted from computer graphics to typify buildings. Li et al. (2017a) considered three steps (number, representation and harmonizing) for the typification procedure based on multi-scale data matching. From the above studies, in summary, it is found that global typification processes more on the entire region and aims to only preserve the global distribution so that global typification considers less about the structural knowledge and local patterns. This may results in some limitations on preserving the local characteristics of building groups, such as the linear patterns.

2.3.2 Local typification

By comparison, local typification is mainly implemented on the level of building groups; thus, the structural knowledge of the groups is largely considered in the process of typification (Anders 2006). Local typification is often combined with building grouping and pattern detection. Many ideas have been proposed to detect building groups and recognize building patterns, which can be referred in Chapter 2.2. Local typification normally concentrates on the buildings with regular patterns, mainly linear and grid patterns. Examples can be found as follow: Anders and Sester (2000) presented a parameter-free graph-based clustering approach and applied it for building typification. Anders (2005 & 2006) also used the relative neighborhood graph (RNG) to detect building groups with grid structures and then reduced or simplified the grid structure using least square adjustment of an affine or Helmert transformation approach. Gong and Wu (2018) regarded typification as a progressive and iterative process consisting of elimination, exaggeration, and displacement to typify linear buildings.

Apart from buildings, the typification of other geographical objects, such as islands, ditches, drainage, façade, etc., also belongs to the topic of local typification (Zhang 2007; Sandro and Massimo 2011). These researches may provide inspirations for building typification. For instance, the issue of facade typification is similar with the typification of grid pattern buildings. Jahnke et

al. (2009) dedicated their efforts to the typification of façade features and presented a user survey for the evaluation of different typification results. Shen et al. (2016) used a user survey to show that the preservation of the shape of facade features is the most important constraint for a reasonable typification process. Based on the survey conclusion, an algorithm was developed to generate perceivably reasonable representation from the original facade.

2.3.3 Comparison analysis

From the above descriptions of global and local typification, the difference between global and local typification mainly lies in the following three aspects.

(1) Number of building

Global typification normally calculates the typified building number based on radical law which was proposed by Töpfer and Pillewizer (1966); for local typification, the typification is normally modeled as an iterative process, and the number of building reduces gradually; for example, some methods of linear pattern typification only remove one building in each iteration.

(2) Position of building

Global typification normally uses the centroids of buildings to replace buildings, which transfers building typification into point selection by mainly considering the density; this may result in disrupting local characteristics. The local typification primarily takes group characteristics into consideration; thus, the new positions for remained buildings must be consistent with the original.

(3) Representation of building

Global typification is often carried out on medium or small-scale maps, where buildings are abstracted as built-up or settlement areas with simple outlines. Local typification is mainly implemented on the large-scale maps, and the buildings are possible with more details after generalization.

2.3.4 Problem analysis

In essence, the typification of buildings belongs to the problems of *m*:*n* relation generalization (Ai and Oosterom 2001). The difficulty lies in how to keep the balance between reducing appropriate number buildings and preserving original linear patterns in the remained buildings after typification. Although the above-mentioned research contributed a lot to this issue, however, there are still some aspects to be further studied.

(1) In the issue of linear building pattern typification, the current methods do not differentiate linear patterns into detail. The existing ideas are mainly developed for typifying buildings with collinear patterns, and few attentions are considered for the curvilinear patterns. For the existing typification method of curvilinear patterns, there are still some parts to be further improved, such as the shape preservation of the curve-distribution (Gong and Wu 2018). The collinear and

curvilinear patterns have different characteristics in distribution, which should be taken into consideration in the process of typification.

(2) To date, most local typification algorithms have been developed for buildings with linear patterns. To the author's knowledge, currently, there is no research about how to typify buildings with the grid patterns. The difficulty of grid pattern typification lies in how to keep the balance between reducing appropriate building amounts and preserving the original grid patterns in the remained buildings after typification. In this dissertation, two algorithms have been developed in this thesis to typify the building groups with linear and grid patterns.

2.4 Summary

In this chapter, a detailed literature review is given about the previous researches on building pattern detection and building generalization, especially the typification operator. By summarizing the method, it can be found that there still exist several aspects to be further studied and improved. From the above summarization, cartographic generalization is a problem and plenty of algorithms have been developed for different sub-problems of generalization. Even though, there are still cases, which are not generalized adequately or in a satisfactory way. In this dissertation, the author aims at proposing some new methods to improve the mentioned problems.

Chapter 3

Using stroke and mesh to recognize building group patterns

Xiao Wang and Dirk Burghardt

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3.1 Abstract

Building patterns are crucial structures and should be preserved in map generalization. However, while building patterns are not explicitly described in building datasets, map readers perceive building patterns effortlessly. Hence, to better support map generalization, it is important to automatically recognize building patterns in such datasets. This paper first proposes an extended and integrated typology of different building patterns. Based on the typology, building patterns are recognized using stroke and mesh. This method first structures the proximity graph of buildings, and then introduces six constraints (distance, size, shape, orientation, elongation, and facing ratio) to refine the original proximity graph. Strokes and meshes are derived from the refined proximity graph, and are used to recognize linear and grid building patterns, respectively. The proposed method is tested in four regions that are representative of different pattern types. The recognition results are evaluated in an expert survey and compared with the minimum spanning tree method. Assessment suggests that the linear and grid patterns in suburban and rural areas are recognized with satisfying results.

3.2 Introduction

Map generalization is the core of multiple representation and map production, which aims to represent the geographic reality as faithfully as possible under map scale restrictions. It is a process of deriving smaller-scale maps from larger ones by keeping the essential structures of features on the source dataset and simplifying unimportant details (Weibel 1995). With the high demands of geographic information in the big data era, the demands for map generalization have also increased significantly in recent years. Automated map generalization inevitably involves generalizing building features. Among all map objects, building features are one of the most crucial and essential components of topographic maps and databases. For reasons of geometry and spatial distribution, building generalization is considered more complex than other map objects. In general, there are two levels of concern in building generalization: operations on individual buildings and strategies for building groups. The strategy for generalizing building groups is usually decomposed into two steps: building grouping and operations executing on different groups (Li et al., 2004) (Yan et al., 2008). Building grouping is also called building clustering, which targets arranging individual buildings into appropriate groups. Existing grouping methods normally determine whether buildings belong to one group by considering the high similarity within groups and the large differences across groups.

For social, architectural and geographical reasons, people have been building their houses following certain rules, and in turn, this leads to the emergence of different urban landscapes. When houses are drawn on maps, they can create simple or complex and regular or irregular patterns. Gestalt psychologists have argued that human beings naturally perceive objects in

organized patterns according to certain laws so that regular patterns formed by neighboring buildings can be easily seen by human eyes (Deng et al., 2017). Although building patterns can be easily recognized by human eyes, these visually well-perceived patterns are not explicitly described in the dataset. Therefore, it is necessary to reveal the patterns among building groups. If building patterns cannot be recognized precisely, it is naturally difficult to preserve them in the subsequent generalization process.

Building patterns are defined as visually salient structures that are illustrated collectively by building groups. Recognizing building patterns is a complex process based on grouped buildings, which aims to describe in a global view whether grouped buildings have a special shape or distribution characteristic. Special building patterns are important local structures that should be well preserved or even enhanced after generalization. In the evaluation of generalization, building patterns are also an important index for measuring how well the characteristics of the original map are preserved. For this reason, recognizing building patterns from spatial databases is a first step in building generalization.

Our study focuses on the issues of building grouping and building pattern recognition. This paper is organized as follows. The next section briefly reviews the research work of building grouping and pattern detection. Section 3 discusses the study area and proposes an extended typology of building patterns. The recognition methodology is described in detail in Section 4. Section 5 presents the experimental results, and a discussion is presented in Section 6. Finally, the conclusion and outlook are given in Section 7.

3.3 Literature review

Building grouping and pattern recognition have been popular topics in recent decades. The indices in the Gestalt principle are widely used in building grouping; for instance, Li (2004) and Yan (2008) used Gestalt principle theories as guidelines to group buildings. Zhang (2013) detected urban building clusters based on urban morphology and Gestalt theory using spatial cognition analysis techniques. Wang (2015) incorporated spatial cognition principles and multilevel graph partitioning to cluster polygons. There are also other strategies to group buildings or to find building clusters, which can be found in the following works. Regnauld (1996) used a minimum spanning tree to detect building clusters. Anders (2000) presented a parameter-free graph-based clustering approach, and he also compared the efficiency of different neighborhood graphs in detecting building clusters (Anders 2003). Ai (2007) applied skeletons to build a Voronoi diagram to cluster buildings. Qi (2008) used constraints hierarchically in the grouping process. Zhang (2009) presented a computational model based on a Voronoi-like auxiliary structure to cluster polygons. Arbelaitz (2013) performed a comparative study of thirty clustering or grouping indices in many different environments with different characteristics.

From the previous work of pattern recognition, many efforts have been made to recognize linear and grid patterns using proximity graph, graph-theoretic and minimum spanning tree (MST). For linear pattern recognition, Boffet (2001) identified building alignments by creating neighbor vectors and triplets, then grouping triplets into structures. Christophe (2002) (2003) projected the buildings into a line to detect linear building alignments and characterized the alignments qualitatively. Zhang (2012) presented two graph-theoretic algorithms to detect align-along-road alignment and unstructured clusters. By integrating computational geometry, graph-theoretic concepts and visual perception theories, Zhang (2013) also proposed a framework and several algorithms to recognize collinear and curvilinear alignments, which can recognize alignment-of-center and alignment-of-side patterns. For grid pattern recognition, Yang (2008) designed different pattern templates to identify building patterns based on user specifications. Wu (2017) used a graph-theoretic and extended minimum spanning tree to characterize the local urban patterns.

Other strategies of grouping buildings and recognizing patterns are as follows. By using syntax and grammar, Du (2016) presented a three-level relation-based approach to formalize and discover arbitrary building patterns. Yu (2016) developed several building pattern metrics and described the co-occurrence matrix (TCM)-based method to evaluate the features of building patterns. He (2018) used a machine-learning algorithm and graph partitioning method to identify building group patterns from potential building clusters. There are also studies to summarize the efficiency of the mentioned approaches. Cetinkaya (2015) presented a comparison of four grouping algorithms for buildings in urban blocks. Deng (2017) presented a comparative analysis of nine typical detection approaches to evaluate the performance of these approaches.

Based on the above literature review, it is summarized that Gestalt principle plays an important role in the grouping process, and the proximity graph is widely used in the pattern recognition process. Previous work has largely developed the skills in building grouping and pattern recognition, which contributes considerably to building generalization. However, there are still several aspects to be further studied or improved. (1) The usage of terminology about building groupings and pattern recognition should be more normative so that the issues in this research field can be described more precisely and clearly; there are several different typologies of building patterns that have similarities and differences, and it is necessary to form an integrated typology. (2) Building grouping and pattern recognition are relatively separated processes; because they relate to each other, it is useful to develop a more integrated method. Although Regnauld (2001) has tried methods to combine the two processes, further study is still needed. (3) To the knowledge of the authors, there are few methods for recognizing grid patterns in buildings. It would still be helpful to develop a new grid pattern detection method. In this paper, we propose a complete

hierarchical typology of building patterns and develop an integrated method which aims to combine building grouping and pattern recognition together.

3.4 Building pattern typology and study area

3.4.1 Building pattern typology

In previous work, researchers used different terminologies in the study of building grouping and pattern recognition. It is necessary to explain the mentioned terminologies. Table 1 lists the definitions of “Group”, “Alignment”, “Cluster”, and “Pattern” in the Cambridge dictionary. The generalized definitions are helpful to differentiate these terms.

Table 3.1 Definitions of terminologies in Cambridge dictionary.

Terminology	Definition
Group	A number of people or things that are put together or considered as a unit.
Alignment	An arrangement in which two or more things are positioned in a straight line or parallel to each other.
Cluster	A group of similar things that are close together, sometimes surrounding something.
Pattern	Any regularly repeated arrangement, especially a design made from repeated lines, shapes, or colors on a surface.

The definition of “Group” only emphasizes objects are put together without describing the characteristic of the group, for instance, how the group looks is not mentioned. Nevertheless, “Alignment” and “Cluster” describe the characteristics of a group. Alignment emphasizes that the objects present a linear-like characteristic, while the objects in a cluster are arranged in an areal distribution. From the perspective of dimension, alignment is a one-dimensional group, and a cluster is a two-dimensional group. Therefore, "Group" is a broader concept than "Alignment" and "Cluster" so that alignment and cluster should be regarded as subsets of group. Pattern denotes a discernible regularity with geometric presentations. Patterns are presented within groups, alignments, and clusters, which show the specific shapes, structures, and distributions. Figure 3.1 displays the affiliation relationships of group, alignment, cluster, and pattern.

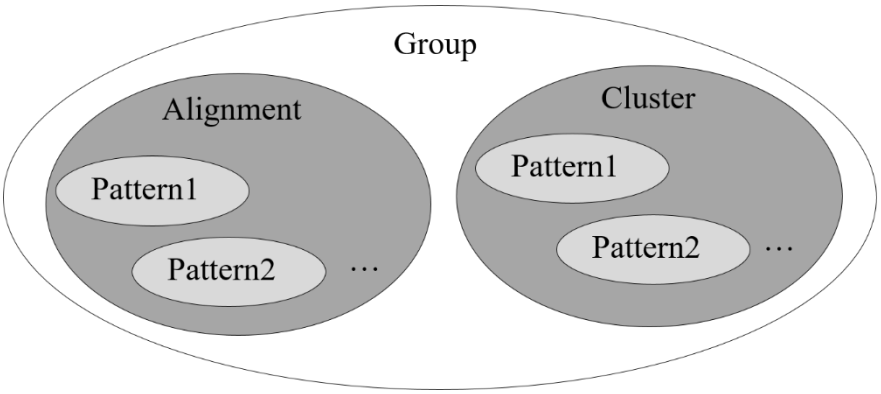


Figure 3.1 Affiliation schematic of terminology.

Based on the affiliation schematic and previous typologies given by Zhang (2012) (2013), Du (2016) and Yang (2008), we improve and extend the hierarchical typology of building patterns (Figure 3.2). With the consideration of building group dimension, the building group is divided into building alignment (one-dimensional group) and building cluster (two-dimensional group). Judging from the pattern shape, building alignment contains two regular patterns: linear pattern (collinear and curvilinear) and enclosing pattern (circle-like and polygon-like. Building cluster contains two regular patterns: grid pattern and grid-like pattern. "Grid" is defined as "a pattern or structure made from horizontal and vertical lines crossing each other to form squares". Buildings in one cluster do not present perpendicularly but still with a regular distribution (parallelogram-like), thus this pattern is named as grid-like pattern. Figure 3.3 shows the examples of different building patterns in dataset.

Based on the affiliation schematic and previous typologies proposed by Zhang (2012; 2013), Du (2016) and Yang (2008), an improved and extended hierarchical typology of building patterns is presented (See in Figure 3.2).

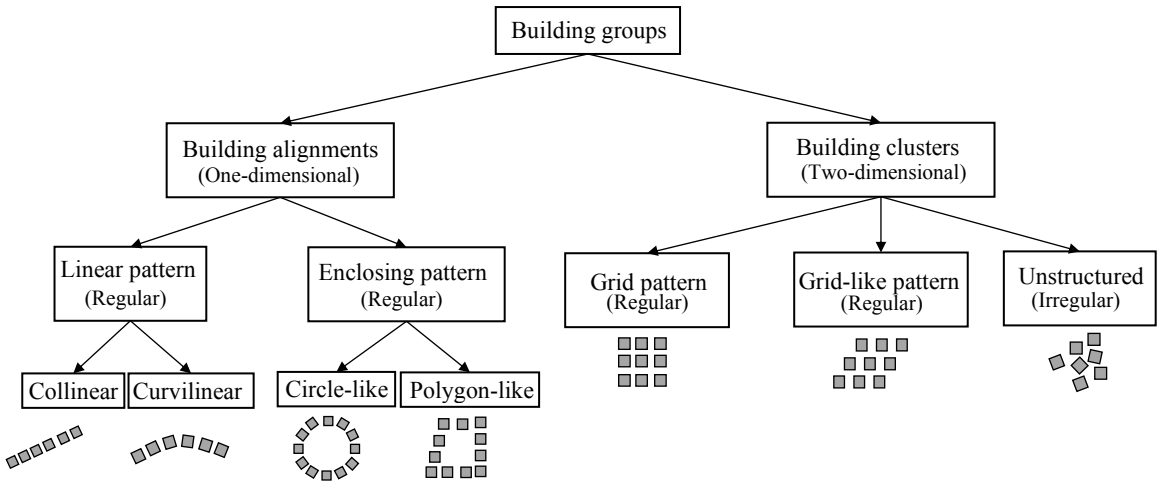


Figure 3.2 Hierarchical typology of building patterns.

With the consideration of building group dimension, the building group is divided into building alignment (one-dimensional group) and building cluster (two-dimensional group). Judging from the pattern shape, building alignment contains two regular pattern-types: linear pattern (collinear and curvilinear) and enclosing pattern (circle-like and polygon-like. Building cluster contains two regular pattern-types: grid pattern and grid-like pattern. "Grid" is defined as "a pattern or structure made from horizontal and vertical lines crossing each other to form squares". Buildings in one cluster do not present perpendicularly but still with a regular distribution (parallelogram-like), thus this kind of pattern is named as grid-like pattern. Figure 3.3 shows the examples of different building patterns in OpenStreetMap (OSM) dataset.

Figure 3.3 Examples of building patterns on OpenStreetMap. (a) Collinear pattern; (b) curvilinear pattern; (c) circle-like enclosing pattern; (d) polygon-like enclosing pattern; (e) grid pattern; (f) grid-like pattern.

3.4.2 Study area

Urban morphology normally classifies urban areas into inner-city, suburban area, and rural area (Figure 3.4). The buildings are built with different distributed characteristics in different areas, which results in different characteristics of building patterns in these three areas. In the inner-city area, building density is the highest, and the intervals between buildings are extremely narrow or neighbouring with each other. It is also pervasive to find buildings with large areas or complex footprints (shopping malls, churches, museums, etc.). By comparison, buildings in the suburban and rural area are mainly residential houses that have a reasonable distance from each other and simple outline shapes. The building density is also lower than inner-city area. The patterns summarized in the hierarchical typology are normally presented by discrete buildings. By observing the buildings structural organization in different urban areas, it is found that in the dense inner-city area, there are fewer regular patterns. In suburban and rural areas, most buildings are discretely located along the road so that it is more frequent to form regular linear and grid patterns. From the above description, out study selects discrete buildings in suburban and rural areas as research objects.

(a) (b) (c)

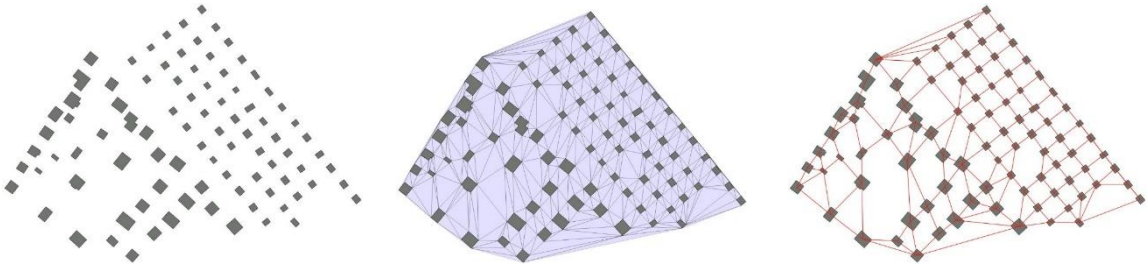
Figure 3.4 Building distribution in different urban areas: (a) inner-city; (b) suburban area; (c) rural area.

3.5 Methodology

3.5.1 Generating and refining proximity graph

(1) Generating proximity graph

The proposed methods are mainly based on proximity graph. Constrained Delaunay triangulation (CDT) is frequently used to detect proximal relationships among buildings (Figure 3.5(b)). In the proximity graph, buildings are modelled as nodes, and any two buildings that are connected by at least one triangle are regarded as proximal. Therefore, a line is connected between the centroids of these two buildings, and this line is the edge of the proximity graph (Figure 3.5(c)).



(a) (b) (c)

Figure 3.5 Generating proximity graph from CDT. (a) Building dataset; (b) generating CDT; (c) proximity graph.

(2) Refining proximity graph

The object is to group buildings and recognize patterns; thus, the proximal edges should be formed only among those buildings that have a higher potential to be part of the same group. This potential reflects in that the buildings in one group should have the same or similar characteristics. Nevertheless, from the original proximity graph, some buildings that have large differences are also connected by proximal edges. These buildings are less likely or even unlikely to be part of the same group. But they are connected by edges, which may lead to incorrect grouping results. Therefore, the original proximity graph should be refined. The principle of refinement is to eliminate the edges that connect buildings with large differences and preserve the edges that

connect buildings with the potential to form one group. The improper edges in the original proximity graph are reflected in six conflicts occurring in the buildings they connect. In Figure 3.6, the improper edges in the original proximity graph are marked with dashed lines. In this paper, we use six constraints to refine the original proximity graph: distance, size, orientation, shape, elongation, and facing ratio. The edges between two buildings with large differences in any one of these six constraints should be removed. The calculations of the six constraints are illustrated as follows.

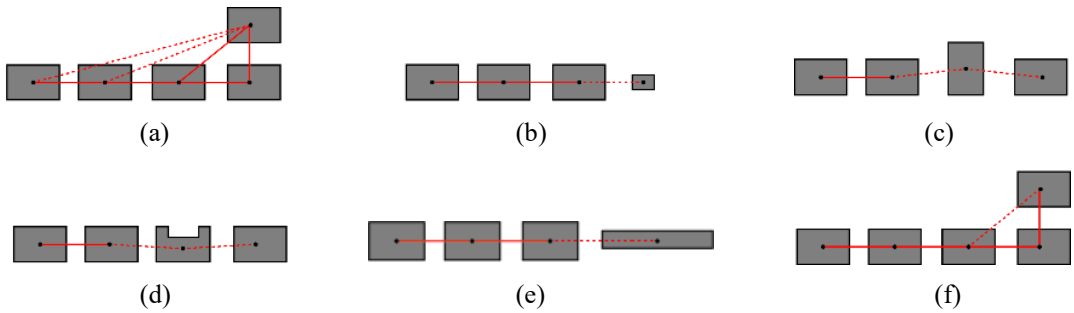


Figure 3.6 Conflicts caused by improper proximal edges. (a) buildings with large distance; (b) buildings with big size difference; (c) buildings with big orientation difference; (d) buildings with big shape difference; (e) buildings with big elongation difference; (f) buildings with visual perception difference.

- **Distance**

The distance directly reflects the closeness degree of buildings. The closer two buildings are, the more possible it is that these two buildings belong to the same group. The distance between two buildings is calculated by their minimum distance. As shown in Figure 3.7, the minimum distance can be obtained by selecting the shortest distance from vertices and segments in building A to the segments and vertices of building B (Amato 1994). If the distance is larger than the given threshold, the corresponding edge should be removed.

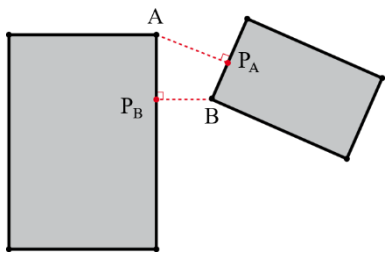


Figure 3.7 Minimum distance calculation of two buildings.

- **Size**

Buildings belonging to the same group should be similar in size. Size is measured by area. If *Area(A)* and *Area(B)* denote the areas of building A and building B, the size similarity $Sim_{(Size)}$ of building A and B is calculated by Equation (3.1):

$$Sim_{(size)} = 1 - \frac{|Area_{(A)} - Area_{(B)}|}{\max(Area_{(A)}, Area_{(B)})} \tag{3.1}$$

If $Sim_{(Size)}$ is less than the given threshold, the corresponding edge should be removed.

- **Orientation**

Buildings belonging to the same group should be similar in orientation. Minimum area bounding rectangle (MABR) is used to calculate building orientation (Figure 3.8). MABR, also known as the smallest minimum bounding rectangle (SMBR) or oriented bounding box (OBB), is an effective way to calculate a polygon's orientation (Duchêne et al. 2003). Because the buildings in our study are mostly simple convex polygons, it is suitable to use the deflection angle between the major axis of MABR and the horizontal line as orientation of the building. For some buildings with relatively complex shape (such as L-shape, H-shape), they have two different orientations, and it is not suitable to compute the orientation by MABR. Here, we treat extremely complex buildings as particular cases, and all the proximal edges connected to them should be deleted. For simple buildings, if θ_A and θ_B refer to the orientations of building A and building B, their orientation similarity is calculated by Equation (3.2):

$$Sim_{(Orientation)} = |cos\ (\theta_A - \theta_B)| \tag{3.2}$$

If $Sim_{(Orientation)}$ is less than the given threshold, the correponding edge should be removed.

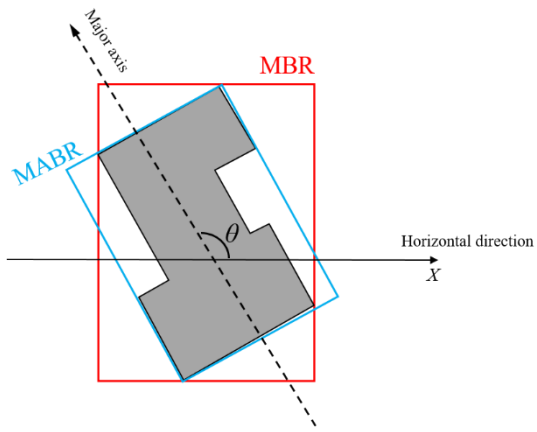


Figure 3.8 Orientation calculation of polygon.

- **Shape**

Buildings belonging to the same group should be similar shapes. The shape of a building is represented in its outline or footprint. If a building's outline consists of many intrusions and extrusions or changes frequently, the shape of the building is regarded as complex. Thus by measuring the complexity, building shape can be described and calculated. Based on the work of Brinkhoff (1995), the complexity of polygon shape is modelled with three quantitative parameters: the frequency of local vibration, the amplitude of local vibration and deviation from the convex hull. If $Complex_{(A)}$ and $Complex_{(B)}$ are the complexity values of building A and building B, their shape similarity is calculated by Equation (3.3):

$$Sim_{(shape)} = 1 - \frac{|Complexity_{(A)} - Complexity_{(B)}|}{\max(Complexity_{(A)}, Complexity_{(B)})} \tag{3.3}$$

If $Sim_{(Shape)}$ is less than the given threshold, the corresponding edge should be removed.

- **Elongation**

Although two buildings are located close and have the same or similar size, shape, and orientation, it cannot assert that these two buildings belong to the same group, because they may have difference in elongation. Elongation reflects the fatness and thinness of a building. The elongation of the building is represented by its MABR's elongation. If $W_{(A)}$ and $L_{(A)}$ are the width and length of building A's MABR, and $W_{(B)}$ and $L_{(B)}$ are the width and length of building B's MABR, the elongation similarity of building A and building B is calculated by Equation (4):

$$Sim_{(Elongation)} = 1 - \left|\frac{W_{(A)}}{L_{(A)}} - \frac{W_{(B)}}{L_{(B)}}\right| \tag{3.4}$$

If $Sim_{(Elongation)}$ is less than the given threshold, the corresponding edge should be removed.

- **Facing ratio**

In some situations, two buildings are the same in the above five constraints, but from our eyes, they still should not belong to the same group. Here, we use facing ratio to measure this visual perception. The facing ratio reflects the degree of two buildings that face each other (Figure 3.9). The higher the facing ratio is, the more possible it is that the buildings belong to the same group. The overlap ratio of projections is used to calculate the facing ratio of two buildings. As Figure 3.10 shows, the building's MABR has a major axis and a minor axis so that a coordinate system is formed by the two axes. Buildings are projected on each coordinate axis (axis X and axis Y). If $ProLength_{(A)}$ and $ProLength_{(B)}$ are the projection lengths of building A and building B on axis X_A, the facing ratio of the two buildings on axis X_A is calculated Equation (3.5):

$$Facing\_ratio = \frac{overlap(ProLength_{(A)}, ProLength_{(B)})}{max(ProLength_{(A)}, ProLength_{(B)})} \tag{3.5}$$

With the same way, another three facing ratios on another three axes (Y_A, X_B, and Y_B) are calculated; thus the maximum facing ratio is obtained. The larger the maximum facing ratio, the higher the facing degree of the two buildings. The examples in Figure 10 shows that building A faces B and C, while building B and C do not face each other. If the maximum facing ratio is less than the given threshold, the corresponding edge should be removed.

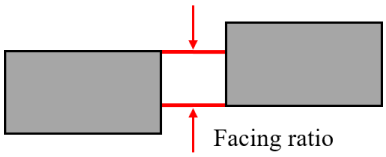


Figure 3.9 Facing ratio of two buildings.

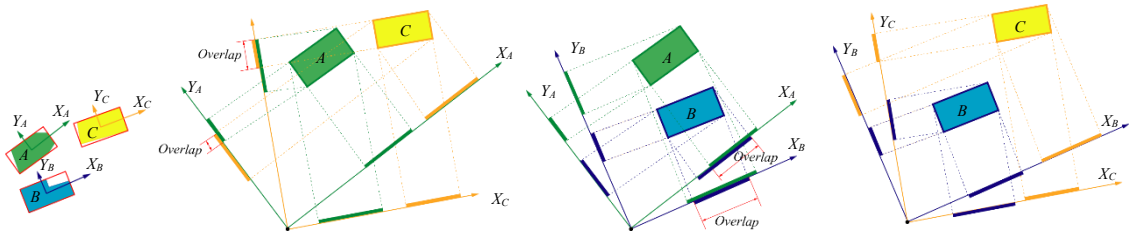


Figure 3.10 Calculating overlay projection length of two buildings.

3.5.2 Generating stroke and mesh

(1) Stroke generation and building alignment formation

The term 'stroke' is prompted by the idea of a curvilinear segment that can be drawn in one smooth movement and without a dramatic change in style. In a network, some segments can be grouped by the good continuation principle (Thomson and Richardson 1999). The newly generated long-line segments formed by the grouped lines are termed a stroke. The proximity graph can be also regarded as a network so that strokes are obtained under the generation principles (Figure 3.11(a-b)). When strokes are overlapped with buildings, it is found that building alignments are formed naturally (Figure 3.11(c)). Buildings connected by the same stroke belong to the same building alignment. Here we consider that building alignments should contain at least three buildings. Therefore, the strokes that only relate two buildings are ignored.

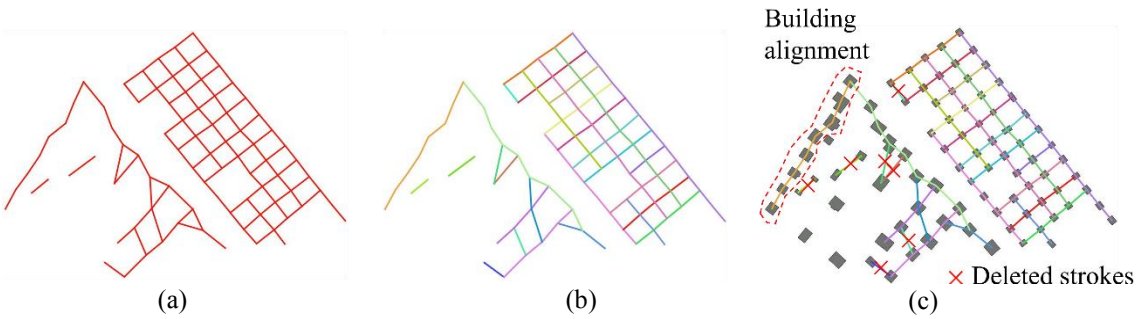


Figure 3.11 Building alignment formation by strokes. (a) Proximity graph; (b) strokes of proximity graph; (c) stroke overlap with buildings.

(2) Mesh generation and building cluster formation

The original meaning of mesh denotes the spaces in nets; thus mesh of the road network is defined as a naturally closed region that does not contain any other regions. Similarly, the mesh of proximity graph is defined as a closed region bounded by several proximal edges and does not contain any other regions (Figure 3.12(b)). By determining the number of composed proximal edges, the meshes of proximty graph are classifed into three types: triangular mesh (three edges), quadrangular mesh (four edges), and polygonal mesh (more than four edges) (Figure 3.12(c)). By removing triangular and polygonal meshes (Figure 3.12(d)), mesh clusters are formed. The meshes that have common edges belong to the same cluster. When the mesh clusters are

overlapped with buildings, it is found that building clusters are also formed naturally (Figure 3.12(e)). Buildings overlapped with the mesh clusters belong to the same building cluster. Here the isolated mesh is ignored because we consider that the building cluster should contain sufficient buildings.

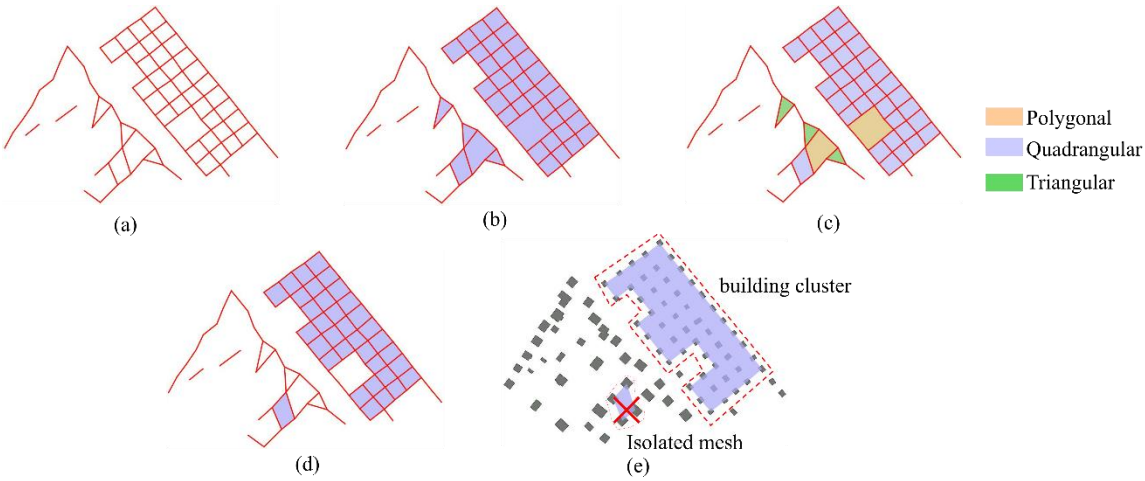


Figure 3.12 Building cluster formation by mesh clusters. (a) Proximity graph; (b) mesh of proximity graph; (c) mesh classification; (d) quadrangular mesh; (e) mesh clusters.

3.5.3 Building pattern recognition

(1) Pattern recognition in building alignments

- **Linear pattern**

Linear patterns are within building alignments, by measuring the straightness of the related stroke, the collinear and curvilinear patterns are distinguished. For a perfect collinear building pattern, the related stroke should be a straight line; thus, the deflection angle between each stroke segment should be equivalent to 180°. However, the real building dataset cannot meet this ideal condition; thus, the threshold for differentiating collinear and curvilinear pattern should be given first. If all the deflection angles are larger than the threshold, indicating that the stroke has high straightness so that the buildings related by the stroke present as collinear; otherwise, they present as curvilinear. For instance, if the threshold is set to 170°, in Figure 3.13, some deflection angles between segments in Stroke1 are smaller than the threshold, while in Stroke2 all deflection angles are larger than the threshold. Therefore, buildings related to Stroke1 present as curvilinear pattern, and buildings related to Stroke2 present as collinear pattern.

- **Enclosing pattern**

The enclosing patterns contain two forms: circle-like and polygon-like pattern. Circle-like enclosing pattern is normally formed by buildings with the same appearance and an end-to-end distribution trend. Polygon-like enclosing pattern is normally located in city blocks, which presents as the combination of several linear patterns. The recognition process is described as

follows: (1) generating the strokes in the refined proximity graph; (2) removing the strokes that only connect two buildings; (3) generating mesh from the strokes; (4) if the mesh boundary is composed of only one stroke, the buildings related by this stroke present as circle-like enclosing pattern (Figure 3.14(a)); if mesh boundary is composed of several different strokes, the buildings related by these strokes present a polygon-like enclosing pattern (Figure 3.14(b)).

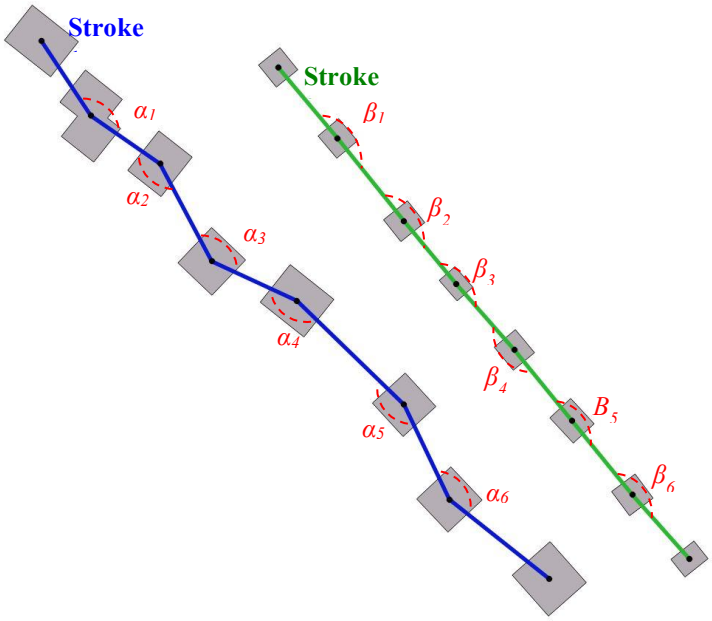


Figure 3.13 Collinear and curvilinear pattern distinguish by measuring stroke straightness.

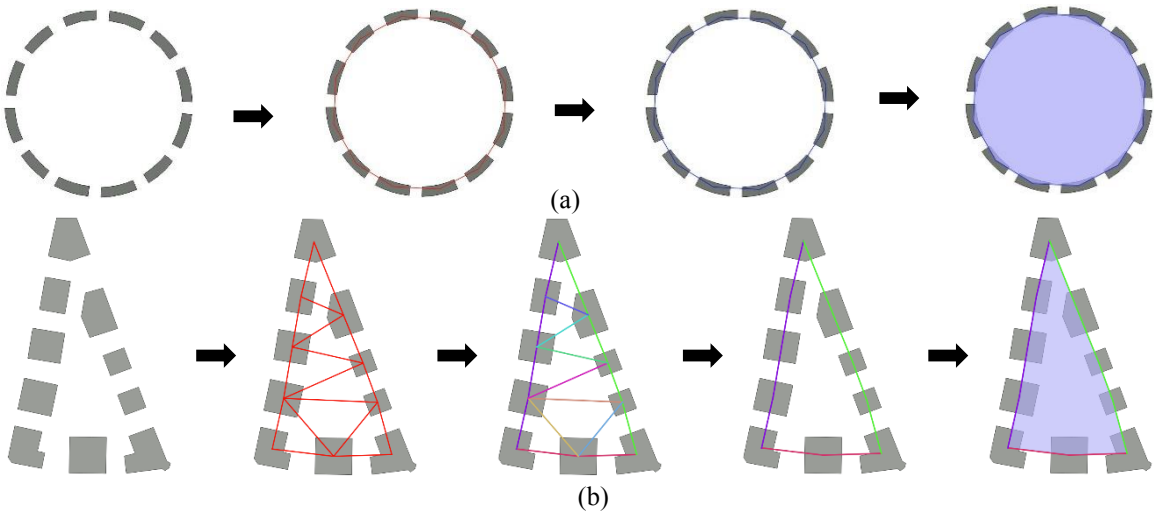


Figure 3.14 Recognition of (a) circle-like enclosing pattern and (b) polygon-like enclosing pattern.

(2) Pattern recognition in building clusters

In building clusters, the recognition task is to distinguish grid and grid-like pattern. By determining the shape of the related meshes, grid and grid-like patterns can be recognized. In Figure 15, building cluster with gird pattern is covered by the meshes with rectangle shape; building cluster with grid-like pattern is covered by the meshes with parallelogram-like shape.

The irregular building cluster is covered by with meshes with irregular shape. To distinguish grid and grid-like pattern, four interior angles of their covered meshes are used to measure their shapes. If α_1, α_2, α_3, and α_4 are the four interior angles, for a parallelogram, the two pairs of diagonal angles should be equal but not a right angle, namely, $\alpha_1=\alpha_3\neq 90°$ and $\alpha_2=\alpha_4\neq 90°$ (Figure 3.15(b)); the parameter *DiagonalAngleDiffer* (DAD) is set to determine whether the mesh shape is parallelogram. Because the rectangle is a special parallelogram with right angles, the parameter *RightAngleDiffer* (RAD) is used to determine whether the four interior angles are right angles (Figure 3.15(a)). If $\alpha_1=\alpha_3=\alpha_2=\alpha_4=90°$, the mesh is rectangle. Through the above shape determination methods, grid and grid-like patterns are recognized in building clusters. If the four interior angles do not meet the above two situations, the meshes are irregular, so that their related building clusters are irregular patterns (Figure 3.15(c)).

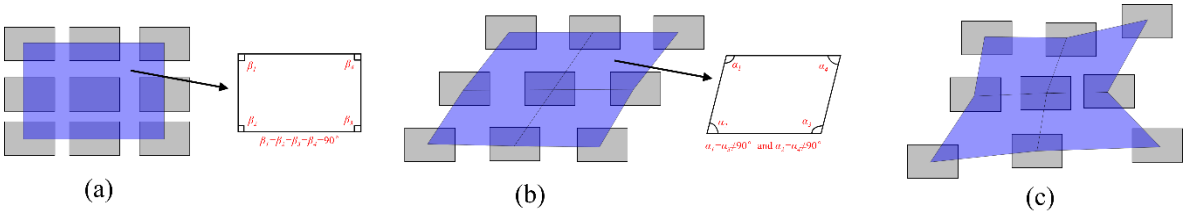


Figure 3.15 Recognizing building cluster patterns. (a) Grid pattern (rectangle mesh); (b) grid-like pattern (parallelogram mesh); (c) irregular pattern (irregular mesh).

3.6 Experiments

3.6.1 Data derivation and test framework

We tested the proposed method with datasets from OpenStreetMap (OSM) (Figure 3.16). The partitioning function of roads was also considered. To test the effectiveness of the proposed methodology, Region A and B are selected from the rural area, while Region C and D are suburban areas close to the city center. Visually, Region A contains amounts of linear and grid patterns; Region B presents a random distribution in general, but with several outstanding linear and grid patterns; Region C contains linear patterns and circle-like patterns; Region D are the city blocks with outstanding linear and enclosing patterns. Therefore, the four test regions involve all the pattern types mentioned in the proposed typology. The characteristics of the four regions are shown in Table 2.

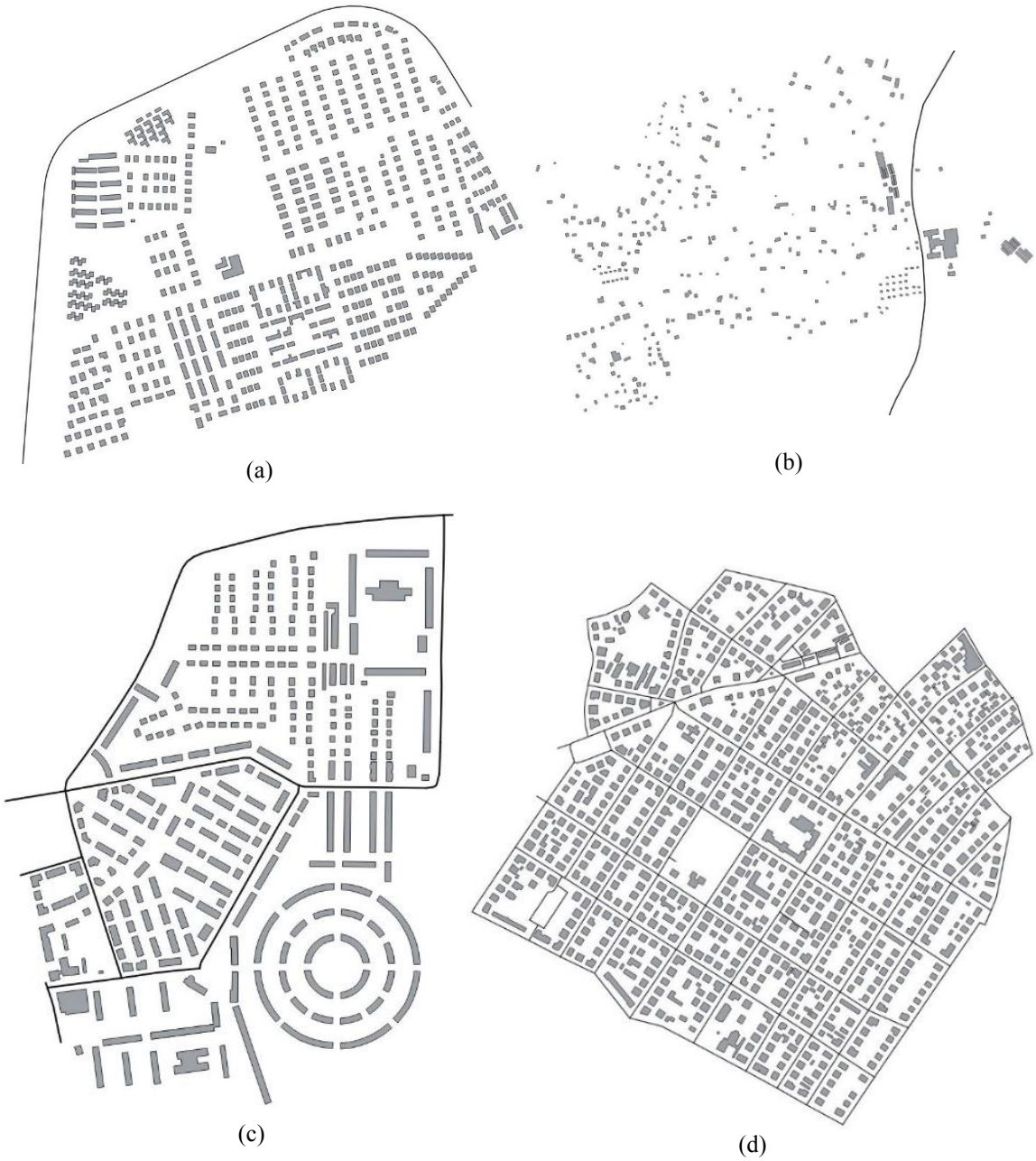


Figure 3.16 Test regions. (a) Region A; (b) Region B; (c) Region C; (d) Region D.

Table 3.2 Summary of the test regions characteristics.

Region	Region type	Region density	Linear pattern	Grid pattern	Enclosing pattern	Building number
A	Rural	Moderate	Yes	Yes	No	593
B	Rural	Low	Yes	Yes	No	328
C	Suburban	Moderate	Yes	No	Yes	309
D	Suburban	High	Yes	No	Yes	937

Figure 3.17 displays the framework of the proposed method: (1) using CDT to generate proximity graph of buildings; (2) based on different grouping requirements, choosing constraints to refine the original proximity graph; (3) changing the value of deflection angle to identify

collinear and curvilinear pattern; (4) generating mesh of strokes to identify enclosing patterns; (5) generating mesh on refined proximity graph to obtain building clusters and judging the shape of mesh to recognize grid and grid-like pattern.

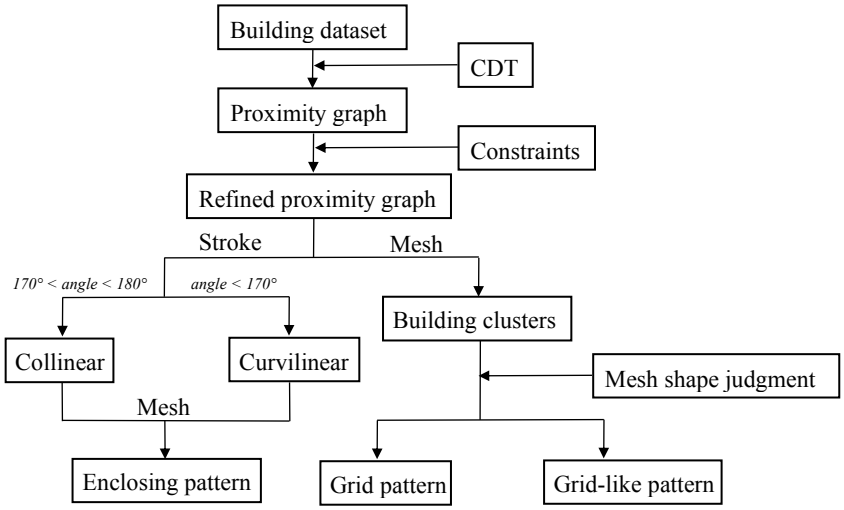


Figure 3.17 Framework of the proposed method.

3.6.2 Pattern recognition results

Figure 3.18 shows the proximity graphs and their refinements in the test regions. Figure 3.19 displays the final recognition results of different building patterns. Buildings connected by the same collinear stroke present as collinear pattern. The curvilinear stroke connects the buildings that present as curvilinear pattern. The mesh generated by a single stroke connects the buildings with the circle-like enclosing pattern, while the mesh generated by multi-strokes connects the buildings with the polygon-like enclosing pattern. For buildings that present grid and grid-like patterns, they are connected by the rectangle mesh and parallelogram mesh, respectively. The thresholds of the six constraints for refinement are listed in Table 3.3. Table 3.4 lists the thresholds of the deviation angles of recognizing collinear and curvilinear patterns. The thresholds of determining mesh shape are also listed in Table 3.4.

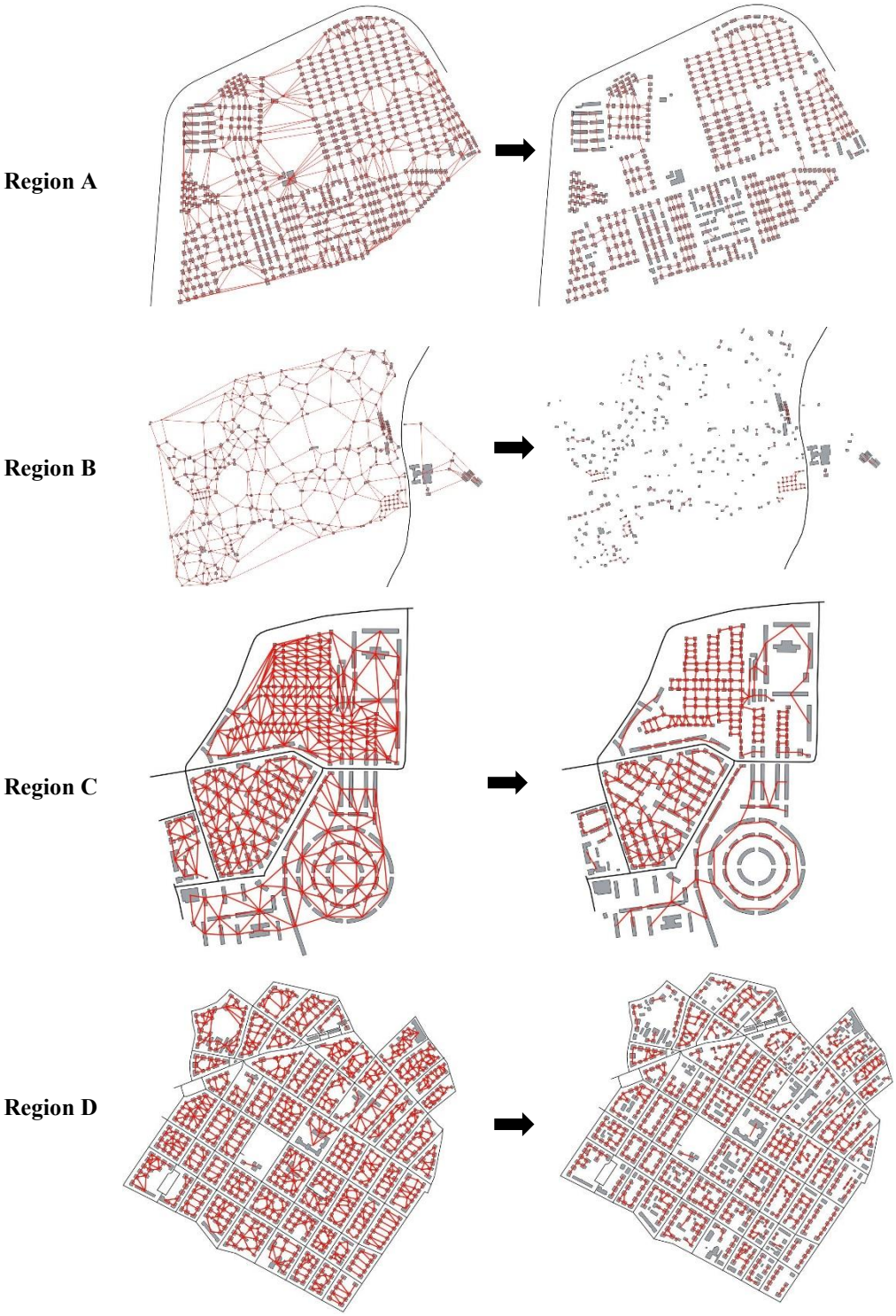


Figure 3.18 Original and refined proximity graphs of the four test regions.

Figure 3.19 Pattern recognition results of the test regions.

Table 3.3 Refinement constraints thresholds (n.c. means not choose).

Region	*distance*	$Sim_{(Size)}$	$Sim_{(Orientation)}$	$Sim_{(shape)}$	$Sim_{(elongation)}$	*facing ratio*
A	< 30 m	> 0.5	n.c.	n.c.	> 0.5	> 0.0
B	< 20 m	> 0.5	n.c.	n.c.	> 0.5	n.c.
C	< 30 m	> 0.4	n.c.	n.c.	n.c.	> 0.0
D	< 30 m	> 0.3	n.c.	n.c.	> 0.5	> 0.0

Table 3.4 The threshold values of recognizing linear and grid patterns.

Region	deviation angle of stroke		mesh shape judgement	
	Collinear pattern	Curvilinear pattern	Grid pattern	Grid-like pattern
A	170°	150°	*RAD* < 5°	*DAD*< 7°
B	170°	140°	*RAD* < 5°	*DAD* < 7°
C	170°	150°	*RAD* < 5°	*DAD* < 7°
D	170°	140°	*RAD* < 5°	*DAD* < 7°

The homogeneities of recognized linear patterns are calculated to measure the consistency of the buildings in the same pattern. The calculation methods from the work of Zhang (2013) are referenced. Distance, size, and shape are considered as the impact factors of homogeneity. The visually stronger pattern has a lower homogeneity value, and the visually weak pattern has a higher homogeneity value. Equation (3.6) calculates the homogeneity of one factor, and Equation (3.7) calculates the integrate homogeneity of the three factors. In Figure 3.20, the patterns with higher homogeneity are marked with broader lines.

$$Homo(C_i) = STD(C_i)/Mean(C_i), C_i \in \{distance, size, shape\} \tag{3.6}$$

$$InteHomo = \sum \omega_i \cdot Homo(C_i), C_i \in \{distance, size, shape\} \tag{3.7}$$

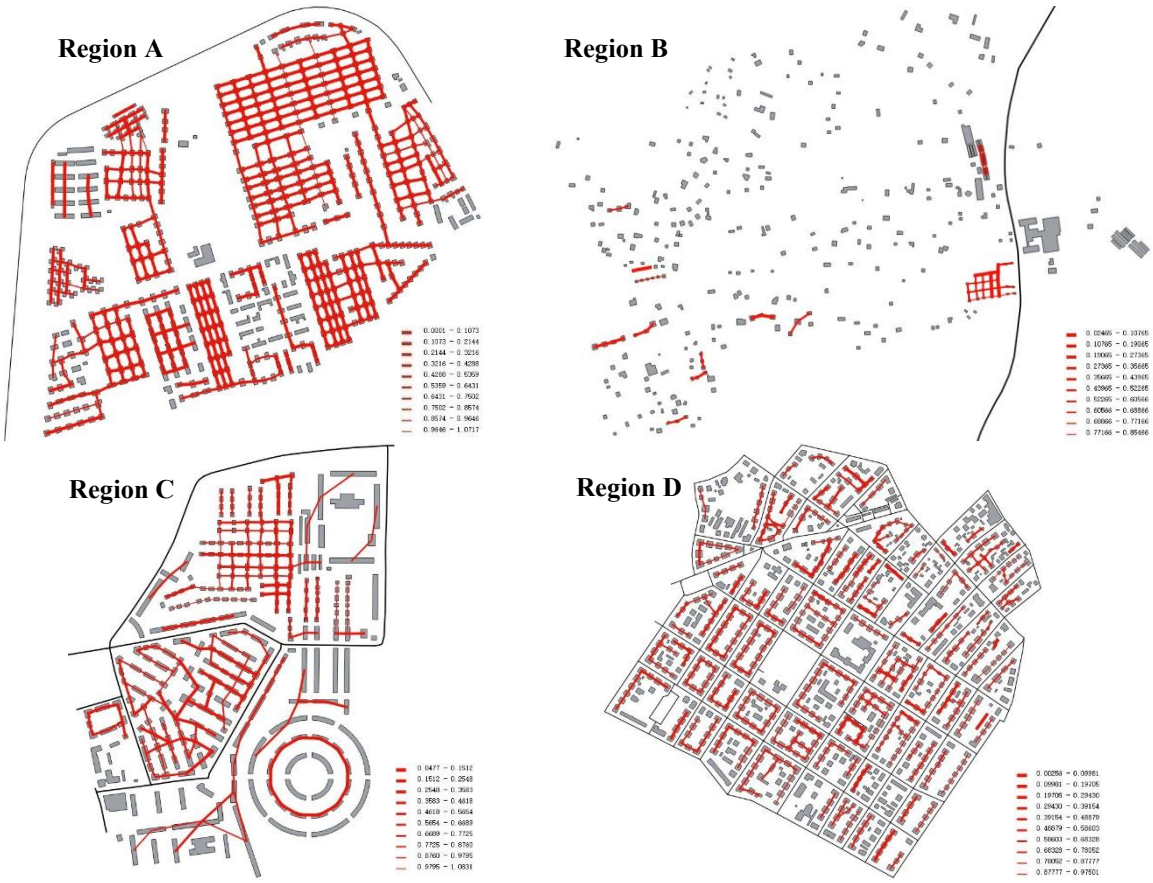


Figure 3.20 Homogeneity of linear patterns.

3.6.3 Evaluation

To validate the quality of the recognition results, the results are compared with an expert identification. In this survey, a cartographer identified the patterns and marked lines on the recognized results (Figure 3.21). By comparing the results of the proposed recognizing method with manually identified results, the precision and recall rate are calculated with the equations proposed by reference (X. Zhang, Ai, et al. 2013) and shown in Table 3.5. The recall rates are approximately 90%, which demonstrates that the proposed method has the ability to discover building patterns. Based on the precisions, the proposed method performs better in *Region A* and *B* than *Region C* and *D*. Because *Region A* and *B* are rural areas with sparser building distribution. Building patterns are presented in sparse areas more outstanding than in dense areas, which makes pattern recognition more definitive. Most differences locate in the recognition of curvilinear patterns. In the recognized curvilinear patterns of the proposed method, most of them only consist of three buildings. Three buildings have little chance for visual identification of curvilinear patterns. From the homogeneity values, it can be also noticed that the recognized curvilinear patterns with only three buildings are less homogeneous than other curvilinear patterns. Therefore, it is necessary to present another rule that the curvilinear pattern should contain more than three buildings.

Figure 3.21 Visually identified building patterns by expert.

Table 3.5 Recall rate and precision.

Region	Recall rate	Precision
A	92.4%	77.9%
B	88.2%	68.2%
C	90.6%	60.0%
D	92.9%	65.3%

3.7 Discussion

3.7.1 Adaptation of parameters

(1) Refinement constraints tuning and comparison with MST

In the proposed method, the proximity graph plays the important role. The generation of stroke and mesh largely depends on the refined proximity graph. If the refined proximity graph has high quality, the subsequent recognition process can benefit from it. The quality of refined proximity graph is considered from two aspects: (1) preserving the edges that connect buildings with a large potential to form the same building group; (2) removing the edges that connect buildings with large differences in geometry. The refinement relies on the thresholds of the six constraints. The real dataset is complex and random, and it cannot guarantee that all the edges are preserved or removed accurately. Therefore, the sensitivity of the six constraints should be inspected. To test the refining effect, only one constraint is used to refine the proximity graph. The original proximity graph is from Figure 5(c), and Figure 3.22 shows the refinement results with single constraint. The curve chart in Figure 3.23 reflects the remaining rate of edges after single constraint refinement.

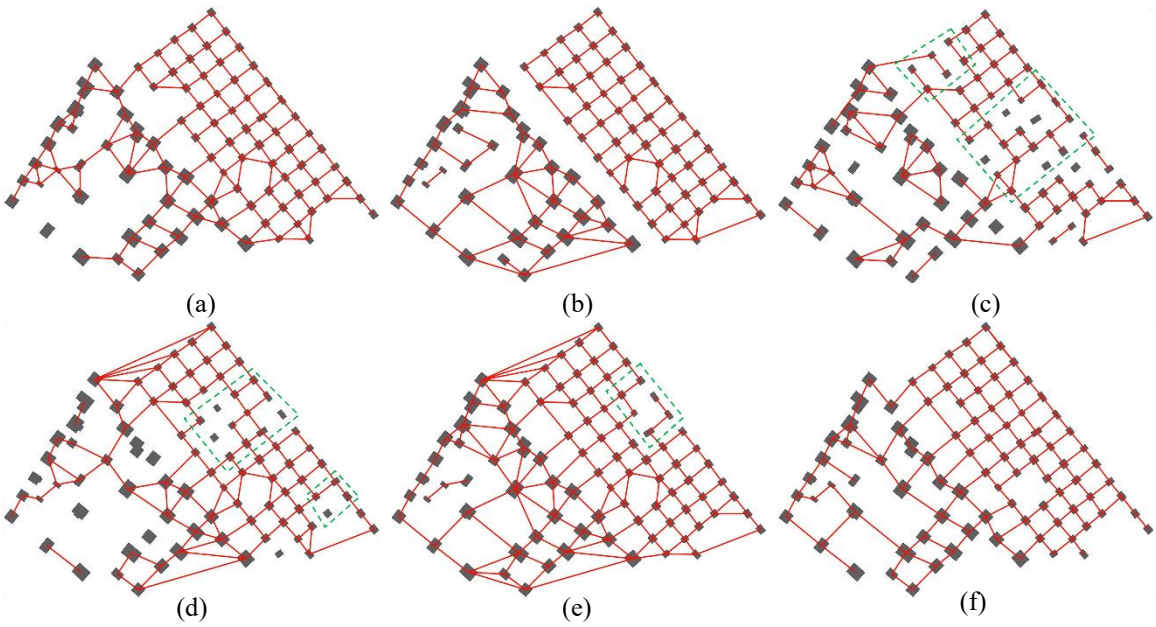


Figure 3.22 Refinement effects by single constraint. (a) Distance < 25m; (b) size similarity > 0.5; (c) orientation similarity > 0.5; (d) shape similarity > 0.5; (e) elongation similarity > 0.5; (f) facing ratio > 0.0.

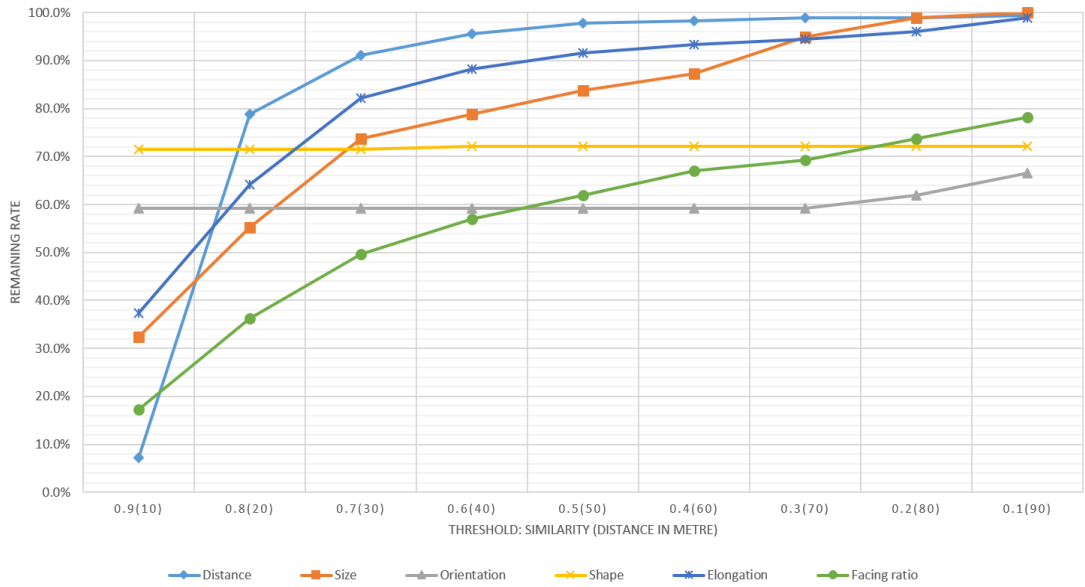


Figure 3.23 Proximal edges remaining rate of single constraint refinement.

From Figure 3.22, the individual refining effects of the six constraints are concluded. Distance and size should be considered first and frequently, because they can obtain good refining effects without disrupting potential patterns. Shape, orientation, and elongation should be used carefully because they are quite sensitive, and their usage may disrupt the potential to form linear and grid patterns (shown in dashed circles). Unless a strong demand is asked that buildings in one group must possess strict orientation, shape or elongation consistency. Facing ratio can achieve great effectiveness in eliminating visual conflicts which should be considered frequently. Therefore, the priority of using the six constraints is presented: Distance>Size>Facing ratio>Elongation>Orientation>Shape.

The refinement process should be controlled. It is not necessary to use all six constraints for refinement in all situations but to select appropriate constraints under different grouping requirements. If the grouped buildings are required to be more similar on size, the threshold of size similarity should be set rigidly, and the other five constraints can have some tolerance or be abandoned. There should be a balance between eliminating differences and maintaining sufficient potentials. Figure 3.24(b) shows a satisfying refinement example with the following thresholds: Distance < 30 m, $Sim_{(Size)} > 0.5$, $Sim_{(Elongation)} > 0.5$, $Facing\_ratio > 0$.

Minimum spanning tree (MST) is a frequently used method to refine the original proximity graph (Regnauld 1996) (Zhang et al., 2013) (Wu et al., 2017b). We compared the refinement effects of the proposed six constraints refining method with MST. In the dashed circles A and B of Figure 3.24, the potentials of forming linear and grid patterns are well preserved with the

proposed refinement method. In contrast, MST partly disrupts the original patterns because MST refining strategy strongly considers keeping the connectivity of the whole graph with the shortest distance. Therefore, the proposed refining method performs better than the MST refining method.

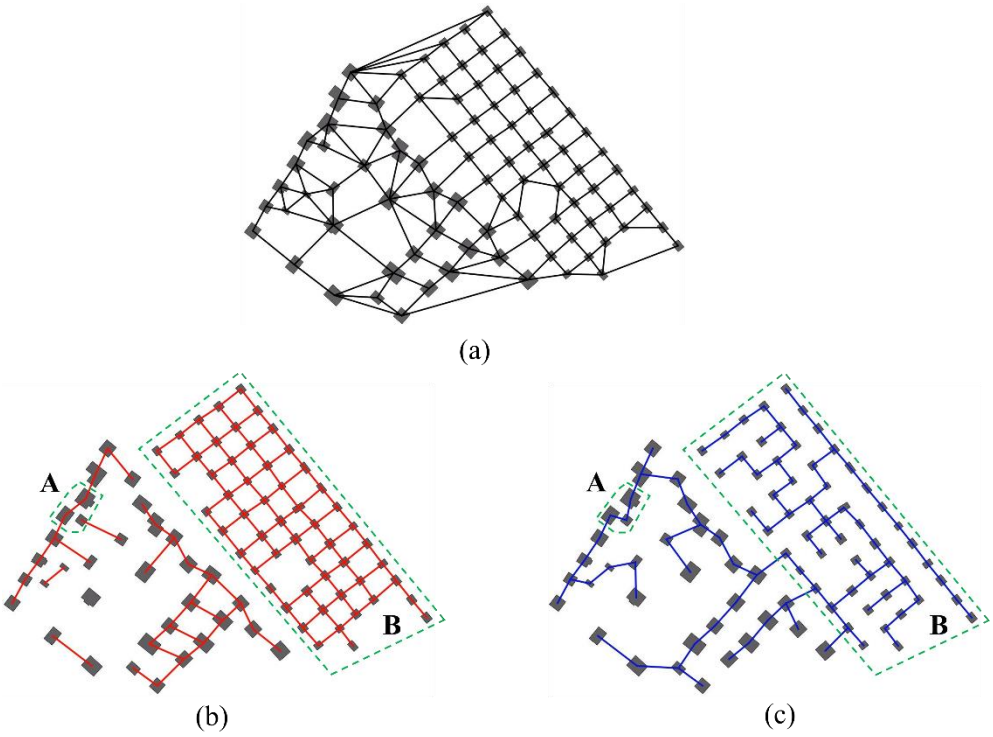


Figure 3.24 Comparison of refining proximity graph. (a) Original proximity graph; (b) refined by proposed six-constraints; (b) refined by MST.

(2) Deviation angle of forming stroke

In the process of forming strokes, the most important threshold is the value of the deviation angle. Figure 3.25 shows the strokes formation results under different deviation angles. As the angle becomes acuter, more strokes are formed. In this example, When the threshold is within 160-180°, the straightness of the strokes is higher which implies more collinear patterns would be recognized; when the threshold is within 140-160°, some strokes become curving which implies the curvilinear patterns could be identified; when the threshold falls below 140°, the strokes formation results are always the same. Therefore, the empirical threshold of deviation angle to recognize collinear pattern should be above 160°, and curvilinear pattern can be identified with the threshold between 140° and 160°.

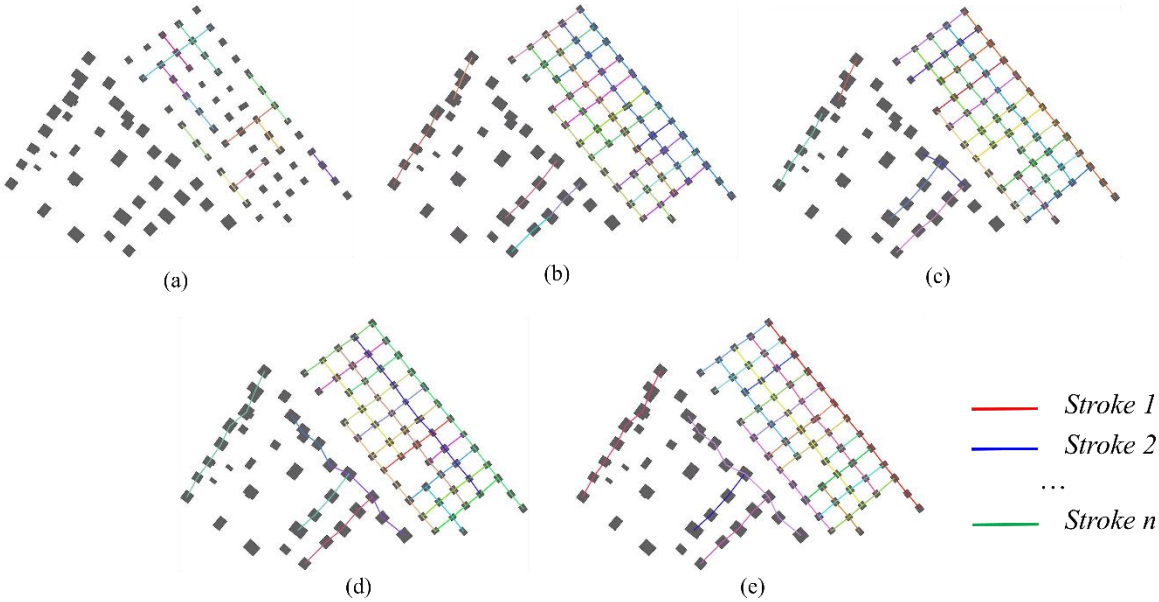


Figure 3.25 Different deviation angles to form stroke. (a) 179°; (b) 170°; (c) 160°; (d) 150°; (e) 140°.

(3) Mesh shape judgement

The mesh shape affects the pattern type of building clusters. Figure 3.26 displays the judgement results by changing threshold *RightAngleDiffer* from 90±0.1° to 90±10°. From the results, it is found that if the grid pattern could be most recognized, the threshold should be set more tolerant.

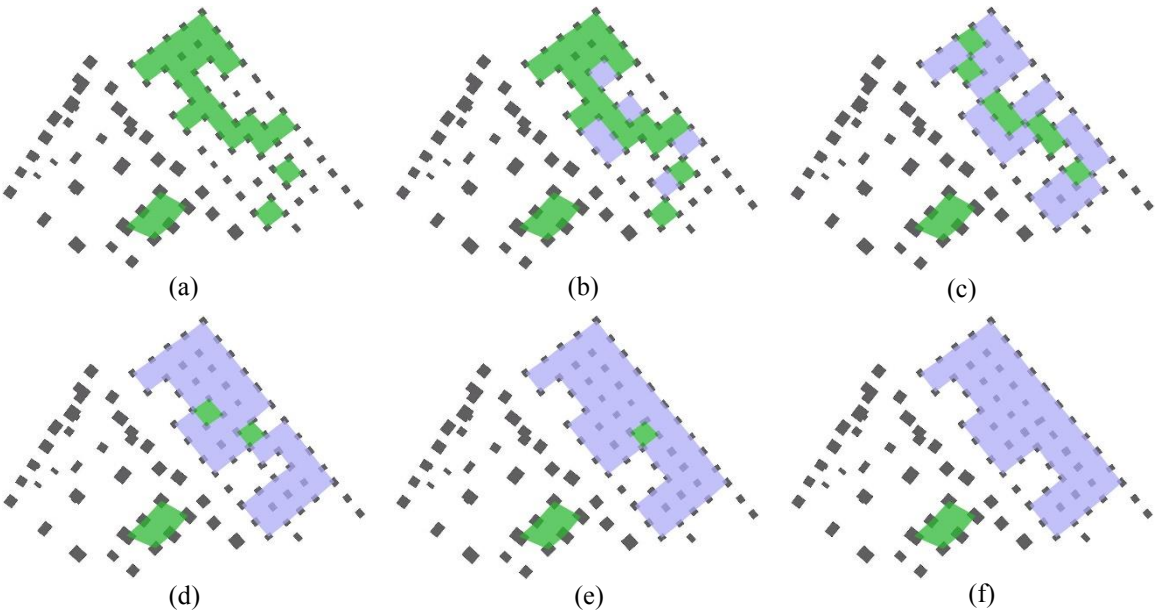


Figure 3.26 Different threshold values to judge mesh shape. (a) 90±0.1°; (b) 90±2°; (c) 90±4°; (d) 90±6°; (e) 90±8°; (f) 90±10°.

(4) Discussion of threshold selection

The selection of the specific threshold should depend on the specific case. The threshold selection process is a tuned, trial and error process, and the end of this process should be based on whether the current thresholds obtain the most satisfying results. For judging the results, it is also a relatively subjective aspect. Taking the collinear and curvilinear patterns as example, the collinear and curvilinear pattern are not absolute, in the specific case, the judgement of collinear and curvilinear depends on the will of the generalization decision maker. The specific thresholds of the proposed tests in Section 5 achieved the best recognition results, which can be regarded as the empirical value for the further pattern recognition tasks.

3.7.2 Ambiguity of building patterns

Building patterns would be easy to recognize if buildings were positioned in perfect configurations, such as equally spaced, aligned to a straight line or other regular shapes, and symmetrically layouts. However, in the real world and datasets, buildings never form such perfect patterns and are only closer to be regular. Different buildings have different vertical and horizontal morphologies, which brings considerable challenges to pattern recognition. The test results show that building pattern recognition is a complex process. Depending on the set threshold the detected patterns differ and may be ambiguous. For example, in Figure 3.27(a), if the thresholds are given with strict values, the collinear pattern may be recognized as curvilinear pattern. Similarly, in Figure 3.27(b), if loose thresholds are given, the curvilinear pattern would be recognized as collinear pattern. This indicates that linear patterns are relatively distinguished by collinear and curvilinear patterns. In some situations, it is better to recognize linear patterns without distinguishing in detail. In Figure 3.27(c), the grid pattern can be considered into several linear patterns, and these linear patterns collectively form the grid pattern.

Building patterns are often ambiguous and complex to detect. Perfect linear or grid patterns hardly exist in the built environment. Hence, we used different thresholds to control the recognition process. For future application in cartographic map generalization, we propose to develop a recognition standard to automatically calibrate the applied thresholds. With the standard, the ambiguity can be eliminated and the patterns can be definitively recognized.

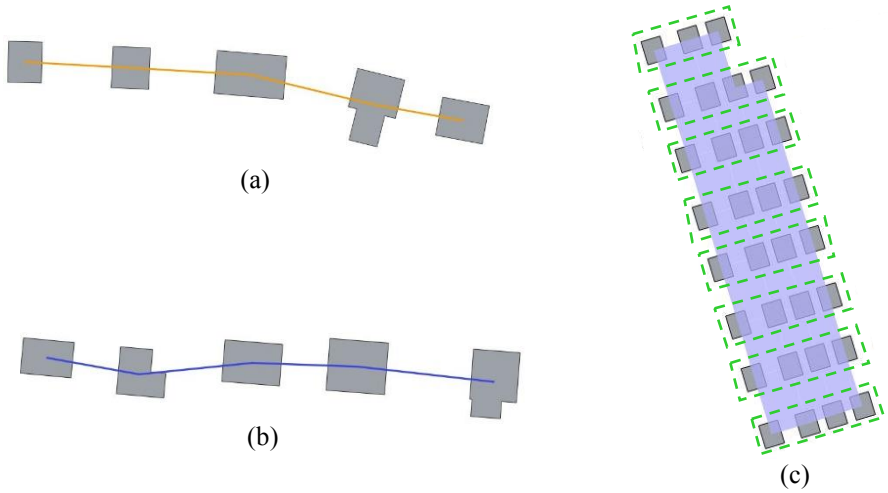


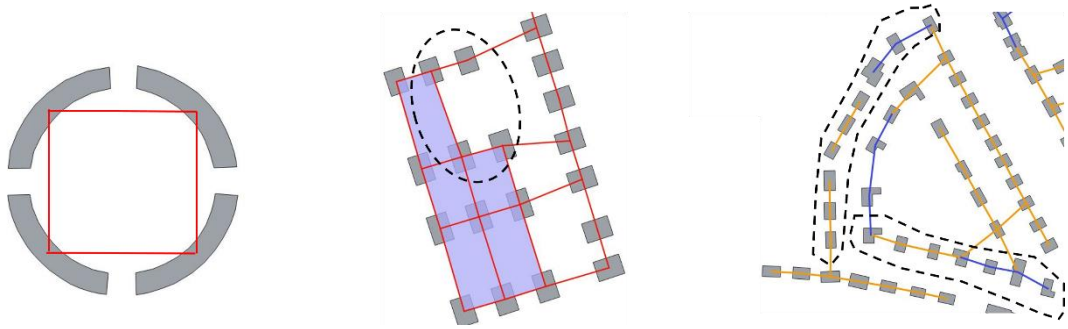
Figure 3.27 Ambiguity of building patterns. (a) Collinear pattern; (b) curvilinear pattern; (c) grid pattern.

3.7.3 Advantage and Limitation

The previous methods treated building grouping and pattern detection as separated parts, which potentially results in that the patterns expected to be identified may be disrupted by the grouping process. The proposed stroke and mesh strategy combines the building grouping and pattern detection together, which ensures the completeness of the patterns expected to be identified. In the proposed approaches, stroke and mesh are used to group buildings into building alignments and building clusters, respectively, which will not disrupt the original patterns. Strokes and meshes have the natural ability to form building alignments and building clusters. In essence, stroke belongs to linear entity (one-dimensional) and mesh is an areal entity (two-dimensional). Because strokes are linear objects, the buildings grouped by stroke are naturally and inevitably presented as linear pattern. Similarly, meshes are grouped into clusters so that their related buildings are also grouped into clusters. With the help of mesh clusters, the issue of recognizing grid pattern in buildings is transformed into recognizing the grid pattern in the network. This transformation simplifies the original issue and reduces the difficulty. The six constraints refinement strategy makes the grouping process more controllable. In different dataset and generalization requirements, there are different situations in grouping process. The six constraints provides more possibilities and flexibilities.

There are also limitations of the proposed method: (1) the centroids of buildings are regarded as the representative of the buildings, which ignores that buildings with special shapes and sizes have trends to form patterns. In Figure 3.28(a), the circle-like enclosing pattern is not recognized; (2) the given thresholds in the refinement of proximity graph may eliminate some edges which take part in forming patterns. In Figure 3.28(b), one edge that consist of grid pattern is eliminated so that the grid pattern cannot be recognized completely; (3) the longer linear patterns may be cut

off by different deflection angles in forming strokes. In Figure 3.28(c), if the isolated collinear and curvilinear patterns are connected together, a longer curvilinear pattern could be formed.



(a) (b) (c)

Figure 3.28 Limitations of the proposed method.

3.8 Conclusion

This paper proposes a method to recognize building patterns using stroke and mesh. Through explaining the definition of related terminologies, the typology of building patterns is integrated and extended. The recognition method is based on proximity graph; stroke and mesh are derived from the refined proximity graph and used to form building alignments and building clusters. The specific patterns are identified by analyzing stroke straightness and mesh shape. Four test regions are chosen to verify the effectiveness. The method has been empirically validated to the visual identification of building pattern by an informed expert cartographer. The main contributions of this study are as follows: (1) six constraints are used to refine the proximity graph, which makes the building grouping process more controllable; (2) building grouping and pattern recognition are integrated by stroke and mesh techniques, which reduces the possibility of disrupting patterns in the grouping process. Future work will focus on the generalization operation based on the recognized patterns. More work is also needed to automatically calibrate the thresholds involved in the proposed methods.

Chapter 4

A typification method for linear building groups based on stroke simplification

Xiao Wang and Dirk Burghardt

Citation:

Wang, X. and Burghardt, D. (2019): A typification method for linear building groups based on stroke simplification. *Geocarto International*. DOI: 10.1080/10106049.2019.1669725

4.1 Abstract

Linear building groups are common patterns and important local structures in large scale maps, which should be carefully generalized. This paper uses the idea of line simplification to typify linear building groups. Firstly, based on the stroke idea, the linear building groups are detected that each building group is related by only one stroke; the collinear and curvilinear patterns are distinguished by calculating the overlap rate between the defined auxiliary polygon and its oriented bounding box. Secondly, the stroke is simplified by removing one node in each iterative step; and the remained nodes are reallocated to the new positions, which serves as the centroids location of the newly typified buildings. Third, the representation (size, shape, elongation, and orientation) of the newly typified buildings are calculated by the geometry information of their corresponding parent buildings. The typification method can be carried out as a progressive process, which iterates over the three steps to derive continuous typification results. The method is tested on two building datasets, and the experimental results demonstrate that the proposed method can achieve good performance by well preserving the original linear patterns in the generalized building groups.

4.2 Introduction

Urban landscapes are planned with certain design so that some patterns are formed by buildings on map. Building patterns denote the visually salient structures that are collectively represented by building groups (Du, Luo, et al. 2016). In general, building patterns can be divided into three types based on their pattern layouts: linear pattern, grid pattern, and irregular pattern (Du, Shu, et al. 2016). Linear and grid patterns are regularly distributed by buildings that can be easily recognized by human eyes, which should be paid more attentions in generalization. These two regular building patterns are important local structures that frequently represented in large scale maps, which should be carefully generalized. Linear building patterns can be frequently found along streets, which creates two specific forms for linear patterns, i.e. collinear and curvilinear. The characteristics of these two forms should be considered in their generalization process, which increases the complexity of the generalization process.

When it comes to map generalization, building generalization is normally decomposed into two steps: group formation of buildings and generalization operator execution (Li et al., 2004). In general, the grouping process is based on the Gestalt theory, that the buildings which are similar in proximity, size, closure, continuity and common fate would be collected into one group. Different patterns are represented in different groups. Many methods have been developed to detect building group through decades. These methods normally use the

Gestalt principle to calculate the similarities in buildings thereby the building groups are formed (Yan et al., 2008; Zhang et al., 2012; Zhang, Ai et al., 2013; Zhang, Deng et al., 2013; Cetinkaya et al., 2015; Deng et al., 2017; Yu et al., 2017). There are also other strategies to detect building groups (Anders 2003; Ruas and Holzapfel 2003; Wang et al., 2015; Du, Shu et al., 2016; Yu et al., 2017; He et al., 2018). After the grouping process, the generalization operators are selected and applied to the building groups. The possible operators for generalizing building groups are selective omission, aggregation, collapse, displacement, exaggeration, simplification and typification (Li et al., 2004). For example, buildings with irregular patterns are simply aggregated into blocks or built-up areas for their high densities. On the other hand, regular patterns are often preserved or even enhanced after generalization. Therefore, it is important to select suitable operators to generalize buildings with regular patterns.

Typification denotes using a relatively smaller number of new objects to represent a group of larger number objects, while preserving the similarities of the initial position, spatial characteristics and structures as much as possible, such as distribution patterns and density, spatial coverage and order, orientation and specific arrangements (Foerster et al., 2007; Sandro and Massimo 2011). Gong and Wu (2018) have already chosen typification as the operator to generalize the linear building groups. Accordingly, based on the definition of typification and the previous research, typification can be considered as an appropriate operator to generalize building groups with linear patterns. To date, several strategies have been created for building typification. From the previous work of building typification, three aspects must be considered to determine the typified buildings: (1) the number of preserved buildings; (2) the positions of the preserved buildings; and (3) the alternate representations of generalized buildings (regarding size, shape, and orientation) (Burghardt and Cecconi 2007). Comparing with other generalization operators, the specificity of typification implies that it is compulsory to create new buildings by considering their numbers, relocations, and representations, which makes typification becoming a challenging topic in automated map generalization.

In this paper, we consider the typification of building groups with linear patterns. The typification of linear patterns belongs to the issue of local typification. Local typification is implemented on the level of building groups, and the structural knowledge of the groups is largely considered in the process of typification (Anders 2006). Local typification normally concentrates on the buildings with regular patterns. Examples can be found as follows: Anders and Sester (2000) presented a parameter-free graph-based clustering approach and applied it for building typification. Mao (2012) developed detection and typification

methods of linear structures for dynamic visualization of 3D city models. Gong and Wu (2018) regarded typification as a progressive and iterative process consisting of elimination, exaggeration and displacement so as to typify linear building pattern. The typification of other geographical objects, such as islands, ditches, drainage, facade etc., also belongs to the topic of local typification (Zhang 2007; Sandro and Massimo 2011).

In essence, the typification of linear building groups belongs to the problems of *m*:*n* relation generalization (Ai and van Oosterom 2001). The difficulty lies in how to keep the balance between reducing appropriate number buildings and preserving original linear patterns in the remained buildings after typification. Although the research mentioned above contributed a lot to this issue, however, there are still some aspects to be further studied. The current methods do not differentiate linear patterns into detail. The existing ideas are mainly developed for typifying buildings with collinear patterns, and few attentions are considered for the curvilinear patterns. For the existing typification method of curvilinear patterns, there are still some parts to be further improved, such as the shape preservation of the curve-distribution (Gong and Wu, 2018). The collinear and curvilinear patterns have different characteristics in distribution, which should be taken into consideration in the process of typification. Therefore, in this paper, a typification method is proposed to generalize building groups with two different linear types. The research mainly considers on suburban and rural regions where linear patterns are largely found. The main objective is to preserve the spatial relationships and original linear patterns as much as possible after typification.

The remainder of this paper is structured as follows: Section 2 introduces the stroke-based method for detecting and recognizing linear building groups. Section 3 describes the typification method based on stroke simplification. Section 4 shows the experimental results of the proposed method. Section 5 displays the comparison test and discusses the advantages and further improvements. At last, the conclusion is given in Section 6.

4.3 Detection of linear building groups

4.3.1 Stroke-based detection method

There are many different ideas to detect the building groups with linear patterns. In this study, the stroke-based method is used to detect linear building groups. Figure 4.1(a) shows the workflow of this method, and the main idea of the stroke-based detection method is described by the following four steps:

Step 1: The proximity graph of the buildings is generated by using the constraint Delaunay triangulation (CDT) (Figure 4.1(c)).

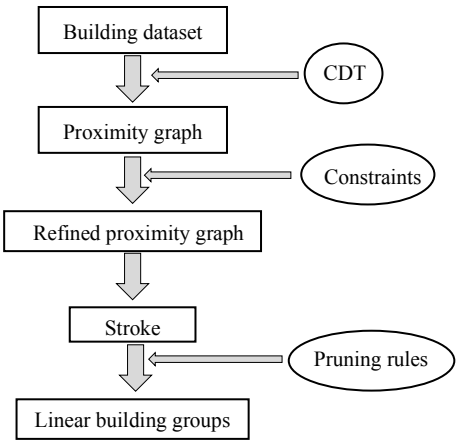
Step 2: The original proximity graph is refined by using the constraints (such as size, distance, shape) (Figure 4.1(d)).

Step 3: Regarding the refined proximity graph as a network, then strokes are generated based on the proximal edges. Here, it requires that the stroke should relate at least three buildings, thus, the strokes which relate only two buildings are deleted (Figure 4.1(e)).

Step 4: Some stokes are intersected with each other so that there exist some buildings (common building) belong to different groups. To decide the belonging of the common building, the strokes should be pruned. As shown in Table 4.1, there are three different intersection types of strokes, which are L-type, T-type and Cross-type. In L-type, the common building locates at the terminal positions of the two groups; in T-type, the common building locates at the terminal position of one group and the middle position of another group; in Cross-type, the common building locates at the middle position of the two groups. To prune the stroke, three rules are proposed as follows.

- **Rule 1**: For L-type, checking whether they can form a larger group with the given threshold α; the aim of this rule is to form a more entire building group.
- **Rule 2**: If the two building groups have the different building number, the common building belongs to the group which has more buildings. If the building number of the group which lost the common building is less than three, it will not be regarded as a building group.
- **Rule 3**: If the two building groups have the same building number, the common building belongs to the group whose related stroke has the most similar orientation with the common building. Similarly, if the building number of the group which lost the common building is less than three, it will not be regarded as a building group.

Table 4.1 shows some specific examples to illustrate the three pruning rules. Figure 4.1(f) shows the pruning results of the strokes. After pruning, the buildings which related by the sane stroke are regarded as a building group.



(a)

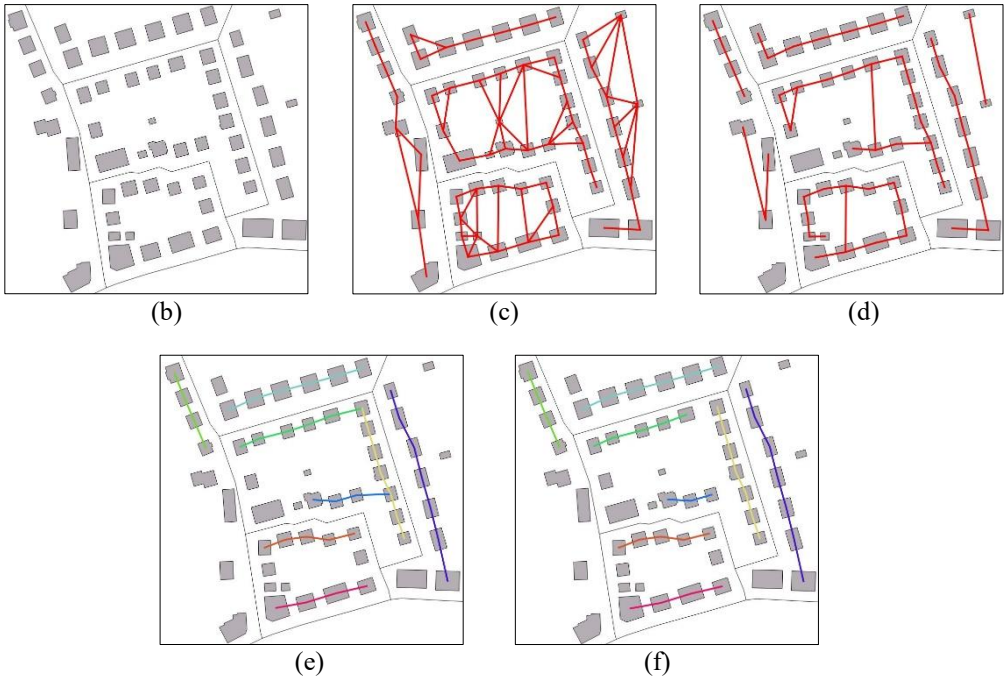
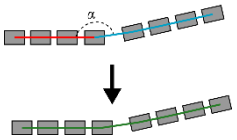
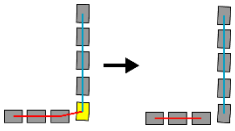
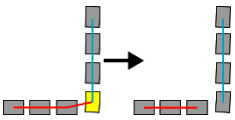
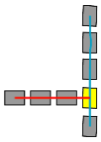
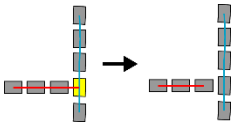
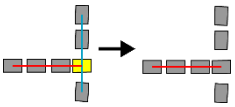
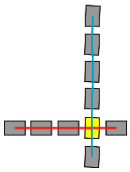
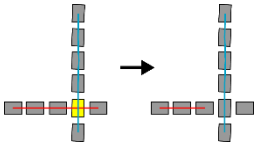
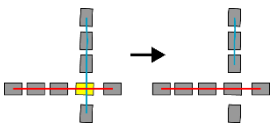


Figure 4.1 Process of stroke-based method for detecting linear building groups. (a) Work flow of the detection method; (b) original buildings; (c) proximity graph; (d) refined proximity graph; (e) stroke generation; (f) pruned stroke.

Table 4.1 Stroke pruning rules.

Type	Rule 1	Rule 2	Rule 3
 L-type			
 T-type	/		
 Cross-type	/		

4.3.2 Distinguishing collinear and curvilinear patterns

Linear building groups have two specific pattern types: collinear pattern and curvilinear pattern (Zhang, Ai et al., 2013). Figure 4.2 displays the typology of the possible linear pattern types in the detected building groups. For the collinear pattern, in the previous work, it has been subdivided into straight pattern and oblique pattern in detail (Du, Luo et al., 2016). For the curvilinear pattern, there are also two different types, which are named as smooth pattern and jagged pattern, respectively. The smooth pattern is normally locates along the roads, and the orientation of the buildings has the smooth tendency while the jagged pattern normally has the curving and wavy distribution.

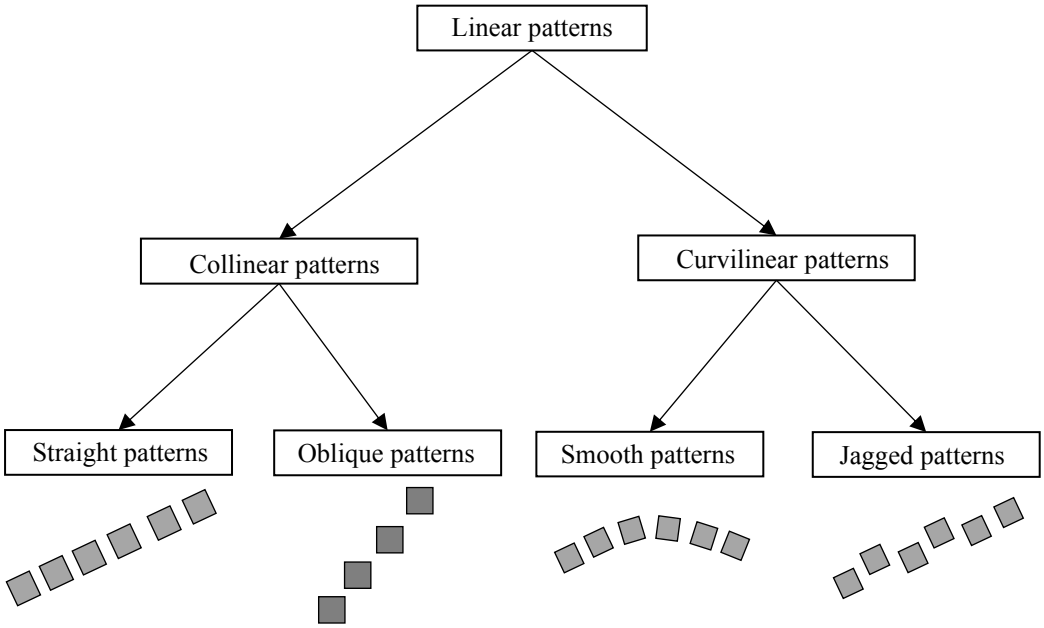


Figure 4.2 Linear pattern typology.

The recognition of collinear and curvilinear patterns is necessary because the subsequent typification process will be affected by the two types. To distinguish collinear and curvilinear patterns, a novel method is proposed. This method includes the following steps: (1) Creating Delaunay triangulation from the building groups; (2) dissolving the isolated triangles into an entire polygon, here the polygon is named as auxiliary polygon; (3) calculating the oriented bounding box (OBB) of the auxiliary polygon; (4) calculating the overlapping ratio (*OR*) between the auxiliary polygon and its OBB.

As shown in Figure 4.3(a-b), for the collinear patterns, no matter the straight pattern or the oblique pattern, the size of the auxiliary polygon is very close to its OBB; thus the *OR* of collinear pattern is normally very high. On the contrary, for the curvilinear patterns in Figure 4.3(c-d), there exists big size difference of the auxiliary polygon and its OBB, so that the *OR* of curvilinear pattern is normally very low. Therefore, if the appropriate threshold

(0.0-1.0) of *OR* is given, the collinear and curvilinear pattern can be distinguished. Specifically, if *OR* is larger than the threshold, the building group presents the collinear pattern; otherwise, it is curvilinear pattern.

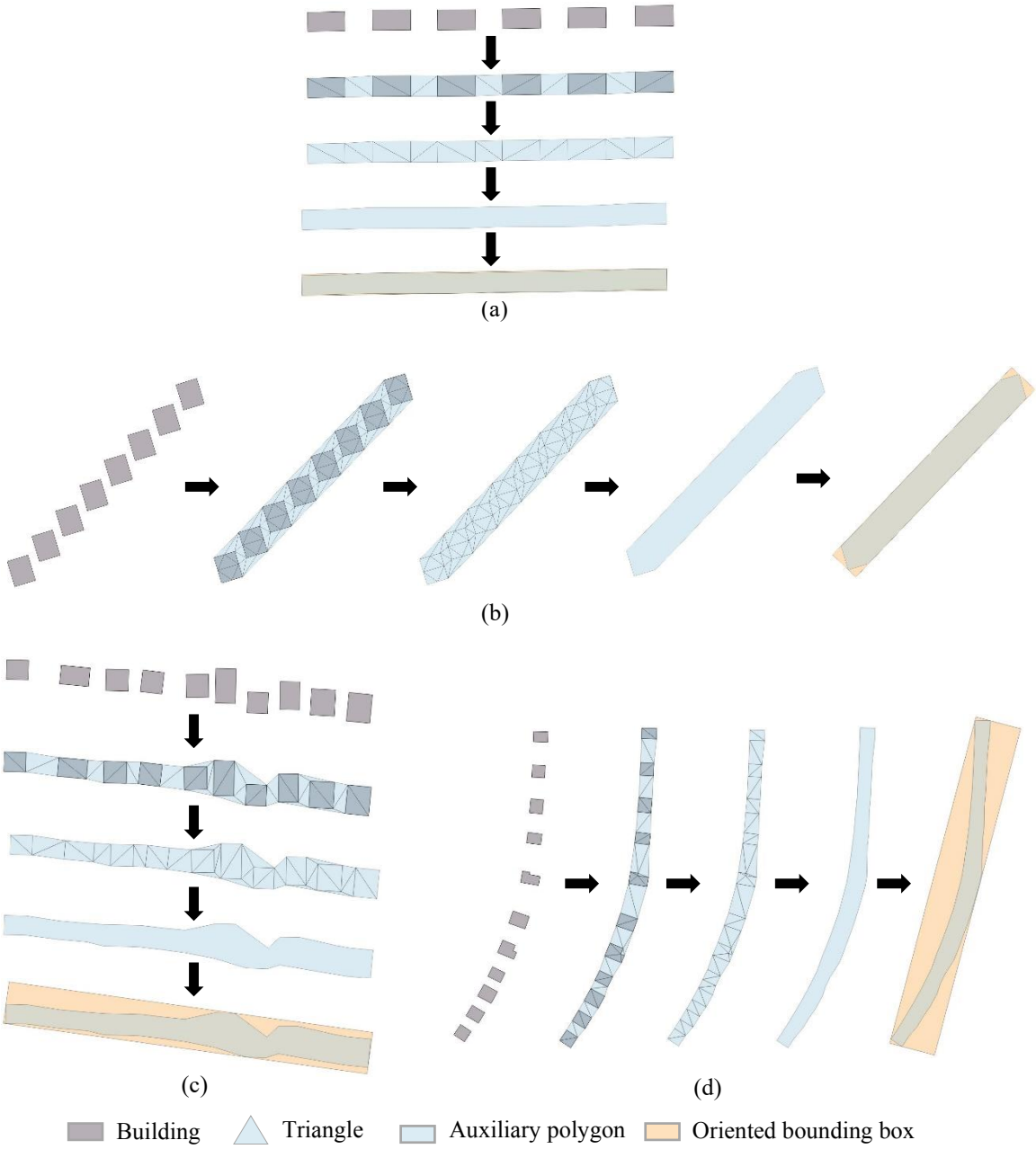


Figure 4.3 Distinguishing collinear and curvilinear patterns. (a) Straight pattern; (b) oblique pattern; (c) jagged pattern; (d) smooth pattern.

4.4 Typification method

4.4.1 Analogy of building typification and line simplification

In this study, the analogy is made between line simplification and linear building group typification. The purpose of typification for linear building group is to reduce building number and keep the original building distribution characteristics. As another important generalization operator, line simplification is a generalization technique in which nodes are selectively removed from a line feature to eliminate details while preserving the line's basic shape (Cromley 1991; Shen 2018). As shown in Figure 4.4, the main purpose of line simplification is similar with building typification, namely, reducing objects number and preserving the consistency of the distribution. By the analogy of line simplification and building typification, these two generalization operators have similarity in some degree. Therefore, the ideas of line simplification can be introduced into the issue of linear building group typification by regarding the buildings as the nodes of the line.

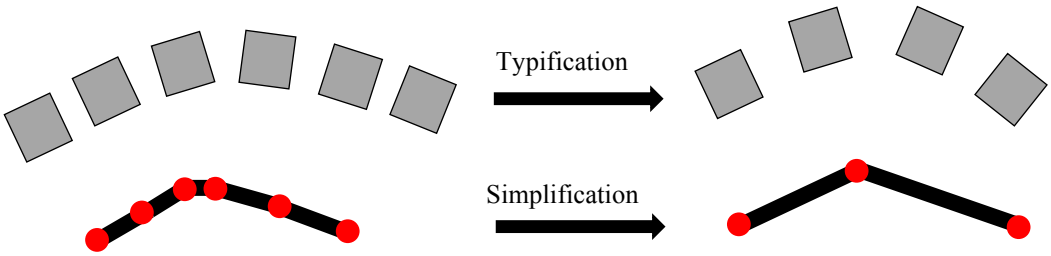


Figure 4.4 Analogy between building typification and line simplification.

4.4.2 Stroke generation

To use line simplification idea solving building typification issue, above all, it is necessary to find a line to represent the buildings. For the first typification, based on the detection process, stroke is regarded as the represent line of its corresponding building group. For the second and subsequent typification, the new stroke should be generated from the newly typified buildings. The generation of stroke is also based on the proximity graph of buildings. First, the Delaunay triangulation network is generated based on the buildings; then, the triangles which connect three buildings should be deleted; next, proximal edges are formed by connecting the centroids of the two buildings which are connected by the same triangle; the proximal edges consist of the proximity graph. The original proximity graph may contain several edges which connect two buildings improperly. Minimum Spanning Tree (MST) is used to prune the proximity graph so that the unique stroke is obtained from the proximity graph (Wu et al., 2017). Figure 4.5 shows the process of generating stroke from the buildings.

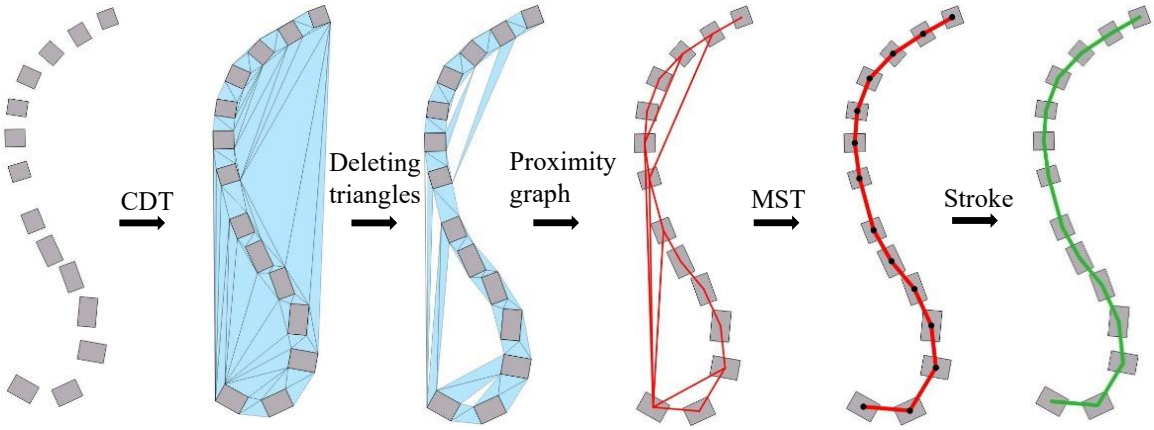


Figure 4.5 Stroke generation from building group.

4.4.3 Stroke simplification

Line simplification methods have been widely developed and used to generalize the geographical features like roads, contour lines, boundaries, trajectories, and linear rivers (McMaster 1986; Cromley 1991; Zhan and Buttenfield 1996; Deng and Peng 2015; Ai et al., 2016; Qian et al., 2016; Li et al., 2017; Samsonov and Yakimova 2017; Bermingham and Lee 2017; Visvalingam 2018). Comparing with the mentioned linear geographic features, stroke is a special line feature whose nodes are derived from the centroids of the buildings. Therefore, the difference between stroke simplification and the classic line simplification lies in:

- The classic line simplification normally aims to eliminate the small curves, while the stroke simplification aims to remove nodes;
- Within the given threshold, the elimination of small curves may result in that more than one node will be deleted from the line; however, the stroke simplification only removes one node in each step in order to get the continuous typification results;
- The classic line simplification only removes the nodes without processing the remained nodes; by comparison, the stroke simplification has to reallocate the remained nodes into new positions to offset the gap enlargement caused by the removed node;
- The shape of the stroke is normally simpler than the classic lines (such as contour line, linear river); moreover, the simplification should be also implemented on strokes with straight shape for the purposes of typifying collinear pattern buildings.

Based on the above differences, the classic line simplification method cannot be directly used to simplify the stroke. It is necessary to develop a new strategy aiming at solving the stroke simplification. The new simplification algorithm should meet the following two rules:

Rule 1: Each simplification step eliminates only one node from the stroke, and the start and end nodes of the stroke cannot be removed;

Rule 2: The remained nodes should preserve the original line structure characteristics as much as possible.

In this paper, a new algorithm is proposed to simplify the stroke. The algorithm includes two steps: eliminating the node which forms the largest deflection angle and reallocating the remained nodes.

(1) Eliminating node

The progressive typification strategy aims to remove only one building after every operation, which also means that only one node is removed from the stroke in every simplification step. The eliminated node is determined by calculating the deviation angles of every two segments. The node which participates to the two segments with the largest deviation angle will be removed from the stroke. The largest deviation angle demonstrates that the shape has the least characteristic in these two segments; thus, eliminating this node has the least loss to the original stroke shape. As shown in Figure 4.7(b), the deviation angles between every two segments are calculated, in this example, θ_3 is the largest angle, thus, node N_3 will be removed first. The corresponding building of N_3 will also be eliminated.

(2) Reallocating the remained nodes

Eliminating nodes will enlarge the gap between the remained nodes. To balance the enlarged gap, the remained nodes should be displaced into new positions, namely, the reallocating the remained nodes. The reallocating process aims at preserving the original linear pattern as well as keeping the gap balance between newly created nodes. The reallocating process only executes on the intermediate nodes, the start and end nodes of the stroke are remained in their original position. The intermediate nodes are displaced towards to the removed node. The specific displacement orientation is along the orientation of its corresponding segment. The displacement distance is calculated based on the distance to the removed node. The nodes which are closer to the removed node will be displaced with the larger distance. The specific distance is calculated by the following equations (4.1-4.2):

$$Dis_1 = (N_R - PosDiffer) * AverLenDiffer \tag{4.1}$$

$$Dis_2 = (N_R - PosDiffer) * \frac{AverLenDiffer}{2} \tag{4.2}$$

where N_R denotes the number of the remained nodes; *PosDiffer* denotes the position number difference between the removed node and the remained node; *AverLenDiffer* denotes the average length difference between the original segments and the new segments, which is calculated by equation (4.3):

$$AverLenDiffer = \frac{L}{N_{seg-1}} - \frac{L}{N_{seg}} \tag{4.3}$$

where L is the total length of the stroke; N_{seg} denotes the original segments number.

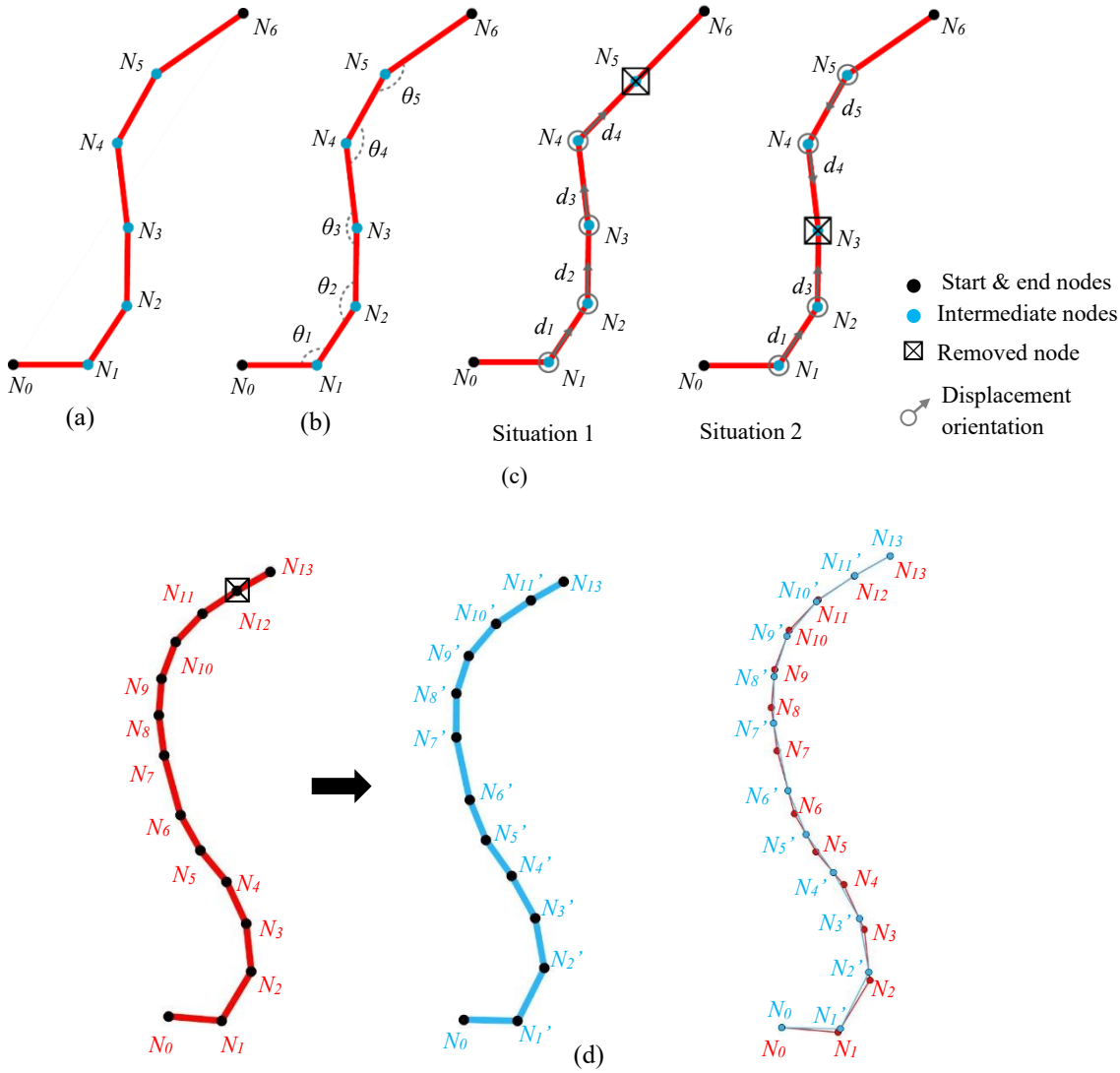


Figure 4.6 Stroke simplification. (a) Original stroke; (b) calculating segment deflection angles of stroke; (c) eliminating node and reallocating remained nodes; (d) example of stroke simplification.

As shown in Figure 4.6(c), the reallocating of the intermediate nodes has two situations, in Situation 1, when the removed node is just the neighbor node of the start or the end nodes, Dis_1 is adopted to calculate the displacement distance; in Situation 2, when the removed node is not the neighbor node of the start or the end nodes, Dis_2 is used as the displacement distance. Figure 4.7 shows two simplification examples of curve stroke and straight stroke, from the results, it is shown that the nodes are removed step by step and the original shape of the line is kept. Moreover, the nodes are always distributed with reasonable gaps.

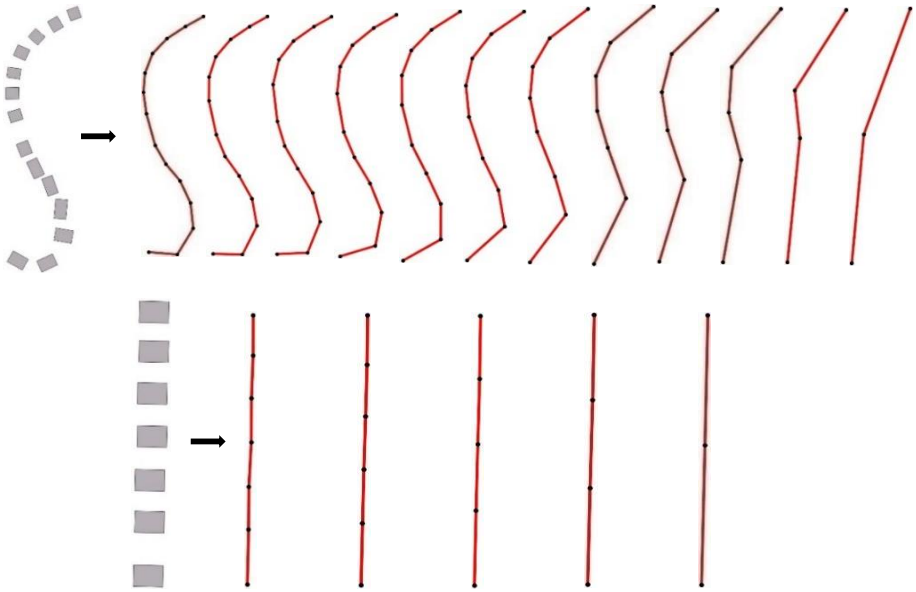


Figure 4.7 Simplification results of curve and straight stroke.

4.5 Representation of newly typified buildings

Building typification should solve three main issues, i.e. the number, position, and representation of the newly typified buildings. For the number of buildings, to achieve the purpose of continuous generalization, the typification of linear pattern buildings is executed progressively, namely, only one building is removed from the building group with one typification operation. After each typification processing, the total building number will be reduced by one. Accordingly, the building number of the typification results will continuously cover from the original number to a minimum value of three. For the positions, the centroids of the newly typified buildings will be allocated to the nodes positions of the simplified stroke.

The representation of the newly typified buildings is an iterative process. Every two neighboring buildings will be captured to create a new building, i.e. the typified building. The representation of the newly typified building (child-building) is calculated based on the geometry information of two original neighboring buildings (parent-buildings). As shown in Figure 4.8, the creation of child building is an iterative process, from the start building to the end building. The specific representation indices of the newly created building includes size, shape and elongation, and orientation. With these three indices, the newly created building can be unique determined. The detailed calculation of these three indices are described in the following paragraphs.

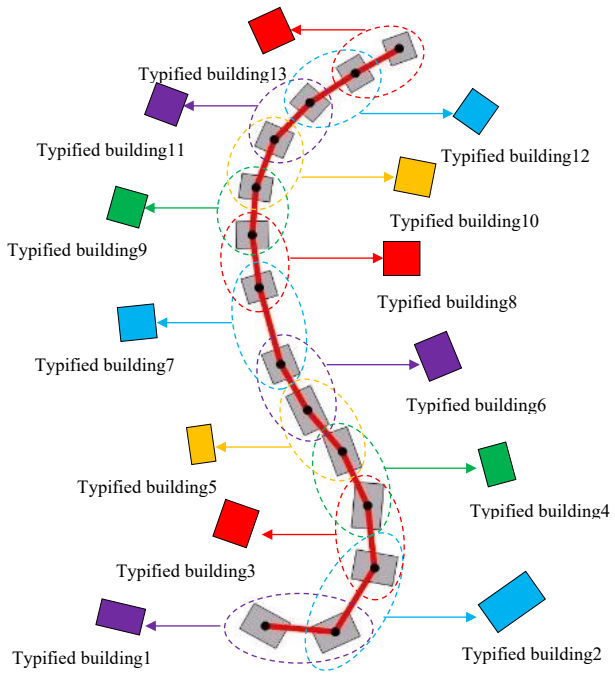


Figure 4.8 Creating child-building from two neighboring parent-buildings.

(1) Size. The size is measured by building area. The area of the newly typified building consist of two parts, the basic area and the compensation area. The basic area is calculated by its parent buildings, that the larger one's area is regarded as the newly created building's basic area. Because typification will reduce the buildings, to keep the area consistency of total building area, the removed building area will be averagely allocated to the remained buildings. The compensation area is calculated by using the removed building area dividing the remained building numbers. The calculation of the newly created building area is shown in Equation (4.4):

$$Area = max\ (Area_{Building1}, Area_{Building2}) + \frac{Area_{Del}}{n} \tag{4.4}$$

Where $Area_{Building1}$, $Area_{Building2}$ denote the areas of the related two parent buildings, respectively; n denotes the remained building number; $Area_{Del}$ denotes the area of the removed building.

(2) Shape and elongation. Typification is implemented to meet the reducing of map scales. In smaller scale, buildings are normally generalized into rectangular shape. Furthermore, the studied region is concentrated on the suburban and rural areas where more residential buildings locate. The original shape of residential building is not complex and mostly rectangular shape. Moreover, it can also omit the building simplification process after typification. Thus, it is reasonable to use rectangle to represent the typified building shape. The elongation of the typified child building is consistent with the elongation of its larger parent building. Because the larger building normally is more outstanding in visual.

(3) Orientation. The orientation of the newly typified buildings are determined differently based on the linear pattern type. For the curvilinear pattern, the orientation is determined by its corresponding segment orientation of the simplified stroke. This can guarantee the typified buildings keep the same tendency of the original curve stroke, which is beneficial for preserving the characteristics of the original curvilinear patterns (See the left figure in Figure 4.9(a)). For the collinear pattern, the orientation of the newly typified building is the same with the larger parent building. The reason is similar with the above size determination because the larger parent building dominates the visual perception. Therefore, the orientation of the larger parent building is calculated as the orientation of the newly typified building (See the right figure in Figure 4.9(a)).

The buildings related in our study are normally with simple shape, so the building orientation is calculated by its smallest Minimum Bounding Rectangle (MBR) (Duchêne et al., 2003). The angle θ between the horizontal line and the major axis of the smallest MBR is calculated as the value of the building's orientation (Figure 4.9(b)).

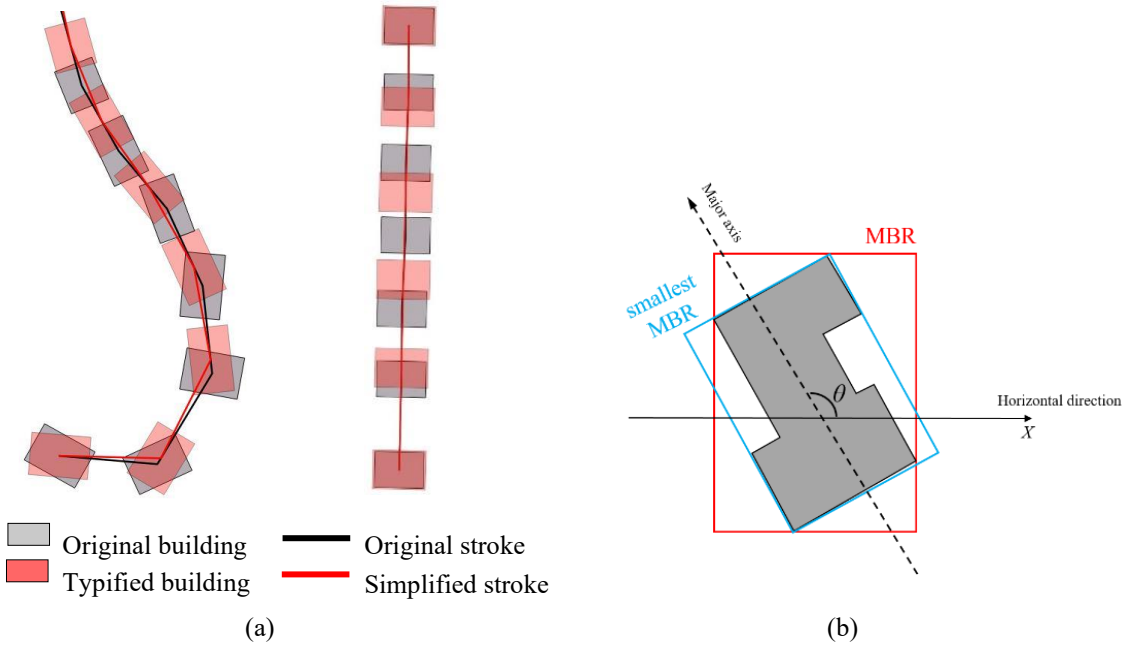


Figure 4.9 Orientation determination of the newly typified building.

4.6 Experiment

4.6.1 Linear building group detection

To test the effectiveness of the proposed detection and typification method, we conducted experiments on two building datasets from OpenStreetMap. Dataset1 (Buehlau) and dataset2 (Loschwitz) are the two villages in suburban area of Dresden. In the test datasets, there exist many buildings built alongside the roads, which forms outstanding collinear and

curvilinear patterns. First, it is necessary to recognize these linear patterns. Based on the adopted stroke-based detection method, the linear patterns are detected from the two datasets. The final detection results of the two datasets are shown in Figure 4.10. The selection of parameters and thresholds in the detection process is described as followings:

(1) In the proximity graph refinement, the constraints and their thresholds are selected as: distance < 40m (the distance between the two connected buildings should be less than 40 meters); facing ratio > 0.0 (the two connected buildings should face with each other); size similarity > 0.5 (the area similarity of the two connected buildings should be larger than 0.5). If the two connected buildings cannot meet all the above three constraints, the proximal edge between them will be removed.

(2) The threshold of deflection angle in generating stroke is set as 150°, which means that only the deflection angle between two proximal edges is within the given threshold, they have chance to form a stroke.

(3) For the pruning rule 1, the threshold of angle α is set as 130°, which aims to check the possibility of forming a larger building group.

Based on the pruned strokes, the building groups are obtained that the buildings related by the same stroke will form a building group. Next step is to distinguish the collinear and curvilinear patterns from the building groups. Through calculating the overlap ratio (*OR*) between the auxiliary polygon and its OBB for each building group, the specific collinear and curvilinear patterns can be differentiated. The left figures in Figure 4.11 shows the *OR* values of the building groups by different line width. The threshold of *OR* is set as 0.7, which means if *OR* is larger than 0.7, the building group is the collinear pattern. Otherwise, it is the curvilinear pattern.

Consequently, there are 11 collinear patterns and 7 curvilinear patterns in Dataset1 while 18 collinear patterns and 7 cuvilinear patterns are found in Dataset2. The buildings with collinear and curvilinear patterns are marked by lines with different colors (Figure 4.11).

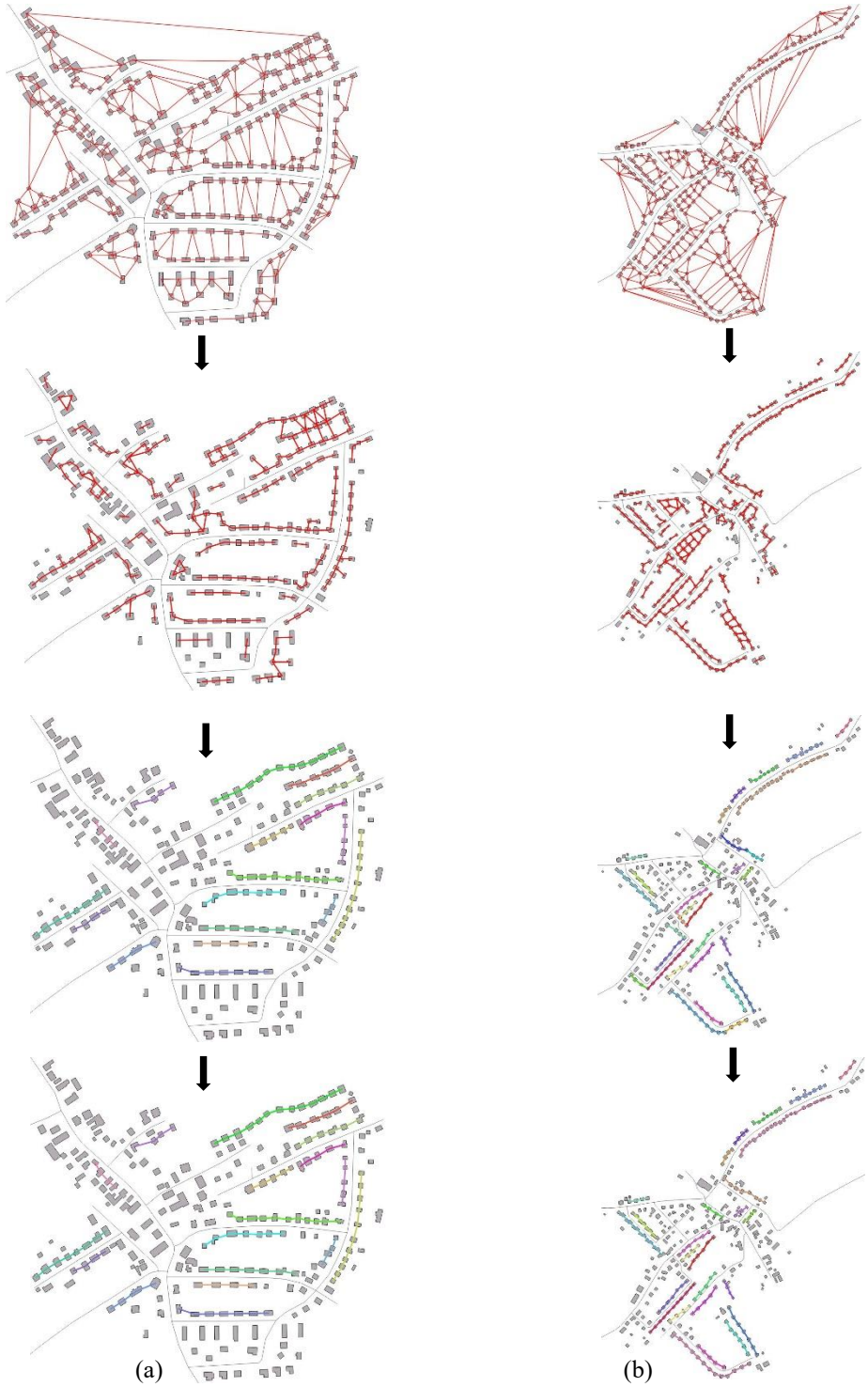


Figure 4.10 Detection of linear pattern building groups in the two test building datasets.

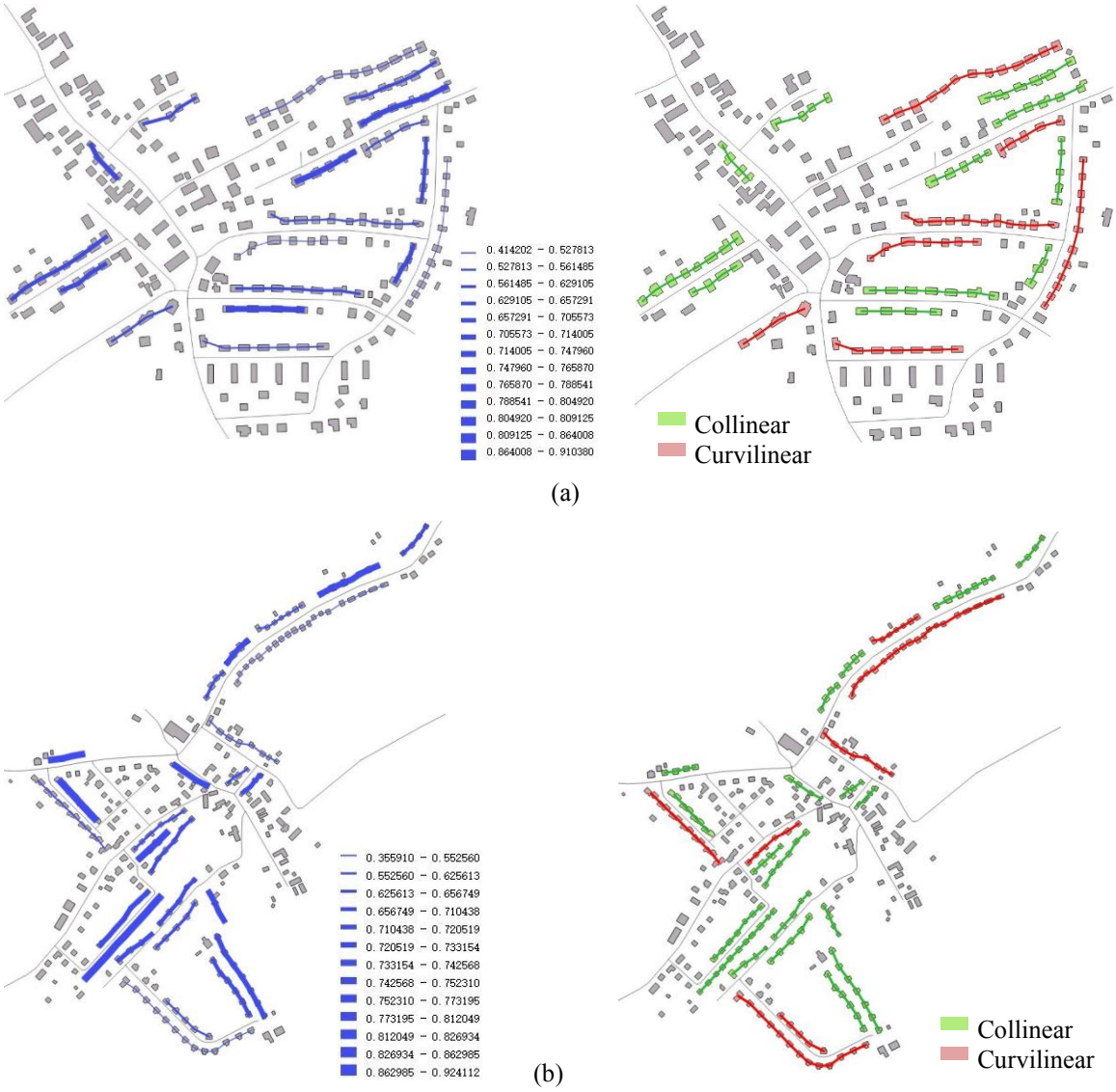


Figure 4.11 Recognition results of curvilinear and collinear patterns. (a) Dataset 1; (b) dataset 2.

4.6.2 Typification results

The typification is executed progressively, only one building is removed from the building groups in each operation. The terminal condition of typification is that after typification, if the number of remained buildings equals to three, then the typification process should be stopped. Figure 4.12 shows the typification results of removing one, two, and three buildings, respectively. From the typification results, it is found that the original linear patterns are kept in the newly typified buildings. The local curve characteristics of curvilinear patterns are also reflected on the newly typified buildings.

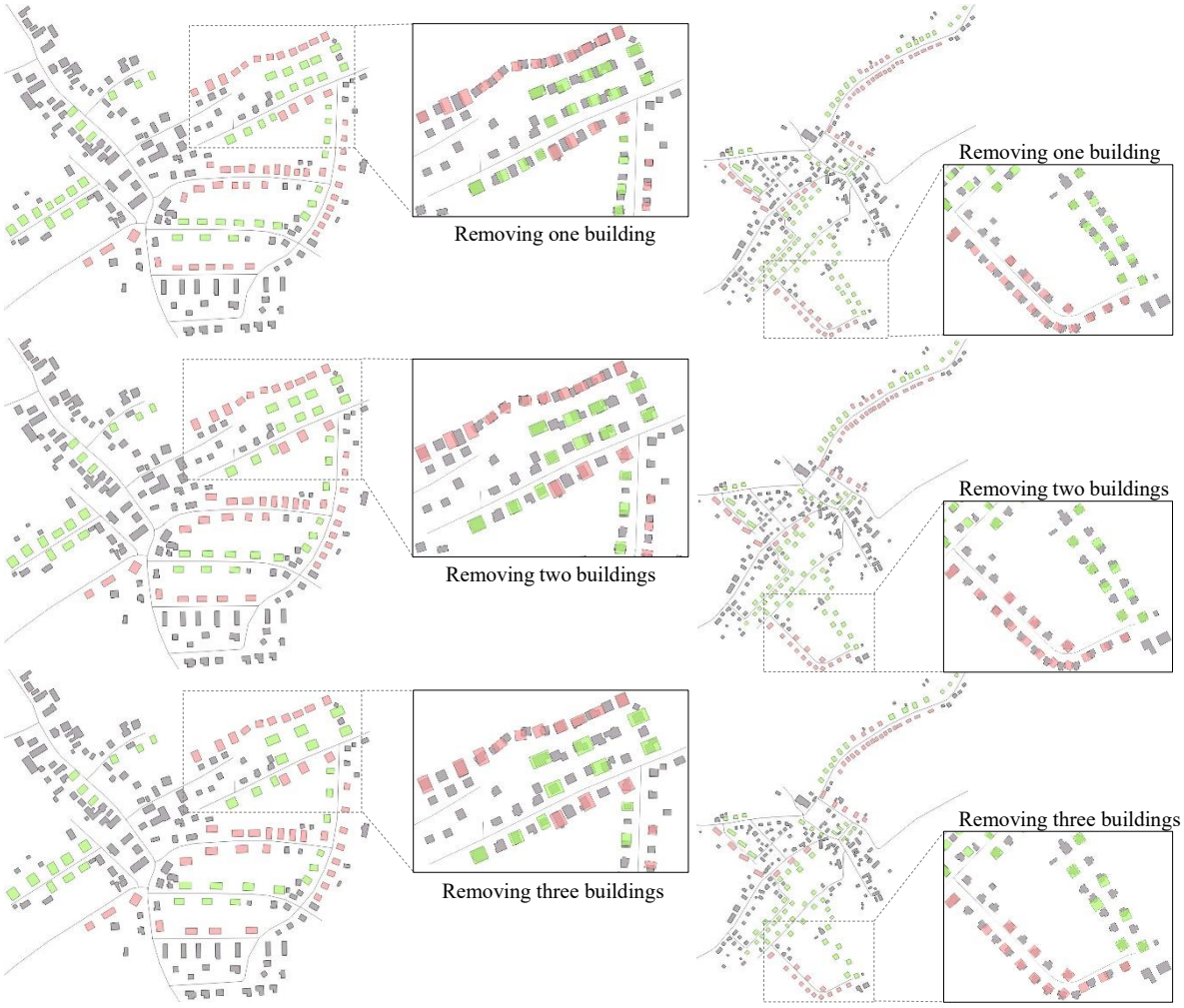


Figure 4.12 Typification results by removing one, two, and three buildings from the linear patterns.

4.7 Discussion

4.7.1 Comparison of reallocating remained nodes

In the work of Mao (2012), he also proposed a reallocating strategy for determining the positions of the typified 3D buildings, thus we conducted a comparison test between the proposed reallocating method with his strategy. The test line dataset is from Mao's work, from Figure 4.13, the proposed method has the similar results with Mao. With removing one and two nodes from the original lines, the results keep the similarity in shape. Nevertheless, there are tiny differences with the proposed method and Mao's method. In marked area A, after removing two nodes, Mao's method lost the line characteristics in some degree. In marked area B, the original line has the denser nodes distribution than other parts, which should be also reflected in the simplified lines after removing one or two nodes. From this

consideration, the distribution of the related nodes in Mao's method becomes more uniform, while the proposed method preserve the original dense distribution characteristics.

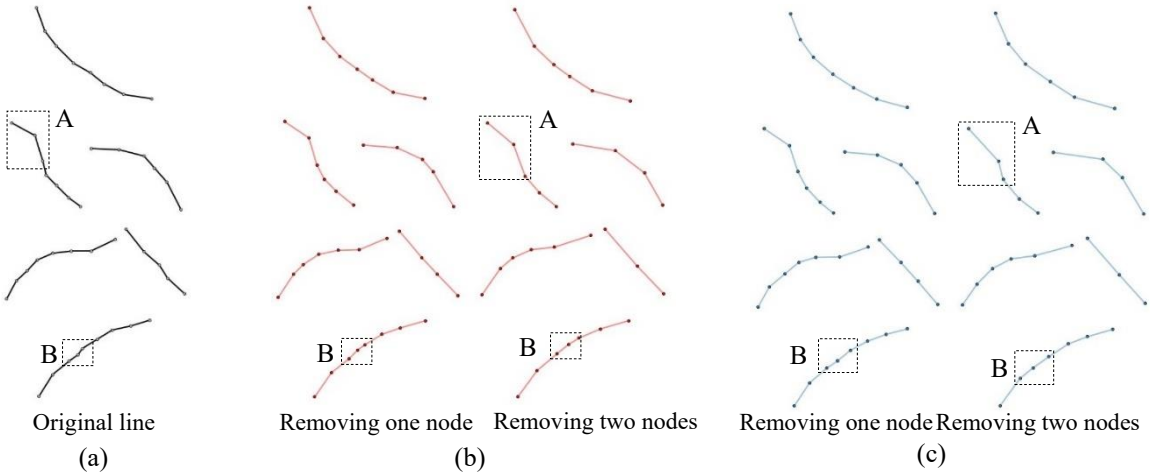


Figure 4.13 Comparison with Mao's building displacement strategy. (a) Original stroke; (b) The proposed method; (c) Mao's method.

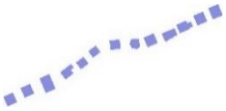
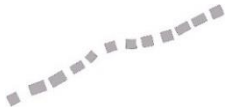
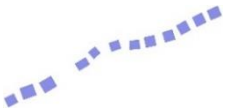
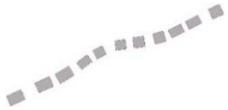
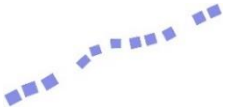
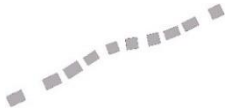
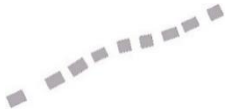
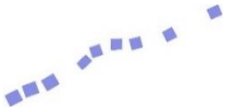
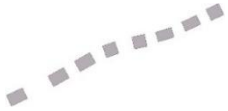
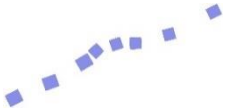
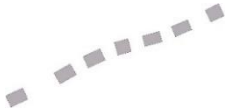
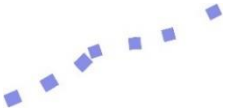
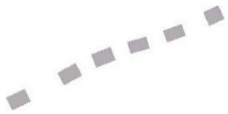
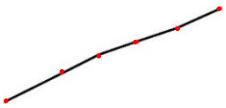
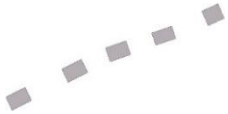
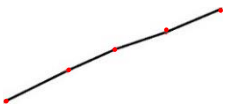
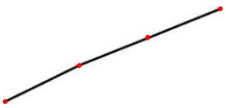
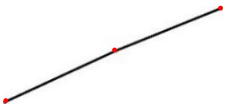
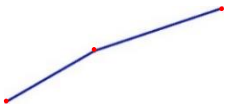
4.7.2 Comparison with classic line simplification method

To prove the superiority of the proposed method, we also use the classic line simplification method to simplify the stroke and to get the typification results. Here, the Douglas-Peucker algorithm is selected as the representative of the classic simplification methods. The comparison is discussed in curvilinear pattern and collinear pattern, respectively.

(1) Curvilinear pattern

Table 4.2 shows the results of the progressive stroke simplification and building typification results. In Table 4.2, the stroke of the example building group is typified with the proposed algorithm and Douglas-Peucker algorithm, respectively. From the results, it is found that the Douglas-Peucker algorithm only removes nodes from the line without reallocating the remained nodes, which leads to the gaps between the typified buildings becoming large and unevenly. The enlarged gaps disrupt the consistency of the original curvilinear patterns. On the contrary, by the proposed simplification method, the remained nodes are reallocated to the new positions, which compensate the enlarged gap between the removed node and its neighboring nodes. This compensation reflects in the typification results that the typified buildings are distributed with the evenly gaps so that the original curvilinear patterns are kept.

Table 4.2 Typification comparison between proposed and Douglas-Peucker simplification.

Building number	Proposed simplification algorithm		Douglas-Peucker simplification algorithm	
	Typification results	Simplified stroke	Typification results	Simplified stroke
13 (Original)				
12				
11				
10				
9				
8				
7				
6				
5				
4				
3				

(2) Collinear pattern

The proposed simplification method can also work on the straight lines. However, for the Douglas-Peucker algorithm, it cannot simplify the straight lines, because its simplification principle is based on eliminating the small curves by the distance parameter. For the detailed two types (straight and oblique pattern) of the collinear pattern, the proposed method can both achieve good typification results. As shown in Figure 4.14, in the progressive typification results, the collinear patterns are kept, and the consistency of the linear pattern is also preserved. Especially, the tendency of the oblique pattern is remained the same with original.

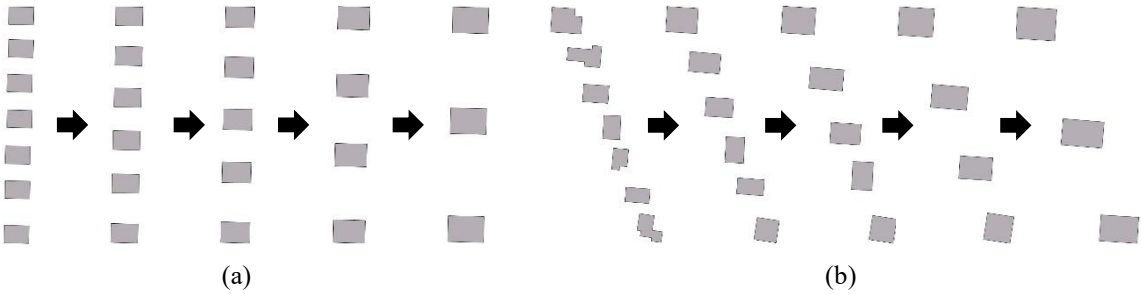


Figure 4.14 Typification results of straight pattern (a) and oblique pattern (b) by the proposed method.

4.7.3 Advantage

Typification of linear pattern buildings belongs to the *m-n* objects generalization. The difficulty lies in reducing appropriate objects number as well as keeping the original distribution characteristics. Reorganizing the newly created objects have to well keep the balance among the number, position, and representation. The advantages of the proposed method is described about this three aspects.

(1) Number. Only one building is allowed to be eliminated in each typification process. The number is reduced progressively so that the buildings are gradually generalized. The progressive idea can provide continuous typification results, which can meet the requirements of different scale maps and give supports to multiple representation.

(2) Position. The positions of the newly created buildings are determined by the nodes of simplified stroke. The proposed simplification method of stroke can preserve the original curve characteristics as well as guarantee the new nodes are evenly distributed. Comparing with the classic line simplification algorithms, their disadvantages lies in: (a) the remained nodes number is determined by distance parameter, not progressively reducing in sequence; (b) the classic simplification method only eliminates the nodes without moving the remained nodes into new locations, which cannot keep the consistency of the building gaps; (c) for straight lines, it is hard for the classic methods to simplify. The proposed simplification algorithm solves the above disadvantages.

(3) Representation. The representations of the newly typified buildings are derived from their parent building. The size, elongation, and orientation of the child building are calculated based on the geometry of its two parent buildings. The local geometry information can be well inherited. This can keep the typified buildings meeting the visual consistency.

Based on the advantages of the proposed typification method, some limitations or further studied points of other scholars work can be improved or solved. In the work of Burghardt and Cecconi (2007), they stated that their approach should be extended to keep the linear patterns in the building dataset. Combining the proposed typification method with linear pattern detection, the typification of linear pattern buildings in their work can be solved automatically. With combination of their proposed mesh simplification algorithm, the whole building dataset can be well generalized.

The limitations stated in Gong (2018) are improved using the proposed method. The mentioned limitation is that the curve-distribution patterns cannot be automatically typified by his strategy, especially the key turning point of the curve. Figure 4.15 shows the dataset in Gong (2018) and the typification results using our proposed line simplification based method. The continuous results illustrate that the key turning point of the curvilinear pattern is well preserved after typification.

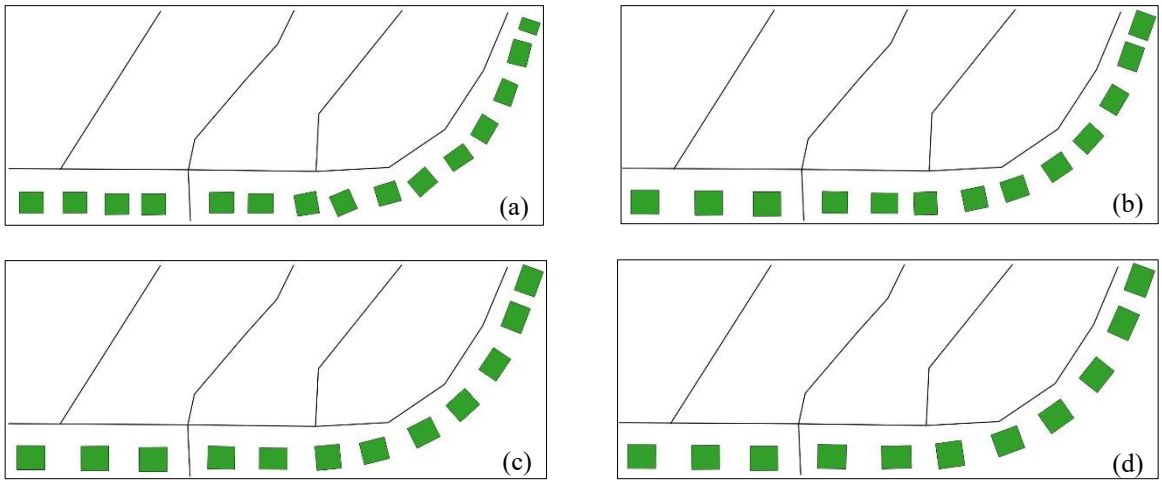


Figure 4.15 Testing results of dataset in Gong (2018) by the proposed typification method. (a) Original dataset; (b) 1st typification; (2) 2nd typification; (c) 3rd typification.

4.7.4 Further improvement

The proposed typification method for linear building groups also has the following aspects to be further improved:

(1) In the proposed line simplification method, to keep the consistency of the buildings covered area, the start and end nodes of the line are not displaced. In some situations, as

shown in Figure 4.16 (a), the gap between the typified buildings T_1 and T_2 is enlarged unevenly. Thus, to get more accurate results, the displacement of the terminal nodes should be considered in the further study.

(2) The proposed typification process enlarges the typified building area, which may create overlaps between typified buildings and other features (such as roads, other non-linear pattern buildings). For example, as shown in Figure 4.16(a), on the 7th typification results, the newly typified building T_3 is overlapped with roads. In Figure 4.16(b), in the 4th typification results, the distance between the newly typified building T_4 and another non-linear building A is extremely close. Thus, after typification, the conflicts should be detected and the displacement operation should be implemented to eliminate the overlaps.

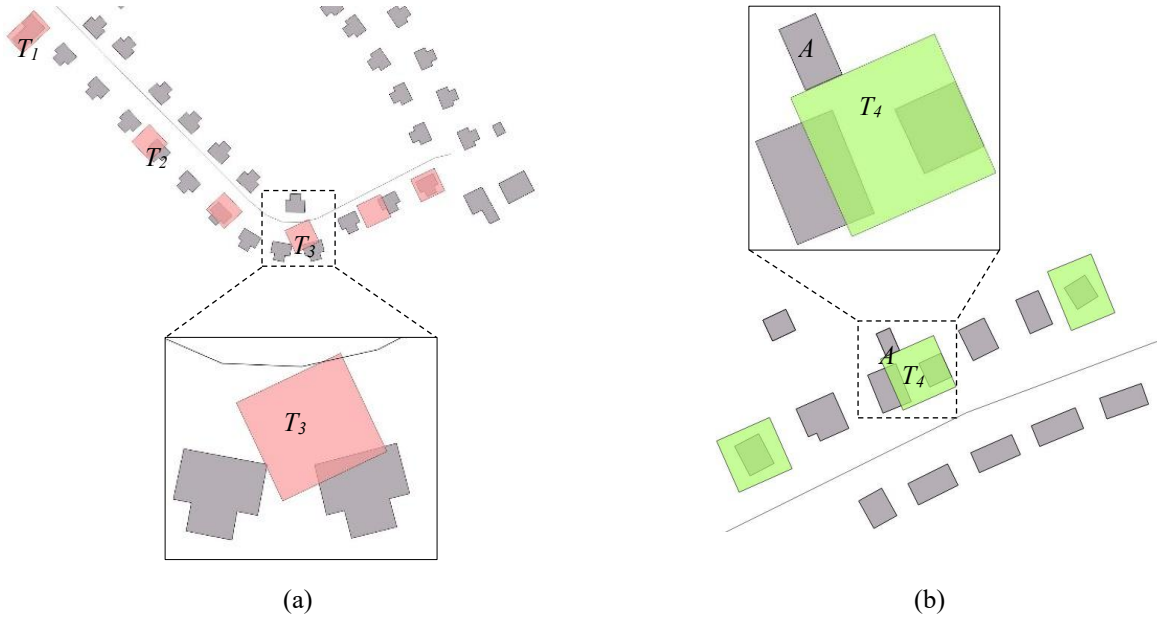


Figure 4.16 Overlap problems of newly typified buildings with (a) roads and (b) non-linear buildings.

4.8 Conclusion

Typification is a challenging task which relates to the research of m-n objects generalization. The typification of buildings with linear pattern have to balance between reducing building number and well keeping the linear pattern. This purpose is analogous to the line simplification, thus a stroke-simplification-based typification strategy is introduced in this paper. With the help of proximity graph, the stroke is extracted from the buildings. The stroke is simplified through eliminating nodes and reallocating the remained nodes. The nodes positions of the simplified stroke determine the centroids locations of the newly typified buildings, and their representation is determined by the two neighboring parent buildings. Experiments on two building datasets achieved satisfying typification results on linear pattern building groups. The proposed strategy is implemented progressively, which

has advantages on keeping the linear characteristics as well as getting continuous building typification results.

Chapter 5

A mesh-based typification method for building groups with grid patterns

Xiao Wang and Dirk Burghardt

Citation:

Wang, X.; Burghardt, D. A Mesh-Based Typification Method for Building Groups with Grid Patterns. *ISPRS Int. J. Geo-Inf.* 2019, *8*, 168.

5.1 Abstract

Building groups with special patterns are common layouts in urban settlement areas, which should be carefully generalized. Typification is considered as an appropriate operator to generalize building groups with grid patterns. As an important operator in building generalization, the purpose of typification is to reduce the number of objects while preserving the original distribution characteristics as much as possible. This study proposes a mesh-based method to typify buildings with grid patterns. Firstly, the pattern is subdivided into perfect grid or grid-like patterns by considering the completeness of the grids. The proposed typification method consists of three steps: (1) generating mesh from the proximity graph of buildings; (2) eliminating triangular meshes; (3) determining the number, positions, and representations of the newly created buildings with the help of the related meshes. The proposed method is modeled as an iterative process to achieve hierarchical typification results, which provides support to the map multiple representation. The experimental results demonstrate that the mesh-based typification method can achieve satisfying results in the perfect grid pattern, as well as the grid-like pattern. The new distribution of the typified buildings preserves the original pattern characteristics.

5.2 Introduction

Map generalization is a core issue in automated map production, which aims at deriving smaller-scale maps from larger-scale maps by utilizing transformation operations (Brassel 1988; McMaster and Shea 1992; Brychtová et al., 2016). Among various geographical objects, buildings attract much attention in map generalization for reasons of their artificial shape and complex spatial distribution (He et al. 2018; Wang et al. 2017; Li et al., 2004). Building generalization is normally subdivided into two steps: building grouping and generalization execution (Li et al., 2004). Building grouping is the process of arranging individual buildings into clusters by considering their similarities and differences. Generalization execution denotes the selection of appropriate operators to generalize the grouped building clusters. The most frequently used operators for building generalization are elimination, collapse, simplification, aggregation, typification, exaggeration, and displacement. These operators have different functions in diverse situations. For example, for an unstructured building cluster, aggregation is normally implemented, while, in a regular linear building group, typification is considered as an appropriate operator.

In some cases of urban and suburban areas, buildings are displayed on maps with specific regular patterns. Linear patterns and grid patterns are two common regular layouts presented in building groups. With the map scale decreasing, the building groups with these two regular patterns should be carefully generalized, in order that the number of buildings is reduced, and the characteristics of the original patterns are preserved. Based on the above generalization

requirements, in general, the typification is considered an appropriate operator to generalize building groups with regular patterns (Li et al., 2004). This study only considers the geometry information of the building groups as a local typification, while the quality and function of buildings are ignored. Typification denotes the process of reducing the number of objects out of a set of similar objects, while preserving their relative spatial density and distribution characteristics. Based on the definition, typification focus on the level of building groups rather than the individual buildings; thus, typification is an ideal operator with regard to contextual generalization (building group generalization). The target of typification is to transform an initial set of objects into a subset, while maintaining the distribution characteristics and patterns of the original set. As an important and frequently used operator in map generalization, typification can provide continuous generalization results for multiple representation (Sester and Brenner 2005). Currently, the existing methods mainly aim to solve the global typification issues by considering the entire region, while few studies were developed for the building groups with local characteristics (grid patterns). The building groups with local structures appear frequently on maps, which dominates the visual effects so that they should be carefully generalized. For this reason, the objective of this study is to develop an operator of typification aiming at solving the generalization issues for building groups with grid patterns. With the proposed typification strategy, building groups with grid patterns can be generalized appropriately and their original characteristics of grid patterns can be preserved after generalization.

The remainder of this paper is structured as follows: Section 2 gives a review of previous work on building typification. Section 3 introduces the proposed typification methods to generalize building groups with grid patterns. Section 4 carries out the experiments to test the proposed methods, and the results are displayed and evaluated with manual generalization maps. Section 5 discusses the advantages and further improvements of the proposed methods. Section 6 gives the conclusions.

5.3 Related work

Over past decades, many studies were carried out on building generalization. Some studies focused on the overall process of generalization, while others were devoted to developing strategies on specific generalization operators. The generalization operators can be categorized into two classes: non-contextual operators for an individual building (such as simplification or exaggeration) and contextual operators for building groups (such as aggregation or typification). Among the contextual generalization operators, typification is a discrete process in which a set of objects is replaced by another set containing a smaller number of objects (Sester and Brenner 2005). In his work, Burghardt modeled the typification procedure as a two-stage process with the steps of “positioning” and “representation” (Burghardt and Cecconi 2007). The “positioning”

step determines the number and the position of the newly created typified buildings, while the "representation" step considers calculating the size, shape, and orientation of the newly created buildings. Compared with other generalization operators, the specificity of typification implies that it is compulsory to create newly buildings by considering number, position, and representation, which increases the complexity and difficulty in the generalization process.

To date, many strategies were created for building typification. Regnauld proposed the idea of "global typification", which processes the entire region as the typification objects instead of just processing one group of buildings (Regnauld 2001). According to his terminology of "global typification", by contrast, the opposite terminology "local typification" is proposed herein because building groups are mainly considered in our study. Global typification regards the buildings in the whole region as inputs, which considers the structural knowledge less. The aim of global typification is to maintain the overall distribution and structure as much as possible and to preserve the similarities and differences between the groups with regard to density, size, and orientation of buildings. Global typification is often adopted in medium or small scales. For example, Bildirici developed "length and angle" methods to typify buildings with point geometries (Bildirici and Aslan 2010; Bildirici et al., 2011). Sester selected optimization approaches for generalization and used self-organizing maps for building typification (Sester 2005). Burghardt used a mesh simplification technique adapted from computer graphics to typify buildings (Burghardt and Cecconi 2007). Li's study considered three steps (number, representation, and harmonizing) for the typification procedure based on multi-scale data matching (Li et al., 2005). From the above studies, it is found that global typification processes more on the entire region and aims to preserve the global pattern; this may result in some limitations on preserving the local characteristics of building groups.

By comparison, local typification is implemented on the level of building groups; thus, the structural knowledge of the groups is largely considered in the process of typification (Anders 2006). Local typification is often combined with building grouping and pattern detection. Many ideas were proposed to detect building groups and recognize building patterns (Regnauld 1996; Christphe and Ruas 2002; Anders 2003; Mesev 2005; Yan et al., 2008; Zhang, Hao et al., 2013; Zhang, Ai et al., 2013; Du et al., 2016; He, Ai et al., 2017; He, Zhang et al., 2018). Local typification normally concentrates on the buildings with regular patterns, such as linear patterns and grid patterns. For example, Anders presented a parameter-free graph-based clustering approach and applied it for building typification (Anders 2000). He also used a relative neighborhood graph to detect building groups with grid structures and then reduced or simplified the grid structure using least-squares adjustment of an affine or Helmert transformation approach (Anders 2005). Gong regarded typification as a progressive and iterative process consisting of

elimination, exaggeration, and displacement so as to typify linear building patterns (Gong and Wu 2018). Apart from buildings, the typification of other geographical objects, such as islands, ditches, drainage, facades, etc., also belongs to the topic of local typification (Zhang 2007; Sandro and Massimo 2017). The above researches can provide inspirations for building typification. For instance, the issue of facade typification has large similarities with the typification of buildings with grid patterns. Jahnke dedicated his effort to the typification of facade features and presented a user survey for the evaluation of different typification results (Jahnke et al., 2009). Shen used a user survey to show that the preservation of the shape of facade features is the most important constraint for a reasonable typification process. Based on the survey's conclusions, an algorithm was developed to generate a perceivably reasonable representation from an original facade (Shen et al., 2016).

From the above descriptions of global and local typification, the difference between these two ideas lies in three aspects. The first aspect is the number of buildings. Global typification normally calculates the typified building number based on radical law; for local typification, the typification is normally modeled as an iterative process and the number of buildings reduces gradually; for example, some methods of linear pattern typification only remove one building in each iteration. The second aspect is the position of buildings. Global typification normally uses the centroids of buildings to replace buildings, which transforms building typification to point selection by mainly considering the density; this may result in disrupting local characteristics. The local typification primarily takes group characteristics into consideration; thus, the new positions for remaining buildings must be consistent with the original patterns. The third aspect is the representation of buildings. Global typification is often carried out on medium- or small-scale maps, where buildings are abstracted as built-up or settlement areas with simple outlines. Local typification is implemented mainly on large-scale maps where the buildings can have more detail after generalization.

Although many works were done previously on building typification, there are still some issues to be further studied or improved. To date, most local typification algorithms were developed for buildings with linear patterns. To the authors' knowledge, there is almost no specific research concerning how to typify building groups with grid patterns that are frequently presented on maps. In essence, the typification of grid-pattern buildings belongs to the problem of *m*:*n* relation generalization (Ai and Oosterom 2001). The difficulty lies in how to keep the balance between reducing an appropriate number of buildings and preserving the original grid pattern in the remaining buildings after typification. Based on the above points, the proposed study works on the local typification level and aims to typify buildings with grid patterns.

5.4 Methodology of mesh-based typification

5.4.1 Grid pattern classification

The word "Grid" is defined as "a pattern, structure or network consist of evenly spaced horizontal and vertical straight lines that cross over each other, and forming squares". The definition emphasizes and demonstrates that the horizontal lines of the grid pattern should be perpendicular with their vertical lines, and their spaces should be the same. Therefore, based on the above definition, the buildings with the grid pattern should meet the following three constraints:

- **C1**: the space between buildings should be the same;
- **C2**: the buildings locate perpendicularly with each other;
- **C3**: the number of buildings in each row and column should be equal.

However, in real building dataset, it is not easy to find such perfect grid patterns meeting all the above three constraints. Nevertheless, it is frequently to find buildings with similar presentations like the perfect grid pattern. Therefore, in this paper, we subdivide the grid pattern into two categories: perfect grid pattern and grid-like pattern.

A perfect grid pattern denotes that the buildings are arranged with equidistant horizontal and vertical forms and equalized on the amount in each row and column (see in Figure 5.1(a)). The perfect grid pattern normally contains *n* rows and *m* columns, which has the distribution form of *n*m*. The number of buildings in each row and column is the same. Grid-like pattern denotes that the buildings are visually like perfect grid pattern, but without meeting all the above three constraints. There are some typical cases that the building groups are presented in grid-like patterns. As shown in Figure 5.1(b), *Type I* building group violates constraint **C3**; *Type II* building group does not meet constraint **C2**; *Type III* building group goes against constraint **C1**. Therefore, these three building groups are not perfect grid pattern, but grid-like patterns. In some building groups, they may violate all the three constraints, but they still look like grid patterns. For example, *Type IV* building group does not meet constraints **C1**, **C2**, and **C3**, however, in this situation, visually it also belongs to grid-like pattern. The grid-like patterns are more common than perfect grid pattern in the real building dataset.

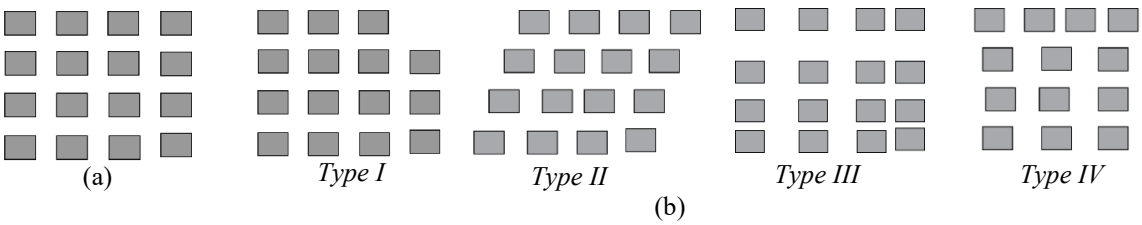


Figure 5.1 (a) Perfect grid pattern; (b) typical types of grid-like pattern.

5.4.2 Mesh generation

Since the proposed typification method is mesh-based, generating meshes is the first step. The mesh is derived from the buildings' proximity graph. In general, constrained Delaunay triangulation (CDT) is used to generate the proximity graph. CDT is preprocessed by removing the triangles which connect three buildings, which aims to avoid generating too many edges in the proximity graph. Afterward, the two buildings which are connected by the same triangle are detected as proximal, and their centroids are connected by a proximal edge. These edges form the proximity graph. Although the preprocessing eliminates some redundant proximal edges, it cannot guarantee that all the proximal edges are generated appropriately. For the above reason, the facing ratio index is calculated between two proximal buildings to further refine the proximity graph. The facing ratio reflects the facing degree of two buildings (Yang 2008). The buildings with a higher facing ratio denote that they are more visually homogeneous. To quantitatively calculate the facing ratio, Equation (5.1) was developed by measuring the projection overlap length of their oriented bounding box (OBB). As Figure 5.2 shows, the building's OBB has a major axis and a minor axis, such that a coordinate system can be formed by the two axes. The two buildings are projected into their four coordinate axes. If $ProLength_{(A)}$ and $ProLength_{(B)}$ are the projection lengths of building A and building B on axis X_A, the facing ratio of the two buildings on axis X_A is calculated by Equation (5.1).

$$Facing\_ratio = \frac{overlap(ProLength_{(A)}, ProLength_{(B)})}{max(ProLength_{(A)}, ProLength_{(B)})}. \tag{5.1}$$

In the same way, another three facing ratios on the other three axes (Y_A, X_B, and Y_B) are also calculated; thus, the maximum facing ratio between building A and B can be obtained. The larger the maximum facing ratio is, the higher the facing degree of the two buildings is. The examples in Figure 5.2 show that building A faces buildings B and C, but buildings B and C do not face each other. Moreover, the maximum $Facing\_ratio_{AB}$ is larger than the maximum $Facing\_ratio_{AC}$. In our study, if the facing ratio between two buildings is equal to zero, i.e., the two buildings do not face each other, as a result, the corresponding proximal edge will be removed from the two buildings. Within the refined proximity graph, the mesh is generated. This mesh denotes the spaces in networks. Here, the refined proximity graph is regarded as a network, while the mesh is defined as the closed region, bound by several proximal edges and without any other regions. After generating meshes from the buildings, the meshes are classified into three types by determining the number of the composed proximal edge: triangular mesh (TM) with three proximal edges, quadrangular mesh (QM) with four proximal edges, and polygonal mesh (PM) with more than four proximal edges. The overall process of generating the meshes from the buildings is displayed in Figure 5.3.

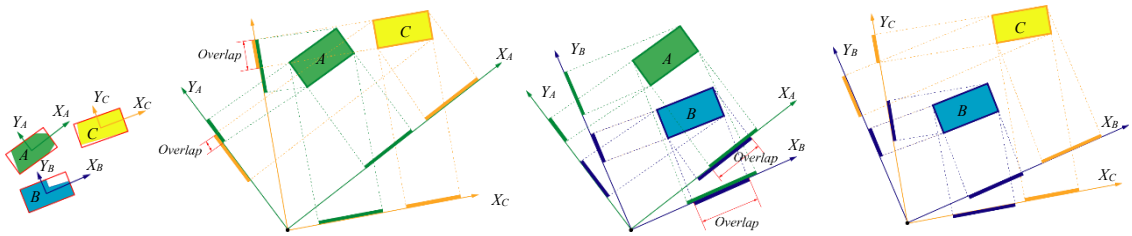


Figure 5.2 Facing ratio calculation.

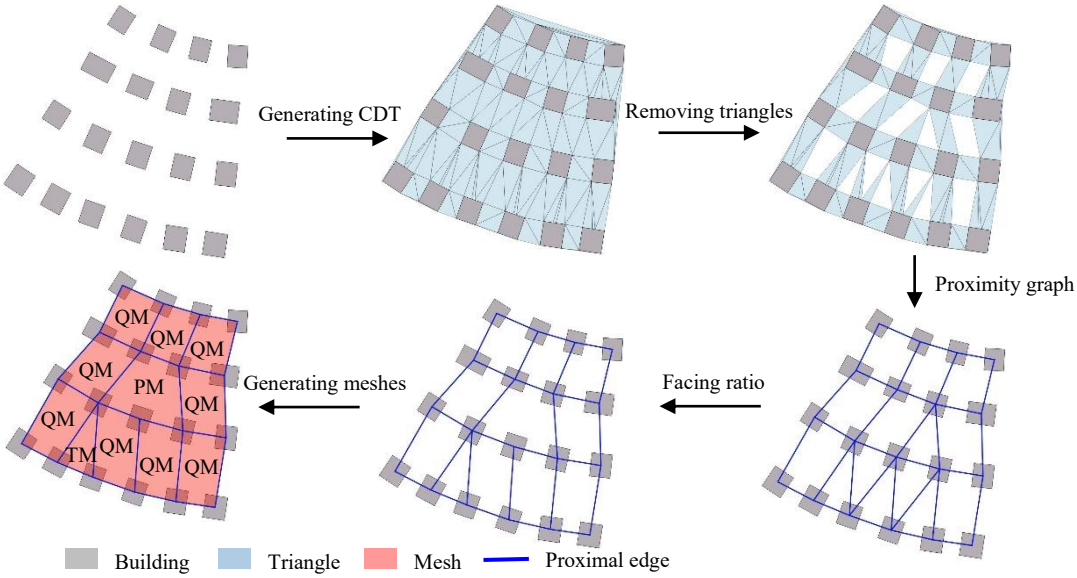


Figure 5.3 Mesh generation process (in last graph, TM: triangular mesh; QM: quadrangular mesh; PM: polygonal mesh).

5.4.3 Triangular mesh elimination

In some grid-like patterns, because of their non-perpendicular distribution and different building numbers between rows and/or columns, some triangular meshes will be generated, which is not beneficial for the further typification steps; thus, with the aim of generating high-quality typification results, the triangular mesh (TM) should be eliminated through the merging process. Afterward, only quadrangular mesh (QM) and/or polygonal mesh (PM) will remain. The merging process is described as follows.

The neighboring (with common boundary) triangular meshes should be detected first, which will form the TM clusters. The TM clusters include the following possibilities:

Situation (1): For one-TM cluster (ITMC), the only one TM should be merged with its smallest neighboring QM (Figure 5.4(a)), if there is no neighboring QM, it should be merged with its smallest neighboring PM (Figure 5.4(b));

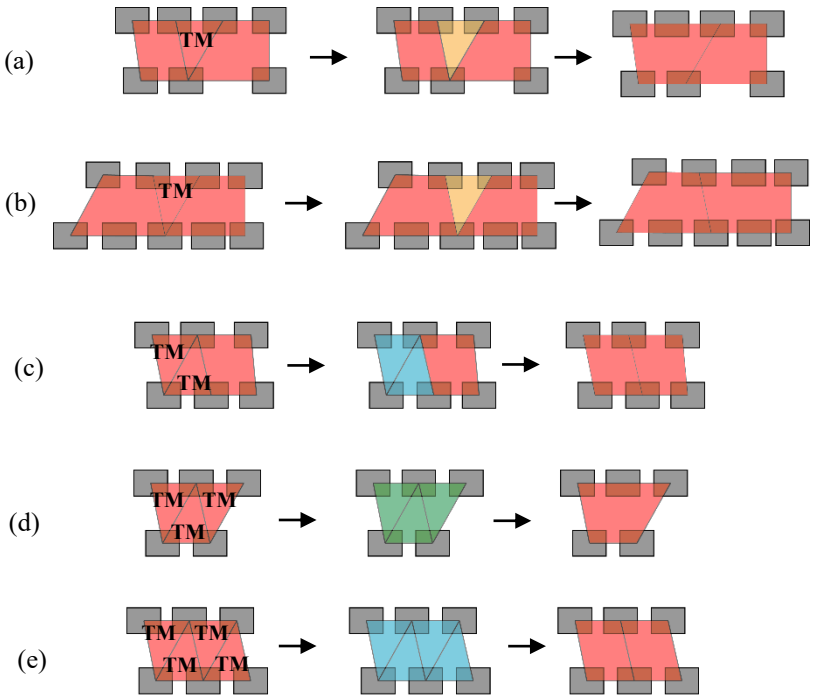
Situation (2): For two-TM cluster (IITMC), the two neighboring TMs should be merged into one QM (Figure 5.4(c));

Situation (3): For three-TM cluster (IIITMC), the three neighboring TMs should be merged into one PM (Figure 5.4(d));

Situation (4): For the cluster with more than three TMs, it can be regarded as the combination of IITMC and IIITMC; then, the next merge process is the same with **Situation (2)** and **Situation (3)**. For example, the four-TM cluster can be regarded as two IITMC (Figure 5.4(e)), and the five-TM cluster can be regarded as one IITMC plus one IIITMC (Figure 5.4(f)). To summary, the *n*TMs cluster can be regarded as the combination of several IITMC plus one IIITMC (as appropriate). The specific calculation is based on Equation (5.2):

$$n\text{TMC} = \begin{cases} \frac{n}{2}\text{IITMC}, & (n > 3 \text{ and } n \text{ is even number}) \\ \left[int\left(\frac{n}{2}\right) - 1\right]\text{IITMC} + \text{IIITMC}, & (n > 3 \text{ and } n \text{ is odd number}) \end{cases} \tag{5.2}$$

where n denotes the amount of TM in the cluster, *int*() means taking the integer from the calculation. When n is an odd number and larger than three, there exists different combination arranges of IITMC and IIITMC. As the examples in Figure 5.4(f), the cluster contains five TMs, based on Equation (5.2), this cluster can be regarded as one IITMC plus one IIITMC. However, there are two arranges. Here, our study rules that the IITMC should be first considered when all the IITMC have been formed, the last three TMs will be formed into one IIITMC. In theory, the amount of the TM cluster can change from one to infinity. But in reality, there won't exist too many TMs in one cluster because the possibility of generating TM is reduced by the previous steps like removing triangles connecting three buildings, and use facing ratio to refine proximity graph. Here, the above process is to make sure that all the triangular meshes are eliminated.



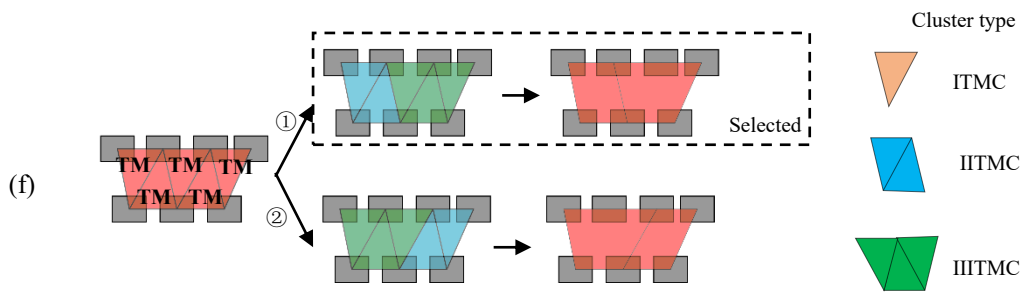


Figure 5.4 Rules of eliminating triangular meshes: (a-b) merging single triangular mesh; (c-f) generating triangular mesh clusters (TMCs).

5.4.4 Number and positioning of typified buildings

From the previous work of building typification, three aspects must be solved to determine the typified buildings, which includes the number, positions, and representations of the new created buildings. The proposed typification strategy uses the meshes as the auxiliary data structure to determine the number and positions of the new created typified buildings. The typified building number equals the mesh number, namely, only one new building will be created in its corresponding mesh. The centroid position of the mesh is considered as the centroid of the new created building. Figure 5.5 shows the iterative process of determining the number and positions of typified buildings in perfect grid patterns. The original perfect grid pattern has the 4*4 structure, after the first typification, the structure becomes to 3*3. Based on the new created typified buildings, new meshes are generated again. If the typification is implemented in second time guided by the same rule, the structure becomes to 2*2. The rest can be done iteratively in the same manner. The end condition of the iteration is that the remained typified buildings cannot generate meshes any more.

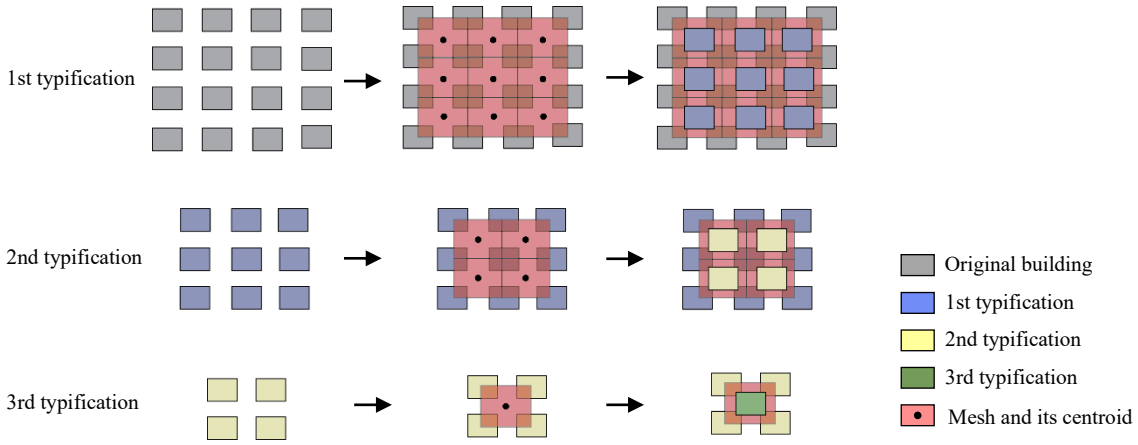


Figure 5.5 Typification process of determining number and position in perfect grid pattern.

For grid-like patterns, the process of determining number and position is generally the same with perfect grid pattern, but with an extra step of eliminating triangular meshes (see Figure 5.6).

The end condition of iteration for grid-like pattern is that the remained buildings cannot generate quadrangular meshes or polygonal meshes any more.

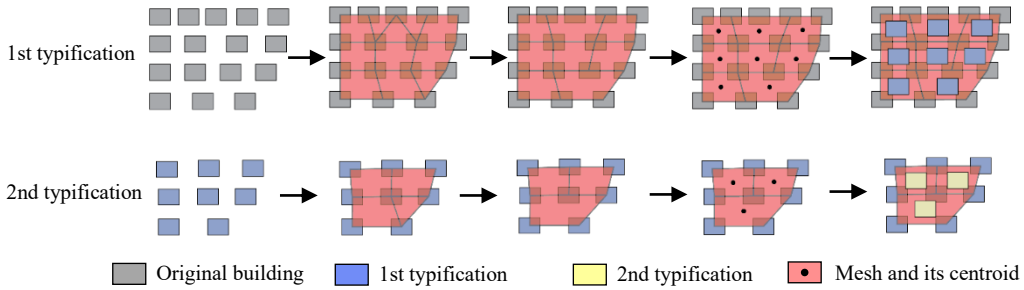


Figure 5.6 Typification process of determining number and position in grid-like pattern.

5.4.5 Representation of typified buildings

After determining the number and position of the typified buildings, another important issue is to determine the representations of the new created buildings. From the above positioning process, the centroid location of the new created building is determined, in addition with another four indicators (size, shape, elongation, and orientation), the new typified building can be uniquely determined and created. These four indicators of the new typified building are calculated based on its related original buildings. The related buildings are determined by its corresponding mesh. The determination of the four indicators is described as follows.

(1) Size

The size is represented by the building area. Here the average area of the mesh related buildings is regarded as the area of the new typified building. The area of the new typified building $\bar{A}$ is calculated by Equation (5.3):

$$\bar{A} = \frac{\sum_{i=1}^{n} A_n}{n} \tag{5.3}$$

where A_n is the area of the mesh related buildings, and n is the number of mesh-related buildings.

(2) Shape

For the shape of the typified buildings, we regard all the typified buildings with the rectangular shape. With the scale becoming smaller, most buildings are strongly simplified with fewer details to meet the minimum separability distance. In the context of web mapping, the minimum separability distances are more severe because of the coarse display resolution. In most situations, the buildings are simplified into the rectangular shape. Moreover, the buildings with perfect grid patterns or grid-like patterns normally located in the residential area of suburban or rural, not like the shopping mall or industrial buildings which have complex outlines, most of the residential houses present as a rectangle on maps. For the above reasons, the shape of the new typified buildings is determined to be rectangular (Pászto et al., 2015; Bayer 2009).

(3) Elongation

Although the issue of shape and size has been solved, the new created building cannot be determined uniquely, because it is necessary to give an elongation value to the new building. Considering the contextual information and effects of visual perception, the elongation value of the largest mesh-related building is chosen as the representative. The building with the largest area can be regarded as the most representative building among the mesh-related buildings because it is more outstanding in presentation than other smaller ones; thus, its elongation can represent the characteristics of the related context.

(4) Orientation

The orientation of the new created building is also determined by the largest mesh-related building. By calculating the deviation angle between the major axis of the building's oriented bounding box (OBB) and the horizontal direction, the orientation value of the new created building is determined. The reason for choosing the largest mesh-related building as the representative is the same with elongation. Visually, the largest mesh-related building gives the most impressive feeling to map reader. Therefore, the largest one has the dominating status in its related context.

With the above four indicators and the centroid location, the newly typified building can be created uniquely. Figure 5.7 is a conceptual graph to show the process of determining the representations of the newly typified buildings based on meshes. As shown in Figure 5.7, the geometry information of the newly typified buildings is derived from the original mesh-related buildings. The original building which has a larger size will dominate the orientation and elongation of the typified building. This strategy is in accordance with the visual perception.

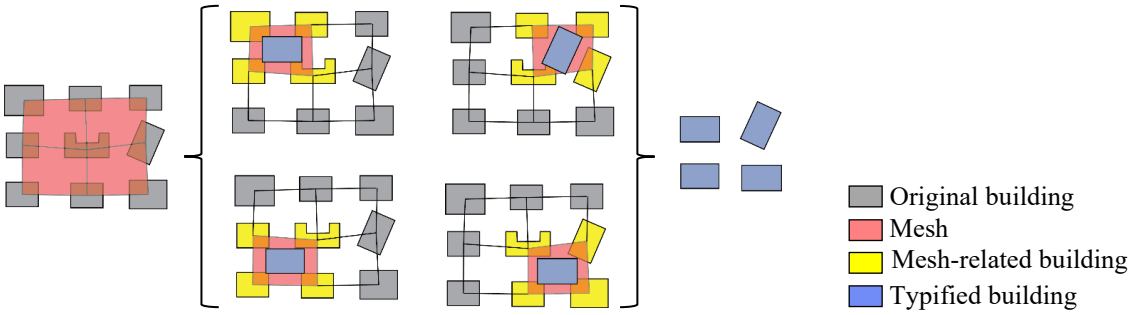


Figure 5.7 Representation determination of new typified buildings.

5.4.6 Resizing Newly Typified Buildings

The number of newly typified buildings must be reduced after typification; thus, the total area of the building group is decreased. To keep the total area consistency of the buildings, the newly typified buildings should be resized. As shown in Figure 5.8, the resizing process takes the center position of the newly typified buildings as the origin and proportionally enlarges the newly typified buildings with the resizing factor *F*. The resizing factor F is calculated using Equation (5.4).

$$F = 1 + \frac{A_O - A_T}{A_O}, \tag{5.4}$$

where A_O denotes the total area of the original buildings in the group, and A_T is the total area of the newly typified buildings.

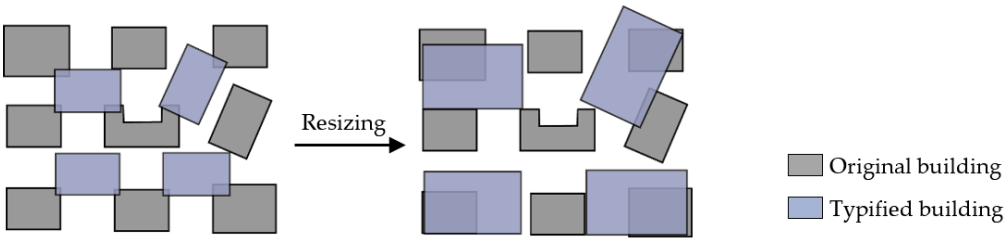


Figure 5.8 Resizing of the newly typified buildings.

5.5 Experiments

5.5.1 Data derivation

To verify the effectiveness of the proposed typification method, we carried out some experiments. The test data is chosen from OpenStreetMap, which includes two datasets.

(1) Dataset I: isolating building groups

We manually selected several isolating building groups with perfect grid patterns and grid-like patterns from the suburban and rural areas in Dresden (See Table 5.1). The selected building groups are divided into five pairs, which are numbered with *A1*, *A2*, *B1*, *B2*, *C1*, *C2*, *D1*, *D2*, *E1*, and *E2*. Each pair has the similarity in distribution and in number of buildings. In the selected groups, *A1*, *A2*, *B1*, *B2*, *C1*, and *C2* were common building groups with reasonable building amounts, while *D1*, *D2*, *E1*, and *E2* were special building groups because only parts of their patterns are presented grid-like. Moreover, these four groups had a large amount of buildings, and their coverages were also larger than normal. The purpose of selecting such groups was to test the universality of the proposed typification method.

(2) Dataset II: building groups from an entire village

The second part of the test dataset involved a whole village named Akarp, from the rural area in Lund, Sweden (See Figure 5.9). This region contains many outstanding perfect grid and grid-like patterns. Based on the results of manual detection, the whole region contains eleven grid pattern building groups, which were numbered from *G1* to *G11*. For the remaining buildings, because they do not present like grid or grid-like patterns, they were not considered and they remained untouched after generalization.

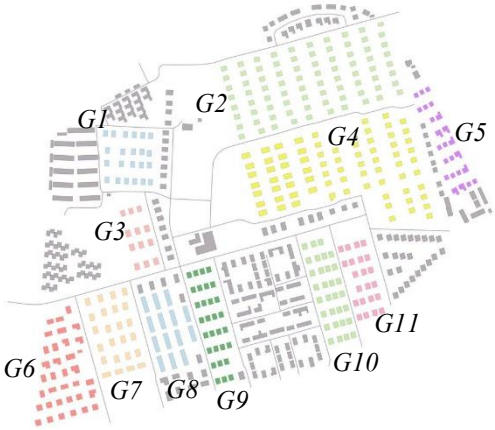


Figure 5.9 Dataset II: manually detected grid-like building groups from village Akarp.

5.5.2 Typification results and evaluation

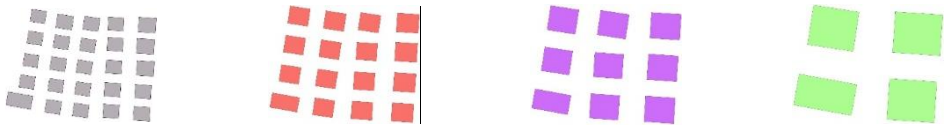
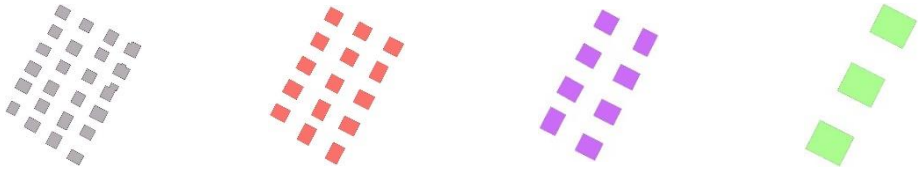
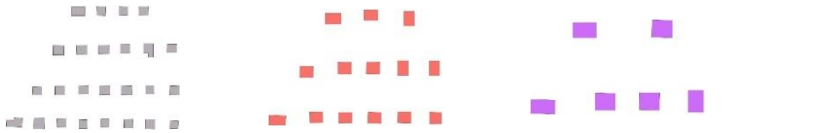
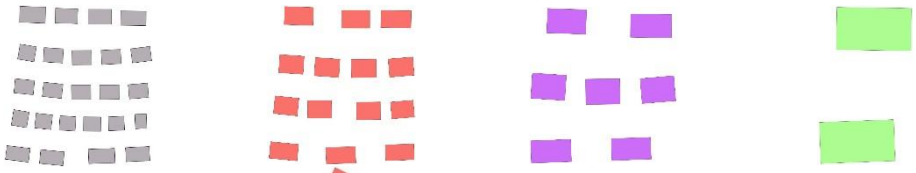
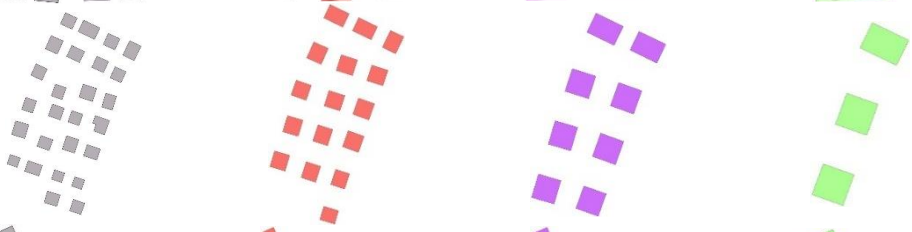
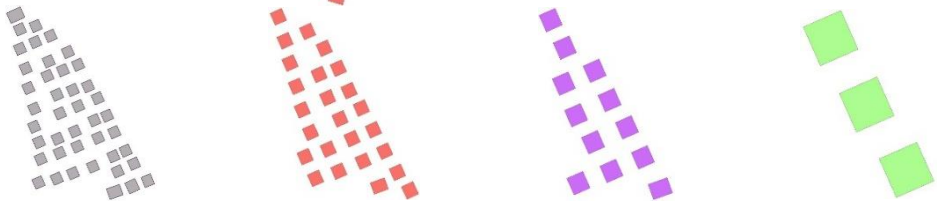
(1) Dataset I

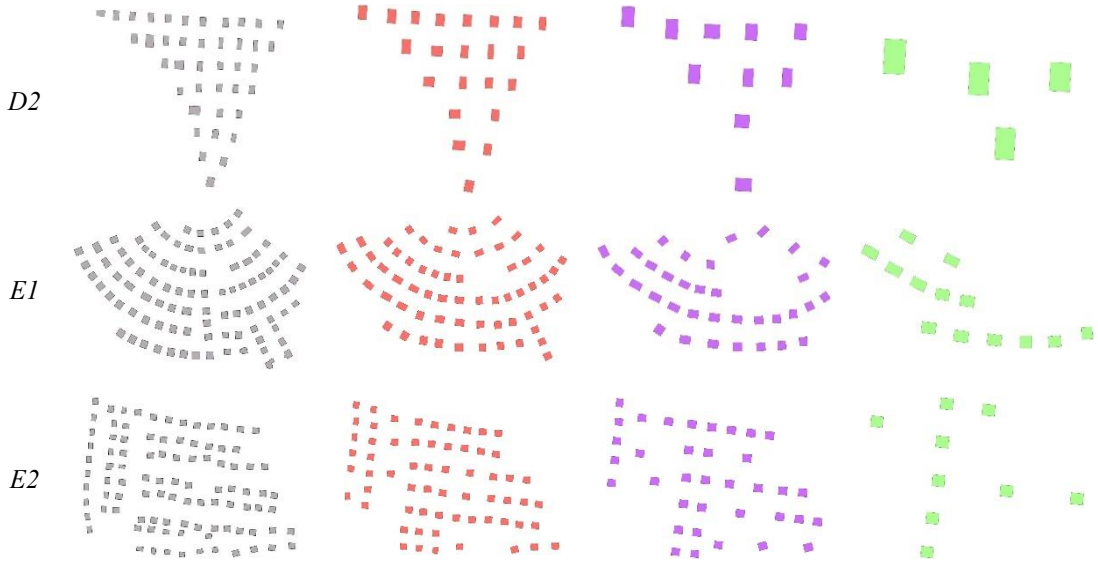
The selected building groups contained various types of grid and grid-like patterns in order to show the universality of the proposed typification method. To get the gradual typification results, the proposed typification method was applied to the building groups in Dataset I with three iterations. The three iterative typification results are shown in Table 5.1. Overall, the typification results were satisfactory, since they could keep the characteristics of the original gird or grid-like distributions. A detailed evaluation is described in the next paragraphs.

Groups *A1* and *A2* were almost typical perfect grid patterns with a regular grid distribution in each row and column. The typification results preserved this regular distribution well. The lower left building in *A1* was quite outstanding in size and elongation compared with the others. The local characteristic of this group was also kept in the iterative typification results. Groups *B1*, *B2*, *C1*, and *C2* were grid-like patterns, whereby the number of buildings was different in each row or column, and the distributions were not always perpendicular within rows and columns. The first and second typification results kept this uneven distribution. The difference in building amounts between rows or columns was also presented in the typified buildings, and the total building amounts decreased gradually. Groups *D1*, *D2*, *E1*, and *E2* were special grid-like patterns which contained more buildings and had larger coverage areas. From the results, it was found that global distributions could be preserved, as well as the local characteristics. For example, Groups *D1* and *D2* had triangular-like outlines in the distribution, while Groups *E1* and *E2* had a circular sector and rectangular global shape, respectively. In the typification results, their global outline shapes kept the same consistency as the original. The original local characteristics were also reflected in the typification results, such as the local difference in building amounts and the uneven distribution.

There were also some weaknesses in the third typification results of Groups *B2*, *C1*, *E1*, and *E2*, which lost some characteristics. The main reasons were as follows: after the previous two times typification, the newly created buildings no longer belonged to grid-like patterns; thus, if the proposed typification strategy was still applied, it would not get satisfactory results. Therefore, after every iteration, the newly created buildings should be checked to see whether they still present grid-like patterns. If not, the iteration process should be stopped, and, for further generalization, the selection of other appropriate operators could be a better solution.

Table 5.1 Typification results of building groups.

No.	Original	1st Typification	2nd Typification	3rd Typification
A1				
A2				
B1				
B2				
C1				
C2				
D1				



(2) Dataset II

For the detected building groups in the village of Akarp, the typification method was implemented two times, with the first and second typification results displayed in Figure 5.10, overlapping with the original ones. Overall, the results are visually satisfactory. The characteristics of the original grid patterns are reflected in the typification results.

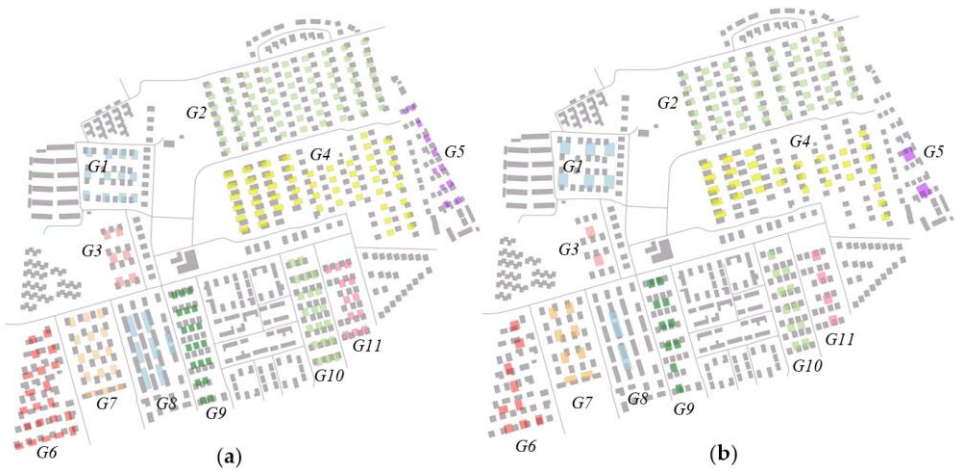


Figure 5.10 Overlapping typified buildings with original buildings (a) 1st typification; (b) 2nd typification.

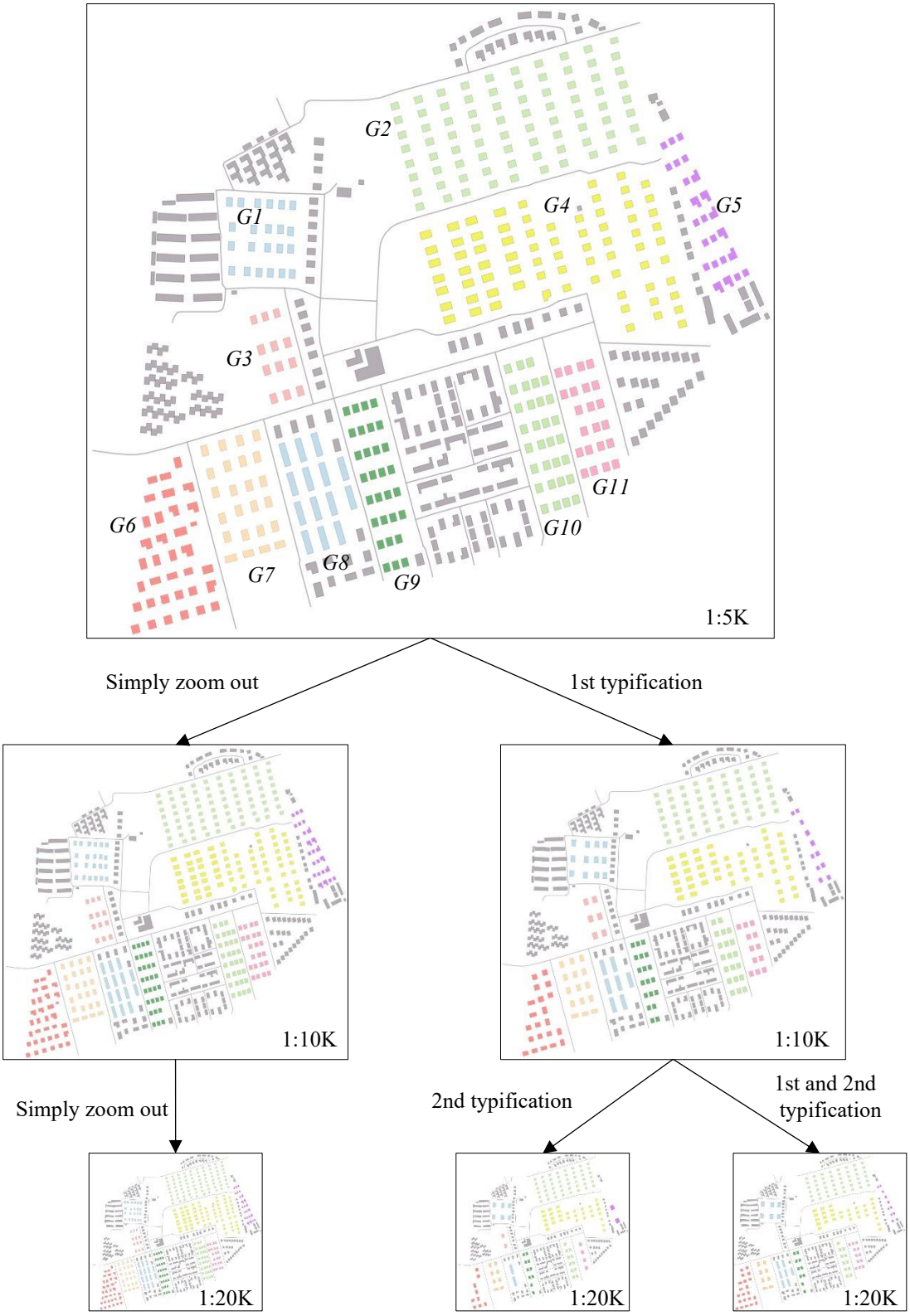


Figure 5.11 Comparison between simply zooming out and typification in different scales.

Figure 5.11 shows a comparison between the building groups with generalization (typification) and simply zooming out on smaller-scale maps. From the comparison, it is obvious that, due to

scale reduction, the buildings shrank which led to congestion problems. The buildings are not easy to recognize; thus, the legibility of the map becomes lower. Thus, just simply zooming out the map is not a good way to represent the buildings on a smaller-scale map. On the contrary, when the first typification results were used to replace the original buildings on a scale of 1:10,000, the readability of the map improved. The original perfect and grid-like patterns in different building groups were also kept with the reduced building amounts. In the smaller scale of 1:20,000, if the original buildings were all replaced by the second typification results, there existed some deficiencies. For example, Groups *G3*, *G5*, and *G8* had only two buildings left, which created an unbalanced distribution on the map. Groups *G6* and *G11* lost their original patterns, due to the same reason as above, whereby, after the first typification, *G6* and *G11* no longer presented grid or grid-like patterns; thus, it was not appropriate to use the proposed typification method to generalize them, and using another operator would be a better solution. Therefore, for different groups, the iteration time of typification should be considered differently based on the group size and building number. Therefore, it was better to use the first typification results for groups *G3*, *G5*, *G6*, *G8*, and *G11*, and the second typification results for groups *G1*, *G2*, *G4*, *G7*, *G9*, *G10*, and *G12*. As shown in Figure 5.11, the building groups with mixed first and second typification results seems more reasonable on the map.

5.5.3 Comparison with official map

The typification results of some selected building groups were compared with the corresponding generalization results in the official map. The official map was derived from the State Enterprise Geobasis information and Surveying of Saxony (GeoSN) (German: Staatsbetrieb Geobasis information und Vermessung Sachsen). The number of the map sheet was L4948 (Scale = 1:50,000) with the edition year of 2004. Building groups *C1* and *A1* were selected to allow a general comparison in the same region on the official map.

As shown in Figure 5.12, for Group *C1*, the official map generalized the original grid-like pattern building group into a 4 × 3 pattern, and this process kept the original grid-like pattern. The first typification results of the proposed method were selected for comparison. The original building groups had a building number difference in rows, and the difference was also reflected in the typified groups. For another Group *A1*, the official map only used two buildings to represent the original groups, such that the original grid patterns were lost. When the second typification result of Group *A1* was overlapped on the official map, the proposed typification method kept the original grid pattern better than the official map. Therefore, if the typified groups can be shown in the corresponding locations, the map can better preserve the original distribution.

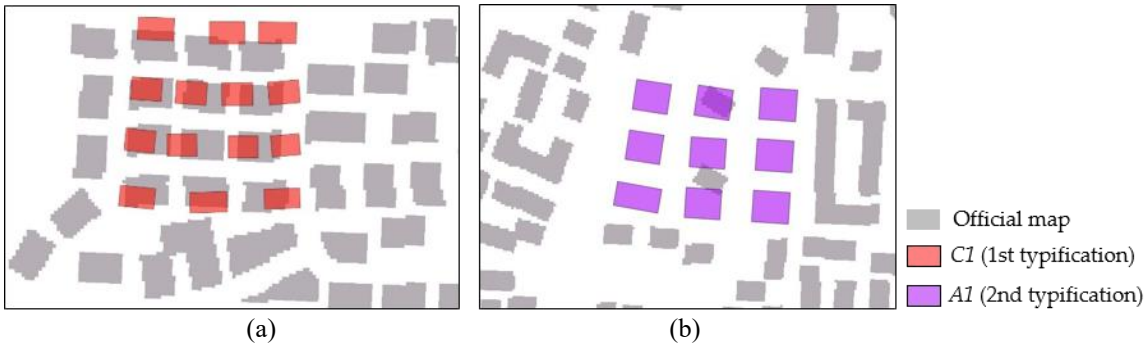


Figure 5.12 Comparison with official map. (a) Group C1; (b) Group A1.

To make another comparison, as shown in Figure 5.13(a), on the marked area of the official map, there exists a building group (*G*) with the obvious grid-like pattern. Figure 5.13(b) displays the generalization results of the same area on the official 1:50,000 map. It is found that Group *G* was generalized into several unstructured buildings, which lost the original grid-like pattern. By comparison, this group was generalized using the proposed typification method. As shown in Figure 5.13(c), when the second typification result was applied on the map instead of the official generalized result, the new solution preserved the original distribution characteristics of this area.

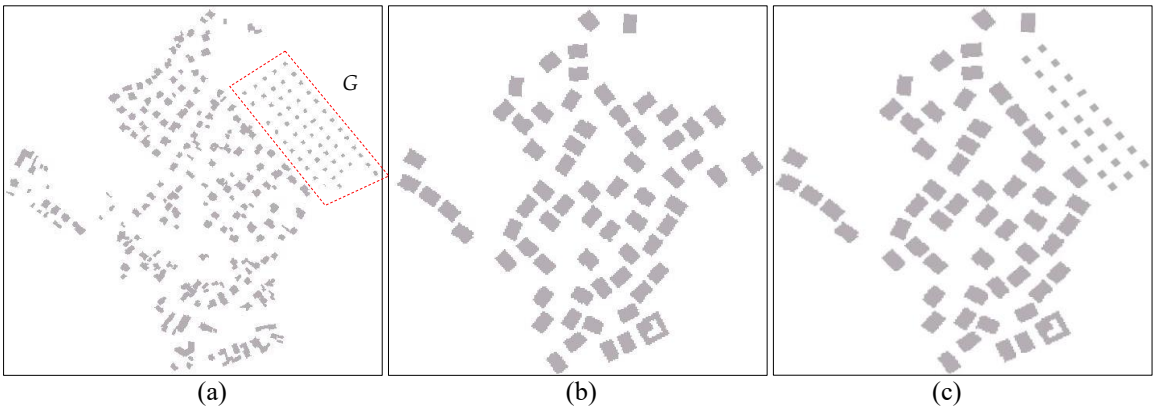


Figure 5.13 Comparison with official map: (a) map of 1:25,000; (b) map of 1:50,000 (original generalization results); (c) results using the proposed typification method.

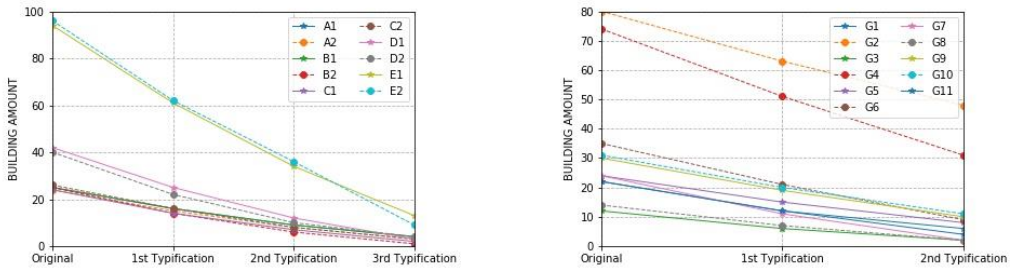
5.6 Discussion

5.6.1 Advantages

Typification belongs to the *m* to *n* generalization problem. The difficulty of grid pattern typification lies in how to create a general rule to determine the remaining number of newly typified buildings, as well as keeping the original grid patterns. The advantages of the proposed mesh-based grid pattern typification method are as follows:

(1) The number of typified buildings can be easily determined by meshes. The number of newly created buildings is equal to the number of meshes. For the perfect grid pattern, the number changes from $m \times n$ to $(m - i) \times (n - i)$ (i= 1, 2, …, $min(m, n) - 1$) in each iterative process. For

the grid-like patterns, the number reduces mildly. Figure 5.14 shows the number of buildings after each typification in the building groups of the two datasets. For a similar original number of buildings, the reducing rate of building number remains consistent, which demonstrates that the proposed method performs steadily in different building groups.



(a) (b)

Figure 5.14 The number change of building groups after typification. (a) Dataset 1; (b) dataset 2.

(2) The mesh-based typification method preserves the global characteristics of the building group, as well as the local details, such as the local convex and concave characteristics and the difference between the number of rows and columns in grid patterns. Not only the grid patterns but also some special local characteristics of the original patterns can be preserved and reflected on the newly typified buildings, which keeps the visual consistency.

(3) The method is modeled as an iterative process, which creates progressive typification results. With several iterative typification processes, the hierarchical typification results of the building groups can be obtained, which is useful for continuous generalization. With the scale reducing, the hierarchical typification results can give support to mapmakers when generalizing building groups on maps. The hierarchical typification results can also avoid large and sudden changes in generalized maps, thereby improving the quality of the multiple representations.

5.6.2 Further improvements

There are also some issues to be further studied or improved. Firstly, the proposed typification method is conducted as an iterative process, which can create a series of hierarchical typification results. The iterative time should be determined based on the group size and building number. Moreover, in different scales, there are different constraints for the features to be represented on maps, e.g., minimum distance and minimum size; therefore, more studies are needed on how many iterations should be made for one building group to give an optimal representation on smaller-scale maps. Secondly, the typification effect is based on the mesh quality. The mesh generation and merging processes cannot guarantee that all the meshes are of good quality in every situation. Therefore, once an unsatisfying mesh appears, revision should be made manually after typification. Thirdly, the orientations of the newly created buildings are determined by the largest mesh-related building, which may disrupt the smooth trends of the building orientations.

As shown in the marked areas of Figure 5.15, with the original orientations, the buildings are presented with a smooth and consistent trend. After typification, the homogeneity of building orientation becomes weak in some places. Lastly, the grid pattern typification strategy enlarges the buildings, which may cause overlap problems with other geographical features, such as roads. When overlaps appear, it is necessary to use the displacement operator to make the refinement.

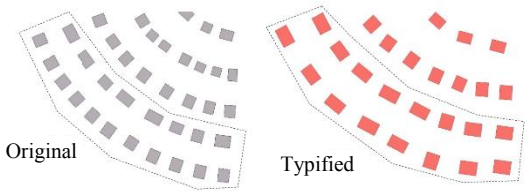


Figure 5.15 Deficiency of keeping orientation homogeneity after typification.

5.7 Conclusion

Typification is one of the most challenging tasks in map generalization for its complex *m-n* relationships. The proposed mesh-based typification method provides a solution for the generalization issue of building groups with grid patterns. The meshes are generated from buildings and they are used to determine the number and position of the newly created buildings. The representations of the newly created buildings are calculated from their corresponding mesh-related buildings. The method can be implemented iteratively such that hierarchical typification results are created, which contributes to multiple representations and continuous generalization. The experimental results show that the original characteristics of the grid patterns can be preserved, and some special characteristics in the grid-like patterns can be also captured and reflected in the typification results. The comparison with the official map demonstrates that this method can preserve the original grid or grid-like patterns in building groups; therefore, the official map can consider the proposed typification results as solutions in the corresponding building groups. This study only focuses on the development of the typification operator; future work should study how to suitably decide the iteration times on different scales.

Chapter 6

Hierarchical extraction of skeleton structures from discrete buildings

Xiao Wang and Dirk Burghardt

Wang, X. and Burghardt, D (Submitted): Hierarchical extraction of skeleton structures from discrete buildings. *The Cartographic Journal*.

6.1 Abstract

Map generalization is a process of reorganizing features hierarchically whereby the global shape of the original datasets can be transferred in different scales. In this study, we propose a stroke and centrality based method to hierarchically extract the skeleton structures from the discrete buildings, which is utilized to support the building generalization. Firstly, the proximity graph network is derived, from which the strokes can be generated. Next, by regarding the strokes as a dual graph, three centrality measures (i.e., degree, closeness, and betweenness centrality) are calculated for each stroke whereby an integrated factor is created to measure the importance level of the strokes. Finally, the hierarchical skeleton structures are extracted based on the stroke importance levels through different selection ratios. The extracted hierarchical skeleton structures support the generalization process by classifying the buildings into different categories. With analyzing the characteristics of the different building categories, we select different operators to implement the generalization operations on them. The experiments are conducted into the discrete buildings from ten different suburban regions near Dresden. The results demonstrate that the extracted hierarchical skeleton structures can represent the global shape of the entire region. Through the support of the hierarchical skeleton structures, the global and local patterns of the original building datasets can be both preserved after generalization.

6.2 Introduction

Buildings accommodate most urban activities and act as the crucial origins and destinations of urban movement, which makes buildings becoming an important aspect of cities and contains crucial information about city organization and evolution (Sevtsuk and Mekonnen 2012). Characterizing and comparing buildings in different regions could then be helpful for a better understanding of urban formation and evolution. On large-scale maps, buildings are important geographical objects, which act as one of the most common types of artificial objects and occupy large map load. As a result, building generalization has long been an active research field in cartographic generalization.

In the real world, the settlement area of different cities shows various patterns due to the division of street networks, historical reasons, geographic surroundings, social-cultural environments, economic conditions, and so on. With repetitive interactions, people living in urban space have the ability to get familiar with the city layout. This layout is stored in people's mental representation which to a large extent is organized hierarchically (Tomko et al., 2008). The effect also occurs during map usage. When people are watching maps of the same city with different scales, no matter they want or do not, remember subjectively or passively, once they have seen the map of a city, the image of that city will be embedded into their mind (Jiang 2013). The

distribution of the map features has been kept in the brain, even with different scales, people have a chance to recognize which city it is. This is due to the spatial knowledge which is organized hierarchically. The distribution of the city will be abstracted with a framework and stored in human brains.

The spatial distribution characteristics are rooted in the cognition process, therefore the results of map generalization should suit human's mental representation and keep the similarity in different representation hierarchies. The essence of map generalization is to reorganize features within multiple representations. Multiple representation should be based on keeping similarity in different display levels in which hierarchies play an important role. As the same as streets, human's perception of the building objects also has the hierarchical characteristic from global to local. Therefore, the study of the hierarchy is beneficial for the multiple representation and has further functions to building generalization. The primal aim of this paper is to extract the hierarchical skeleton structures from buildings and use them as the support to guide the generalization process.

The remainder of this paper is organized as follows. Section 2 reviews the previous work of building generalization and hierarchy studies in the street networks. Section 3 discusses the study area. Section 4 describes the formation process of the hierarchical skeleton structures. Section 5 describes the generalization strategy under the control of the extracted hierarchical skeleton structures. In Section 6, the experiments are tested in ten regions and the results are evaluated and discussed. At last, the conclusion summarizes the proposed work and indicates future directions.

6.3 Related work

Map generalization is a technique to produce smaller-scale maps deriving from larger-scale ones, and it can be also regarded as a process of similarity transformation (Yan et al., 2016). For the topic of building generalization, the previous researches mainly concern two aspects: holistic generalization strategy and individual generalization operators. For the holistic generalization strategy, the common procedure is to decompose the building generalization into two steps, i.e. building grouping and generalization execution. The related work is described in the following works: Regnauld (1996) recognized the building clusters for generalization. Christophe and Ruas (2002) detected the building alignments for generalization purposes. Li et al. (2004) used Gestalt principles to provide criteria for the building grouping. Zhang et al. (2013) presented a spatial cognition-based urban building clustering approach for generalization. Yan et al. (2008) proposed a multi-parameter approach to automated building grouping and generalization. Pilehforooshha and Karimi (2018) proposed an integrated framework for linear pattern extraction in the building group generalization process. Wei et al. (2018) used the spatial distribution of buildings to guide the generalization process. The frequently-used operators for building generalization include

aggregation (Su et al., 1997; Regnauld and Revell 2007; Cheng et al., 2015), typification (Regnauld 2001; Burghardt and Cecconi 2007; Gong and Wu 2018), and simplification (Bayer 2005; Haunert and Wolff 2010; Cheng et al., 2013). These operators are developed only for the geometric transformation within a local level, normally applied to the building groups.

From the above-related works, the previous methods group buildings into different local clusters, which can well preserve the local characteristics of the original distribution. However, these methods lack of global constrains to control global shape preservation. Thus, the objective of this paper is to present an integrated method from the global view for the full process of building generalizations.

The global constraints lie specifically in the hierarchy of the objects. Hierarchy is a predominant principle in nature and in human organizations. Humans tend to organize their environment in hierarchical structures. Hierarchy emerges often in spatial systems, in the various map features, the hierarchies of the street network is naturally the first considered and frequently studied. For a long time, cartographers consider streets as the backbones of cities, and by exploring street patterns, it can reveal many underlying features of a city (Lin and Ban 2017). There are many studies concerning the formation of street network hierarchy (Jiang and Claramunt 2004; Li and Zhou 2012; Gülgen 2014; Jiang 2015). The hierarchy formation is widely used in street network generalization, such as road network selection or selective omission (Shoman and Gülgen 2017). From the above descriptions, the hierarchical structure is obvious in street due to its network properties, as another basic artificial feature, buildings, if the hierarchical skeleton structures could be formed, it will be much beneficial to the building generalization.

The study about the hierarchical structures often relates network analysis and network theory. The network is ubiquitous in nature and society, including computer networks, technological networks, social networks, biological networks, and geological networks (Newman 2003). A network is a structure defined by nodes and links between them. The network can be also found in geographical features on maps, such as road network, hydrographic network and pipeline network. Network theory is built upon the foundation of graph theory, which is a branch of discrete mathematics. Network theory has long been widely used in cartography and geo-information science, such as the study of street networks analysis and generalization (Mackaness and Beard 1993; Heinzle et al., 2005). From the above-related work, it can be seen that network theory is fairly little applied in building generalization, for reasons that buildings are two-dimensional discrete features on maps, which is not easy to form a network directly. People construct buildings with some purposes and this reflects on the map that there are different building patterns, which makes buildings with more topological relationships to be regarded with

network properties. Therefore, the introduction of network theory is expected to give more inspirations to building generalization.

6.4 Study area

In urban morphology, cities are divided into different regions, such as urban area (also known as cities, towns, and metropolitan area), suburb area (also known as suburban) and rural area (also known as village, countryside). The urban area is a human settlement with a high population density and infrastructure of a built environment, and it normally denotes the central or inner-city areas. Suburb area exists either as part of an urban area or a city or as a separate residential community within commuting distance to the city center. In general, they have lower population densities than the inner city and most residents commute to central cities. The rural area is a geographic area which locates outside towns or cities. Rural area has a low population density and small settlements. Based on the population density, buildings are constructed with different purposes and functions, which results in that buildings in different regions present different distribution patterns. In the urban area, buildings normally distribute in the street blocks which have high density and intensive distribution, while in suburb or rural area, the buildings have a lower density and mostly with a discrete and sparse distribution. In most cities, taking Dresden as example, from Figure 6.1(a), buildings in the city center are normally connected with each other (Case A) and for the individual buildings, they are probably those with large size (Case B), high elongation rate (Case C) and complex shape (Case D). For the generalization of buildings in the urban area, cartographers prefer to use the built-up area to present the original buildings rather than isolated building. In the suburb or rural area, buildings are built mostly for residential purposes, the individual building is more rectangular-like and with the simple shape and small size. Moreover, buildings in such areas are mostly planned and built along the main streets, which makes it easier forming building groups with special regular patterns, such as linear-like pattern (Case E in Figure 6.1(b)). Buildings in the suburban and rural area are organized mostly along the road, which results in the frequent appearance of linear patterns. By analyzing the distribution characteristics of buildings in urban area and suburb or rural area, our study is mainly conducted on the buildings locating within the suburb and rural areas where buildings are presented discretely and sparsely.

(a) (b)

Figure 6.1 Building distribution characteristics in different areas. (a) Central area of Neustadt Dresden; (b) suburban area in village Bühlau, Dresden.

6.5 Hierarchical extraction of skeleton structures

6.5.1 Proximity Graph Network (PGN) of buildings

The proximity graph is a data structure that can detect the proximal relationships among discrete buildings. Normally, the proximity graph of buildings is generated from the constraint Delaunay triangulation (CDT). Two buildings connected by a common triangle can be detected as proximal. Afterward, a line is drawn to connect the centroids of the two buildings. These lines will be regarded as edges of the proximity graph. Figure 2 shows the process of the generation of the proximity graph. Notably, the constraint triangles which connect three buildings are deleted (Figure 6.2(b)). This operation can reduce the redundant proximal edges in the proximity graph. Even though, the original proximity graph has still some limitations violating the perception of the nearest neighboring objects. As shown in Figure 6.2(c), for example, some distant or oblique distributed buildings are still detected as proximal. Therefore, the original proximity graph should be refined to remove the visual conflicting edges.

Currently, there are many refinement approaches, for instance, Nearest Neighbor Graph (NNG), Minimum Spanning Tree (MST), Relative Neighborhood Graph (RNG), and Gabriel Graph (GG) (Anders 2003). The existing approaches normally refine the proximity graph by judging the topological relationships, in our study, the refinement operation aims at removing the edges between oblique distributed buildings as much as possible. Thus, the facing ratio between two buildings is selected as the index to refine the original proximity graph. Facing ratio reflects the degree of two buildings that face each other (Yang 2008). The two buildings with a higher facing ratio indicate that they are more possible to be regarded as proximal, whereby the edges between two oblique distributed buildings can be detected.

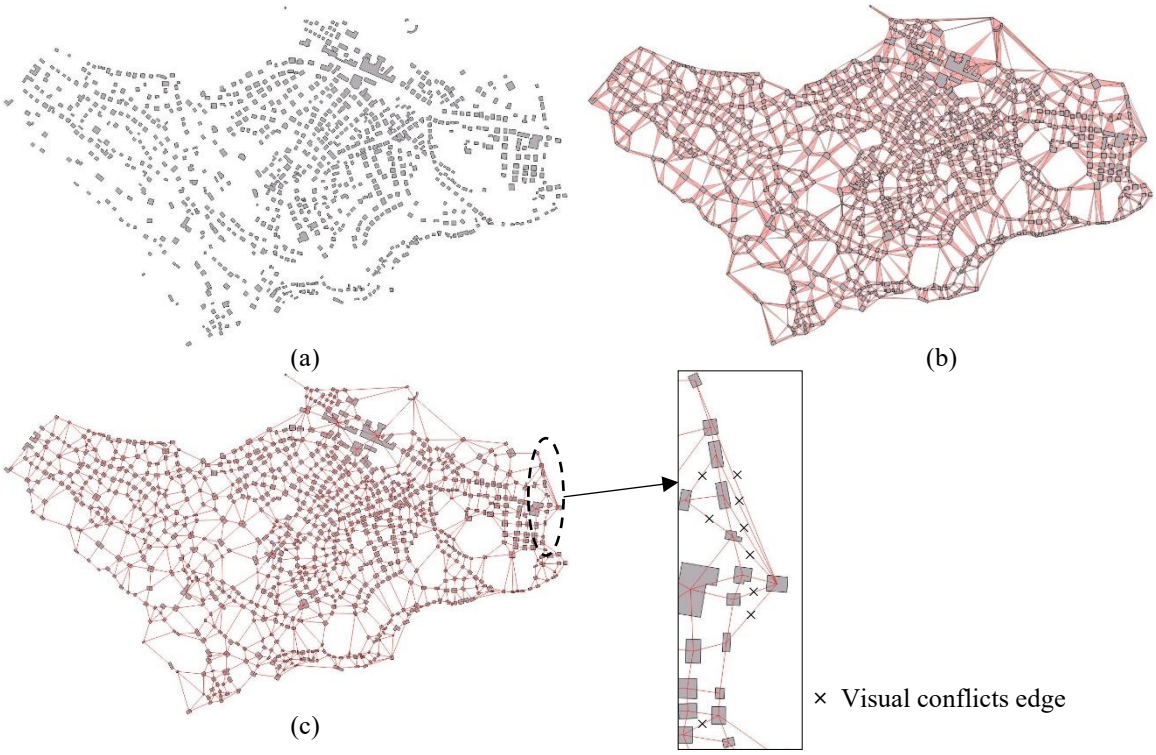


Figure 6.2 Proximity graph generation from discrete buildings. (a) Original buildings; (b) constrained Delaunay Triangulation; (c) original proximity graph and conflicting edges in local.

The facing ratio between two buildings is calculated by Equation (6.1)-(6.2):

$$Facing\_ratio_{AB} = max\ (fr_{XA}, fr_{YA}, fr_{XB}, fr_{YB}) \tag{6.1}$$

$$fr_{XA} = \frac{overlap(ProL_{XA(A)}, ProL_{XA(B)})}{max\ (ProL_{XA(A)}, ProL_{XA(B)})} \tag{6.2}$$

where fr_{XA}, fr_{YA} fr_{XB} fr_{YB} denotes the facing ratio values based on the four axes of building *A's* and building *B's* corresponding oriented bounding boxes (OBB) (Duchêne et al. 2003), respectively. Taking the calculation of fr_{XA} as the example, $ProL_{XA(A)}$, $ProL_{XA(B)}$ denote the projection lengths of building *A* and *B* on the *X*-axis of building *A*'s oriented bounding boxes. As shown in Figure 3, when calculating the facing ratio of two buildings, firstly, the OBBs of the two buildings are obtained; then, the OBBs are projected to their four axes, respectively; and the length on the corresponding axis is the projection length. The overlap rate of the projection length is calculated as their facing ratio in this axis. The maximum facing ratio of the four axes is regarded as the final facing ratio of these two buildings. If the facing ratio equals to 0, it means that the two buildings do not face each other. In the examples of Figure 6.3, through calculation, $Facing\_ratio_{AB}$ is 0.912, $Facing\_ratio_{AC}$ is 0.474, and $Facing\_ratio_{BC}$ is 0.0. Thus, it concludes that building *A* faces with building *B* and building *C*. Building *B* does not face with building *C*.

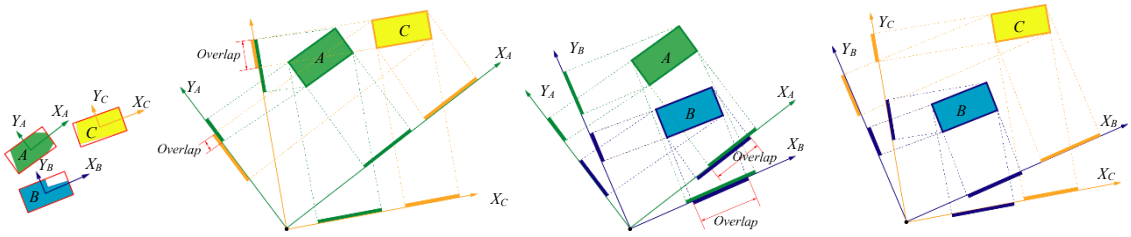


Figure 6.3 Facing ratio calculation of buildings.

Based on the facing ratio, the original proximity graph is refined. Based on the given threshold, if the facing ratio of two buildings is smaller than it, the proximal edge between them should be deleted. In this study, the threshold is set as 0.0, which means that the buildings should face each other. This refinement strategy removes the redundant proximal edges from the original proximity graph. As shown in Figure 6.4(a)-(b), after refining, the number of proximal edges changes from 2005 to 1509. The refined proximity graph can better reflect the proximal relationships among buildings.

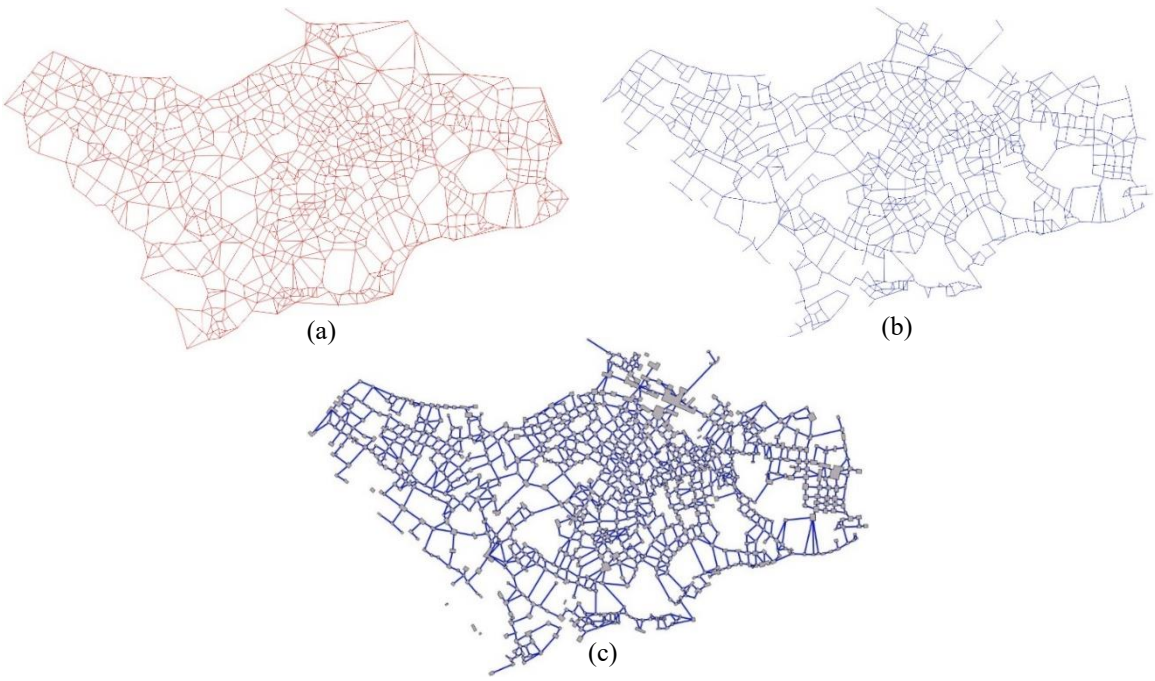


Figure 6.4 (a) Original proximity graph; (b) refined proximity graph; (c) overlapping buildings with PGN.

The refined proximity graph can be regarded as a network, here it is named as Proximity Graph Network (PGN). Overlapping the PNG with buildings (Figure 6.4(c)), buildings are located at the junction positions of the network so that the operations to the network can be transferred to the corresponding buildings. Therefore, it is possible to use network theory to guide building generalization.

6.5.2 Centrality analysis of proximity graph network

(1) Centrality indices

In network theory, centrality is crucial for understanding the structural properties of the complex relational networks. The centrality can answer the question "what is an important node in a network." Centrality is a fundamental concept in network topological analysis. It has diverse and adequate measures to capture significant and complex patterns in a network. Centrality measures are used to identify the importance of the nodes within a network. Depending on the definition, centrality can be understood as meaning proximity between nodes, accessibility from other nodes, or being in a strategic position for connecting a couple of nodes (Strano et al., 2012). Centrality concepts were first developed in social network analysis and have been applied to the topic of generalization for many years (Mackaness and Beard 1993; Weiss and Weibel 2014; Jiang 2005). There are four important centrality indices, i.e. degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Their detailed definitions and calculation methods are described in the following paragraphs.

- **Degree centrality (DC)**

Degree centrality is the simplest node centrality. It measures the number of connections between a given node and other nodes within a graph. The idea comes up with that the important nodes in a graph should connect to the other nodes as much as possible. In a graph, a node with a higher degree centrality value means that this node connects more other nodes. The degree centrality of a given node i can be calculated as (see Equation (6.3)):

$$C_i^D = \sum_{j \in N} a_{ij} \tag{6.3}$$

where N is the total number of nodes; a_{ij} equals 1 if there is a connection between node i and node j, and it equals 0 otherwise.

- **Closeness centrality (CC)**

Closeness centrality measures the shortest distance from a given node to all other nodes. This type of centrality shows how close the node is to the other nodes in the graph. In a connected graph, the normalized closeness centrality of a node is the average length of the shortest path between the node and all other nodes in the graph. Thus the more central a node is, the closer it is to all other nodes. The closeness of a given node i can be calculated as (see Equation (6.4)):

$$C_i^C = \frac{1}{L_i} \frac{N-1}{\sum_{j \in N; j \neq i} d_{ij}} \tag{6.4}$$

where L_i is the average distance from node i to all the other nodes; N is the total number of nodes; d_{ij} is the shortest distance between node i and node j.

- **Betweenness centrality (BC)**

Betweenness centrality provides the means to quantify the likelihood a graph node will lie on the shortest path between two other nodes of the graph. It evaluates the number of shortest paths that pass through each node. Betweenness centrality measures the extent of a given node that is located between the paths that connect all other nodes. It quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. In the graph, a node with a higher betweenness centrality value means that this node locates at the center position of the graph. The maximum betweenness centrality in a network specifies the proportion of shortest paths that pass through the most important node. The betweenness centrality of a given node i can be calculated as (see Equation (6.5)):

$$C_i^B = \frac{1}{(N-1)(N-2)} \sum_{j,k \in N; j \neq k; k \neq i} \frac{n_{jk}(i)}{n_{jk}} \tag{6.5}$$

where N is the total number of nodes; n_{jk} is the number of shortest paths from node j to node k, and $n_{jk}(i)$ is the number of shortest paths from node j to node k that pass through node i.

- **Eigenvector centrality (EC)**

Eigenvector centrality is a measure of the influence of a node in a network. It assigns relative scores to all nodes in the network based on the concept that connections to high scoring nodes contribute more to the score of the node in question than equal connections to low scoring nodes. Eigenvector centrality shows. In the graph, a node is important if its neighbors are important. For a given graph $G = (N,E)$ with N nodes and E edges. Let $A = (a_{i,j})$ be the adjacency matrix, i.e. $a_{i,j}=1$ if node i is linked to node j , and $a_{i,j}=0$ otherwise. The eigenvector centrality score of node i can be defined as (see Equation (6.6)):

$$C_i^E = \frac{1}{\lambda} \sum_{j \epsilon M(i)} C_j^E = \frac{1}{\lambda} \sum_{j \epsilon G} a_{i,j} C_j^E \tag{6.6}$$

where $M(i)$ is a set of the neighbors of i and λ is a constant.

(2) Centrality analysis on different levels of PGN

To better understand the functions of the above four centrality indices in network analysis, the centrality values of each index are calculated in the proximity graph network on three levels: node level, edge level, and stroke level.

- **Nodes level**

In node level, the four centrality indices are calculated based on the nodes. Because the nodes are represented by building centroids, the nodes' centrality analysis can be directly reflected in the corresponding buildings. Figure 6.5 shows the values of the four centrality indices of each building. From Figure 6.5, it concludes that buildings with large size normally have higher degree centrality values. The buildings which locate in the central position of the region have higher

closeness centrality values. The buildings which present linear patterns have higher betweenness centrality values. From the eigenvector centrality values, some building clusters are formed.

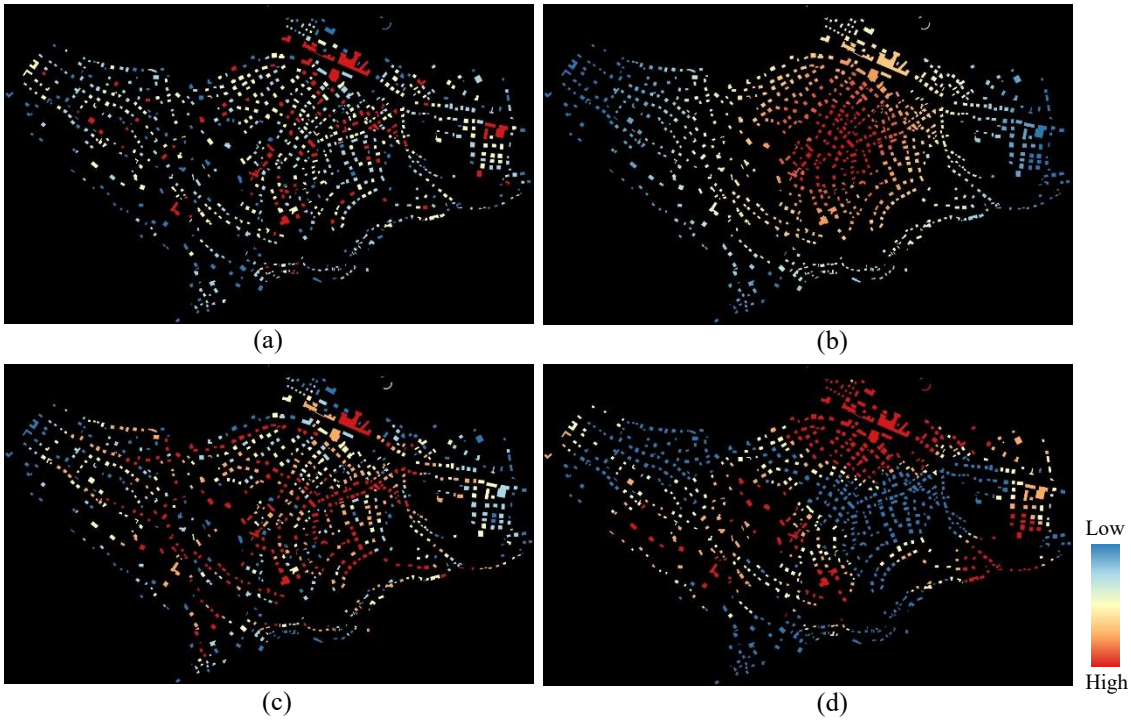


Figure 6.5 Centrality values of proximity graph network on node level. (a) Degree centrality; (b) closeness centrality; (c) betweenness centrality; (d) eigenvector centrality.

- **Edge level**

To get the centrality values in the edge level, we should transfer the proximity graph network into the dual graph, which means that in a dual graph, the edges in the network are regarded as nodes and the connections between edges are regarded as edges. Based on the proximity graph network, a dual graph can be formed by taking the proximal segments as nodes and proximity graph nodes as edges of the dual graph. The visualization of the four centrality values on the edge level is shown in Figure 6.6. From Figure 6.6, it found that the similar distribution characteristics with the node level.

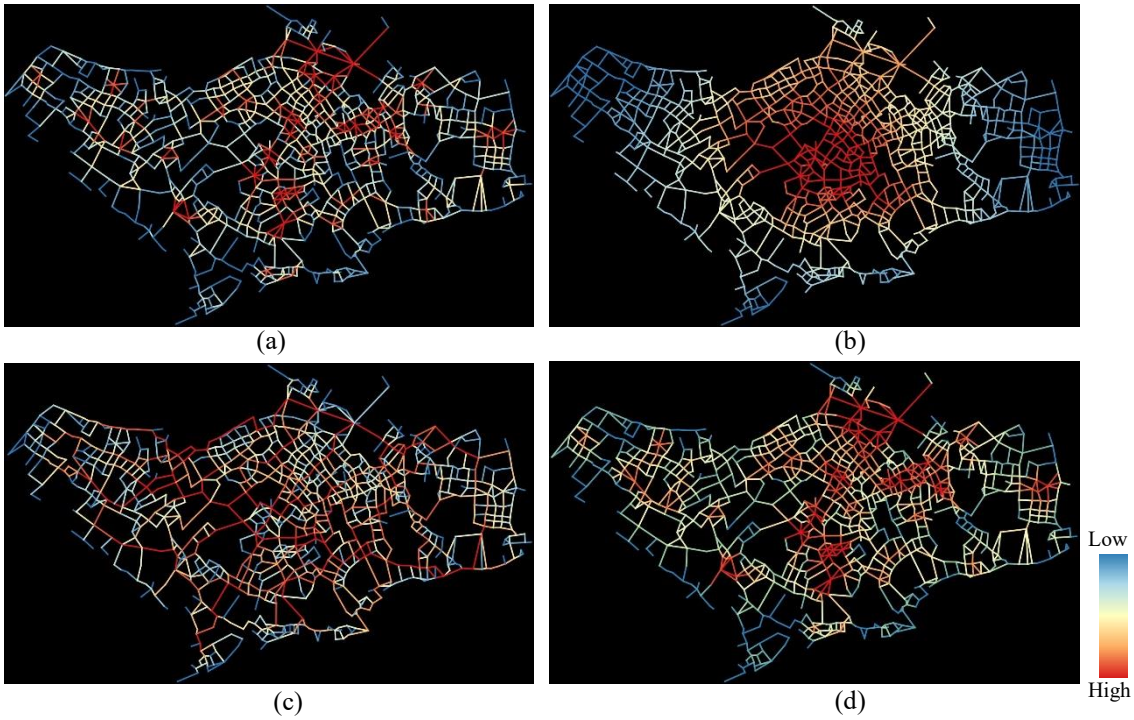


Figure 6.6 Centrality values of proximity graph network on edge level. (a) Degree centrality; (b) closeness centrality; (c) betweenness centrality; (d) eigenvector centrality.

- **Stroke level**

The term 'stroke' comes from the idea of a curvilinear segment which can be drawn in one smooth movement and without a dramatic change in style. Strokes are widely used in the research field of the road networks. In general, a stroke is composed of a set of road segments based on the principle of optimal continuity from perceptual grouping (Thomson and Richardson 1999). In road network, strokes are products of a higher-level aggregation of road segments which can reflect functional importance and perceptual significance that is associated with them in human spatial mental conceptualizations, which is of vital importance for network analysis, street selection, and map generalization (Yang et al. 2011). The stroke technique has long been applied in the generalization and hierarchy formation of the road networks (Benz and Weibel 2014, Weiss and Weibel 2014, Yang et al. 2011). In a broad sense, every network has the possibility to form strokes. In this paper, strokes are generated from PGN by calculating the deflection angle of two edges. The stroke generation process can be described as following: for every edge in PGN, all the connected edges are found out first, and among them, selecting the connected edge with the largest deflection angle (the largest deflection angle should larger than the threshold).

For the generation of the strokes, the deviation angle is the most important parameter, different thresholds of deviation angle will create different stroke results. To detect the affection of the deflection angle in generating strokes, different thresholds of deflection angle are tested. Based on the statistical information of the strokes under different deflection angles (See in Table 6.1), it

can be summarized that with the deflection angle changes from 179° to 90°, the stroke amount gradually increases and trends to be stabilized. If the deflection angle is too acute (from 90° to 120°), the generated strokes have a longer length and the continuity cannot be well reflected on the strokes. On the contrary, if the deflection angle is too obtuse (160° to 180°), the stroke amount reduces quit a lot. Therefore, the intermediate threshold should be given to the deflection angles; thus, 140° is set as the threshold in this study. Figure 6.7 displays the stroke generation results from the proximity graph network.

Table 6.1 Stroke statistical information under different thresholds of deflection angles.

Angle	Stroke amount	Total number of nodes in strokes	Average node number in each stroke	Total stroke length	Average stroke length
179°	25	80	3.20	1647.49	65.90
170°	76	316	4.16	7022.96	92.41
160°	88	414	4.70	9685.35	110.06
150°	87	450	5.17	10919.22	125.51
140°	88	476	5.41	11615.31	131.99
130°	88	484	5.50	11814.75	134.26
120°	86	483	5.62	11868.26	138.00
110°	85	482	5.67	11868.26	139.63
100°	84	486	5.79	12036.90	143.30
90°	82	486	5.93	12079.95	147.32

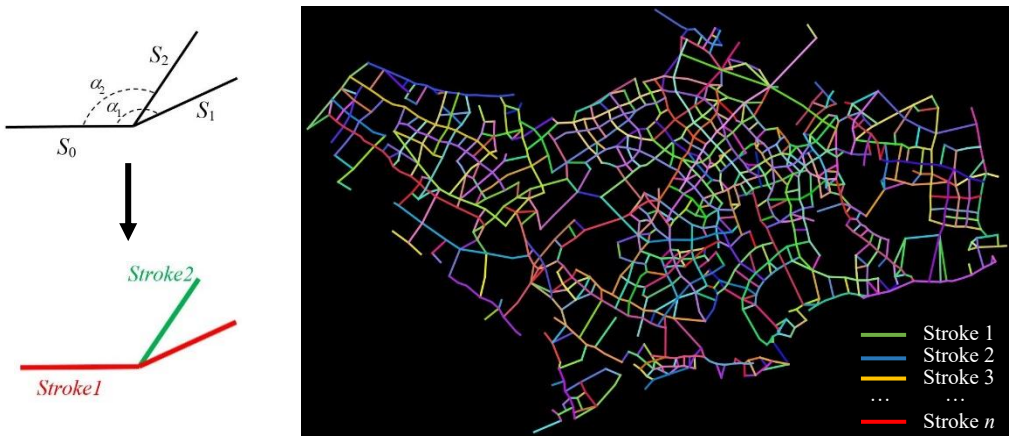


Figure 6.7 Formation of strokes by deflection angles in PGN.

With the formation of strokes, the proximity graph network is transferred into a stroke network. For the purpose of calculating centrality values, the stroke network should also be transferred into a dual graph. In the dual graph, the strokes are regarded as nodes and their connection relationships are the edges. Figure 6.8 shows the four centrality values of the proximity graph on the stroke level.

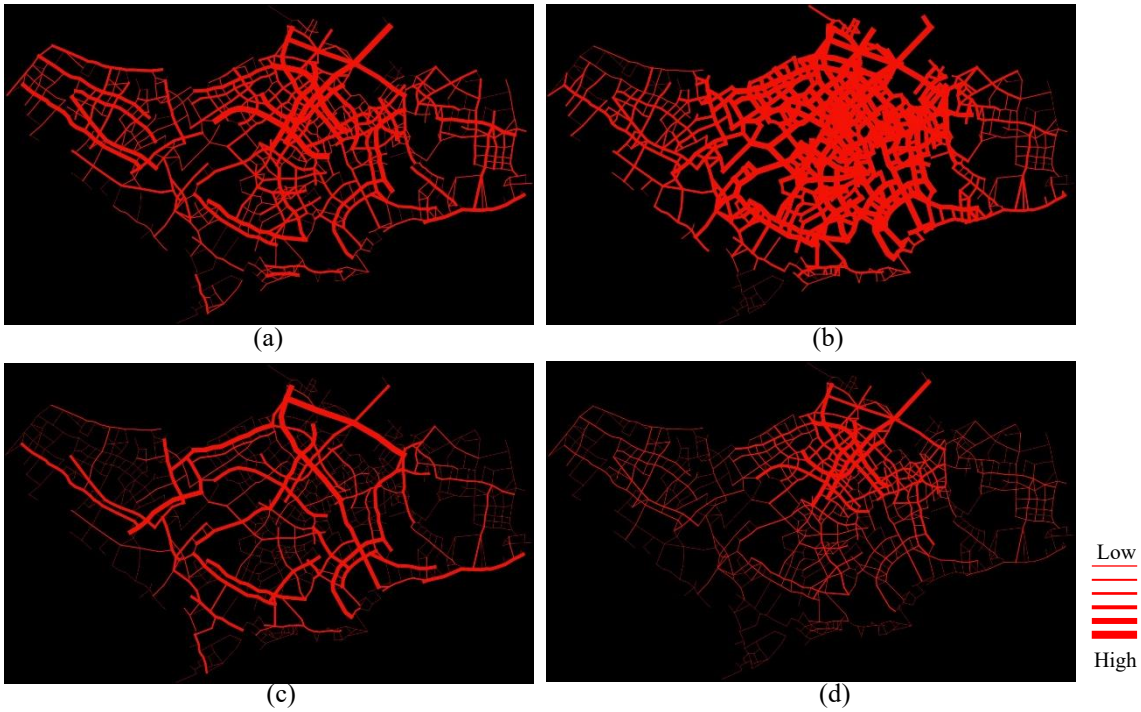


Figure 6.8 Centrality values of proximity graph network on stroke level. (a) Degree centrality; (b) closeness centrality; (c) betweenness centrality; (d) eigenvector centrality.

6.5.3 Hierarchical skeleton structures of buildings

To create the hierarchical skeleton structures in building datasets, the stroke level of proximity graph network is selected because the formation of strokes considers the importance from a global view and the analysis based on strokes can reflect the functional importance and perceptual significance of a network. From the functions of the above four centrality indices, it can be concluded that: (1) Degree and eigenvector centrality shows the local character of a node within a network, and closeness and betweenness centrality reflects the global character. (2) With the degree centrality, the nodes which have large connection ability in a network can be found. (3) With the closeness centrality, the central area and the outer area of a region can be distinguished so that closeness centrality has certain boundedness. (4) Betweenness centrality can detect the linear pattern in a network graph. (5) The eigenvector centrality can be used as a measure to find clusters in a graph. To sum up, to evaluate the grade and importance of each stroke, an integrated factor is created. The integrated factor should consider the functions of the above centrality indices. By referring to the work of Xu (2012), the integrated factor is formulated as shown in Equation (6.7):

$$F_k = C_k^{Be} * L_k / (C_k^{De} + 1) \tag{6.7}$$

where F_k is the integrated factor of stroke k, C_k^{Be} is the normalized betweenness centrality value of stroke k, L_k is the relative length of stroke k, C_k^{De} is the normalized degree centrality value of stroke k. From the equation, it found that the integrated factor only considers betweenness

centrality, degree centrality, and length while the closeness centrality and eigenvector centrality are ignored because of their limitations. The betweenness centrality considers the accessibility of the network, and it is directly proportional to the integrated factor. The length involves the range of a stroke, it is also directly proportional. The degree centrality is inversely proportional to the integrated factor. By calculating the integrated factor value of strokes, the strokes can be sorted by the values. The results are shown in Figure 6.9 and Table 6.2 (only listing ten strokes as example). From the results, overall, the integrated factor reflects the importance of the strokes, and the hierarchies of the stroke can be obtained by the sorting of strokes with their integrated factor values.

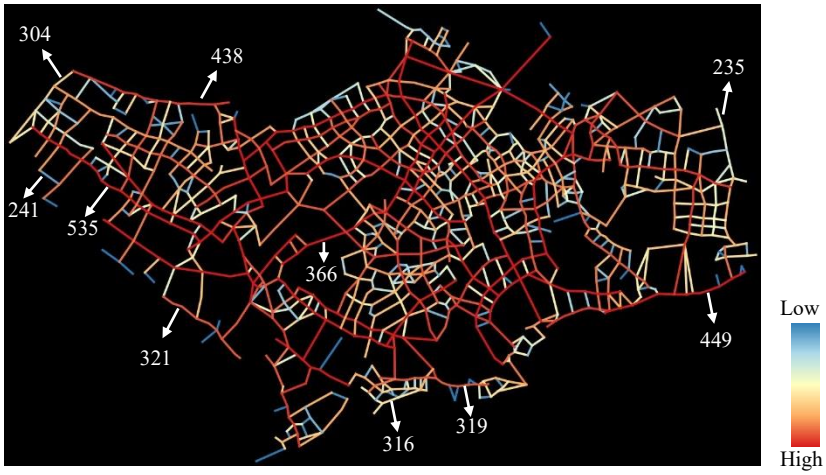


Figure 6.9 Integrated factor values of strokes.

Table 6.2 Indicator values of example strokes.

Stroke ID	*Length*	*DC*	*CC*	*BC*	*EC*	*Integrated factor*
321	283.439	5	0.139	0.009	0.028	0.00480
449	419.199	15	0.149	0.074	0.116	0.02143
535	583.787	18	0.148	0.066	0.197	0.02247
438	455.819	12	0.125	0.023	0.091	0.00899
304	269.917	7	0.117	0.001	0.071	0.00038
235	201.086	5	0.112	0.0002	0.044	0.00011
366	331.114	12	0.206	0.081	0.257	0.02259
241	69.358	2	0.115	0.00001	0.016	0.000004
316	150.808	6	0.124	0.001	0.050	0.00037
319	154.066	9	0.140	0.031	0.051	0.00532

By the given selection rate, the strokes are selected based on the value of the integrated factor from high to low. The buildings corresponding to the selected strokes are the skeleton structures of the region. As shown in Figure 6.10, with the selection rate (*SR*) reducing, it can be seen that: (1) in each selection rate, the remained strokes cover the global range of the original network, which shows satisfied homogeneity; (2) in each selection rate, the original network structures can be preserved; (3) in each selection rate, the global density of network are well kept; (4) with the selection rate increasing, the new added strokes are reasonable, which reflects the hierarchical structures of the original network. The remained buildings can have a good representation of the region. Therefore, the hierarchical skeleton structures are generated.

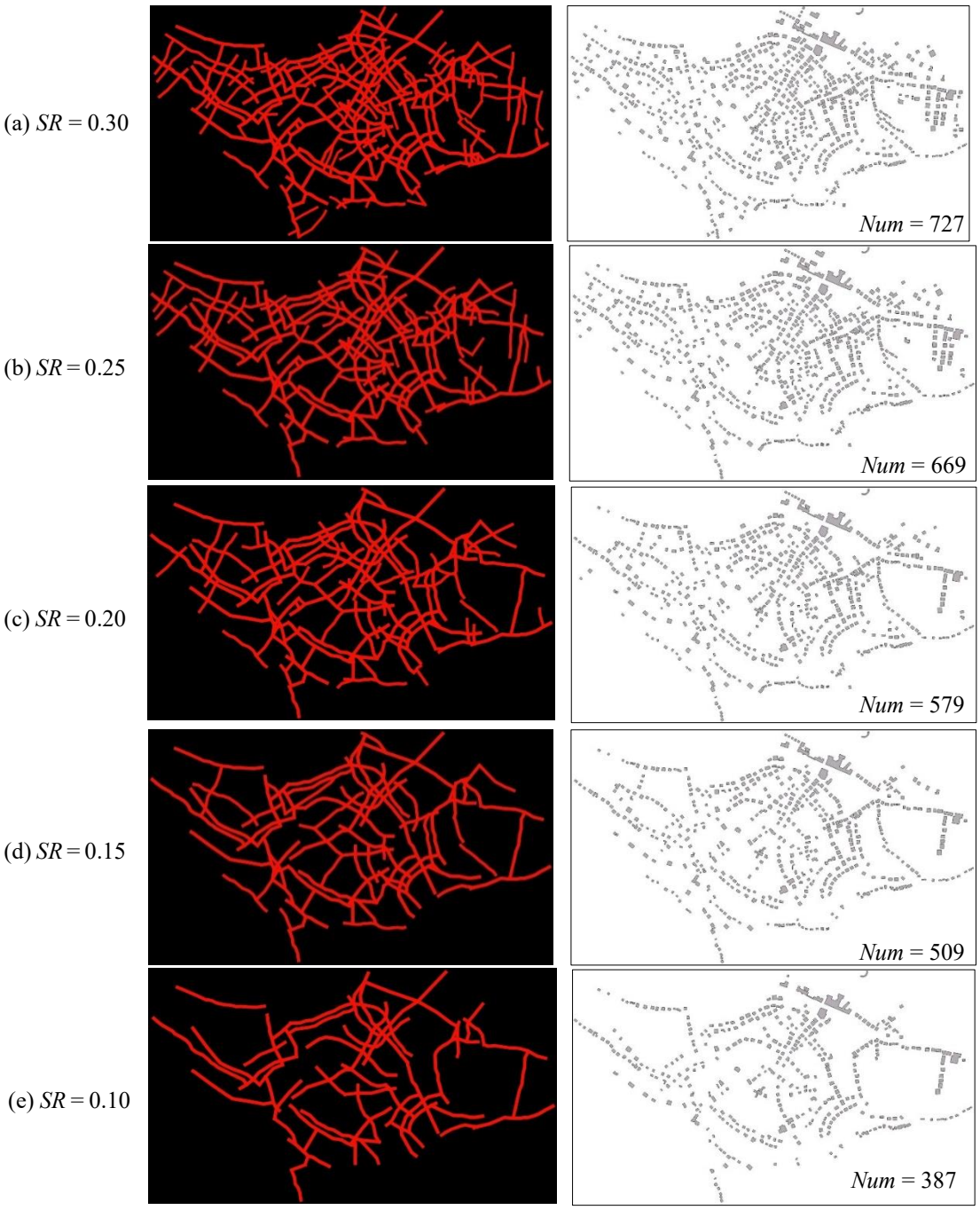


Figure 6.10 Strokes selection results and related buildings in different selection rates.

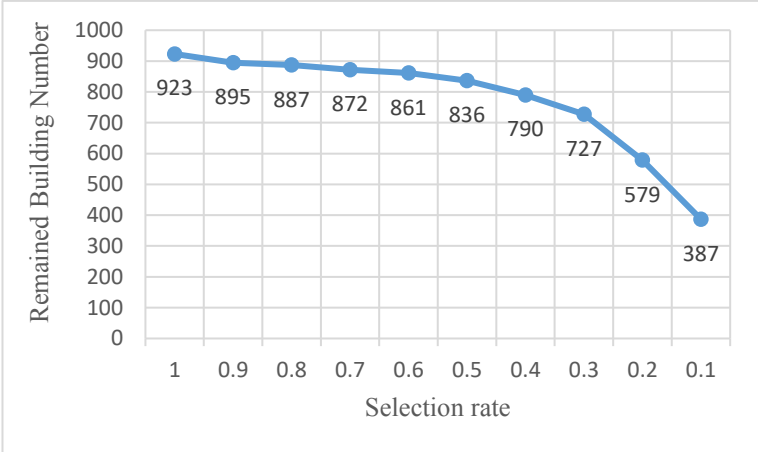


Figure 6.11 Curve graph of stroke selection rate and remained buildings number.

Figure 6.11 shows the curve graph of different selection rate and the remained buildings number. It can be seen that when the selection rate changes from 1 to 0.4, the remained buildings number changes quite a few. When the selection rate is less than 0.4, the remained building number changes gradually. Therefore, to get the hierarchical skeleton structures, the selection rate should have a start from 0.4 and reduce gradually.

6.6 Generalization application

Map generalization is a procedure that utilizes transformation operations such as elimination, aggregation, typification, displacement, and simplification to solve spatial conflicts and derive smaller scale maps from larger-scale maps (Shea and Mcmaster 2017). When generalizing map features, selecting appropriate operators is important and determines the generalization quality. In this study, the extracted hierarchical skeleton structures are regarded as the backbones of the buildings to control the generalization process. As shown in Figure 6.12, in this hierarchy level (selection rate = 0.1), by judging whether the building is related by the selected strokes, the original buildings can be divided into two categories: skeleton buildings and general buildings.

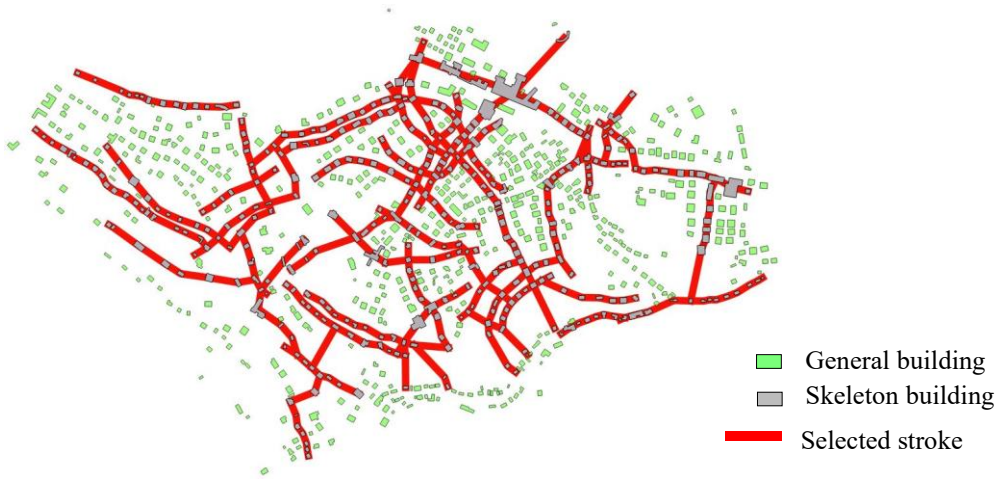


Figure 6.12 Building classification based on the skeleton structures.

The skeleton buildings are within the hierarchy so that they constitute the main framework of the region. Because the skeleton buildings are related by the strokes, most of them are presented with linear patterns. To select appropriate operators to generalize skeleton buildings, as shown in Figure 6.13, based on their locations within the strokes, the skeleton buildings are classified into four types: junction building, linear building alignment, double buildings group, and individual building. Based on the classification of the skeleton buildings and their distribution characteristics, different operators are selected to generalize these four-type skeleton buildings.

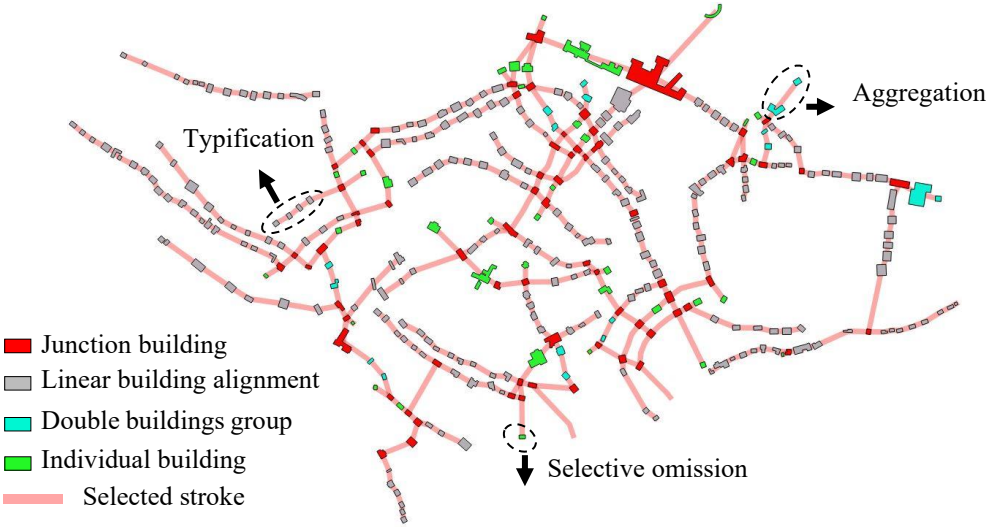


Figure 6.13 Generalization operations of skeleton buildings.

(1) Junction building

The junction buildings locate at the intersection positions of the selected strokes. For the junction buildings, their locations are quite important which determines the main structure of the corresponding hierarchy. Therefore, to keep the main structure, the junction buildings should be preserved. If the junction building is too small, it should be exaggerated after generalization.

(2) Linear building alignment

The buildings in the linear building alignment locate at the positions between two junction buildings. In this study, it requires that the alignment should contain at least three buildings. As the name implies, the linear building alignment has a straight distribution. After generalization, the linear pattern should be preserved. For this reason, typification is selected as the optimal generalization operator.

Typification is one common type of generalization operation, which reduces density and simplifies the structural pattern without destroying the overall impression of a feature group at a smaller scale. It aims at transforming the initial set of objects into a subset while keeping the certain pattern or distribution characteristics of the original set (Burghardt and Cecconi 2007). Building typification can be classified into two directions: global typification and local

typification. Global typification regards all the buildings in the region as a whole, and the typification strategies are designed for the whole area without considering the structural knowledge; thus, the local patterns may lose after global typification. Examples can be found in the researches of Sester (2005) and Burghardt (2007). On the contrary, local typification normally first detects buildings into different groups or alignments with regular patterns (linear and grid pattern), and the typification strategies mainly focus on the group so that the patterns can be well preserved. Researches of local typification can be found in the work of Anders (2006), Bildirici (2011) and Gong (2018).

In this study, the typification of linear building alignment belongs to the local typification. The selected typification strategy only removes one building in each operation to keep the gradual change in building numbers. Here the parameter is named as reduced number (*RN*).

(3) Double buildings group

The buildings of a double buildings group also locate at the position between two junction buildings, but the group only contains two buildings. For the double buildings group, the aggregation is selected as the generalization operator. Aggregation is another frequently-used operator in building generalization. Aggregation operator differs from the typification operator in that it is used to combine polygons within a certain distance of each other creating a bigger polygon that combines all the smaller ones and at the same time represents the boundary of the former small features. In this study, if the two buildings in the group are too close within the given threshold, they should be aggregated. The parameter of aggregation is distance (*D*).

(4) Individual building

The individual buildings locate normally at the terminal position of the stroke or between two junction buildings. For the individual buildings, the selective omission is selected as the operator. If the size of the individual building is smaller than the given threshold, the individual building should be eliminated. Here the parameter is set as *Minarea*.

(5) General building

For the general buildings, they are less important than the skeleton buildings, and most of them present irregular patterns. Although there are some buildings still presenting linear patterns, however, based on the centrality analysis, these linear patterns are less important than the ones related by the strokes. Therefore, aggregation is selected as the operator to generalize the general buildings, the parameter and threshold should be set the same with double buildings group.

6.7 Experiment and discussion

6.7.1 Data statement

In the experiments, the datasets are selected from the suburban and rural area of Dresden. Based on the administration partition, this region can be divided into ten different villages: Weißer

Hirsch, Bühlau, Loschwitz, Rochwitz, Gönnsdorf, Wachwitz, Pappritz, Helfenberg, Niederpoyritz and Rockau. To well conduct the proposed methods, the ten villages are redistricted into ten regions and numbered from Region 1 to Region 10 (Figure 6.14).

The test vector datasets in the experiment were downloaded from OpenStreetMap (OSM). Before forming their hierarchical skeleton structures, the original building datasets have been preprocessed by two steps. Firstly, the buildings which share the same outline were merged into one building; secondly, the small buildings whose area is smaller than the threshold (100m^2) have been deleted. Figure 6.15 displays the buildings after preprocessing. The building number of the original datasets and preprocessed datasets are listed in Table 6.3.

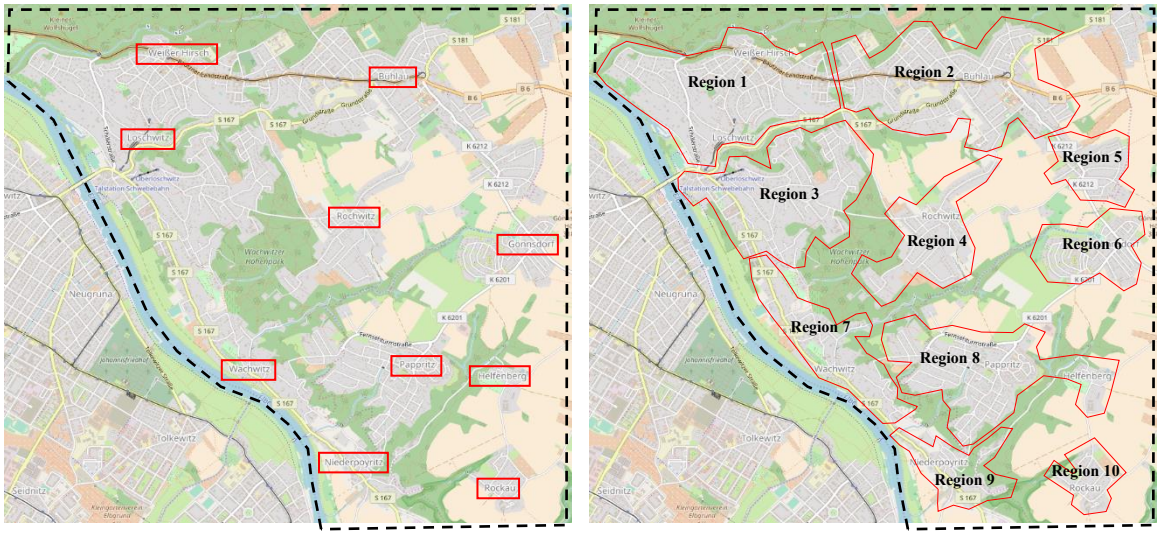


Figure 6.14 Experimental region partition. (a) Administrative villages; (b) ten test regions.

Figure 6.15 Preprocess of the test building data.

Table 6.3 Building number of original and preprocessed datasets.

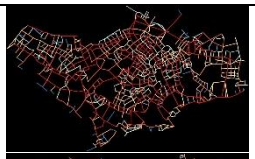
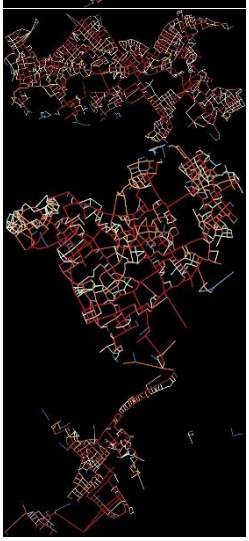
Region No.	1	2	3	4	5	6	7	8	9	10	Total
Original	951	1161	912	426	310	490	431	878	291	217	6067
Preprocessed	923	1127	846	400	274	409	393	812	252	205	5641

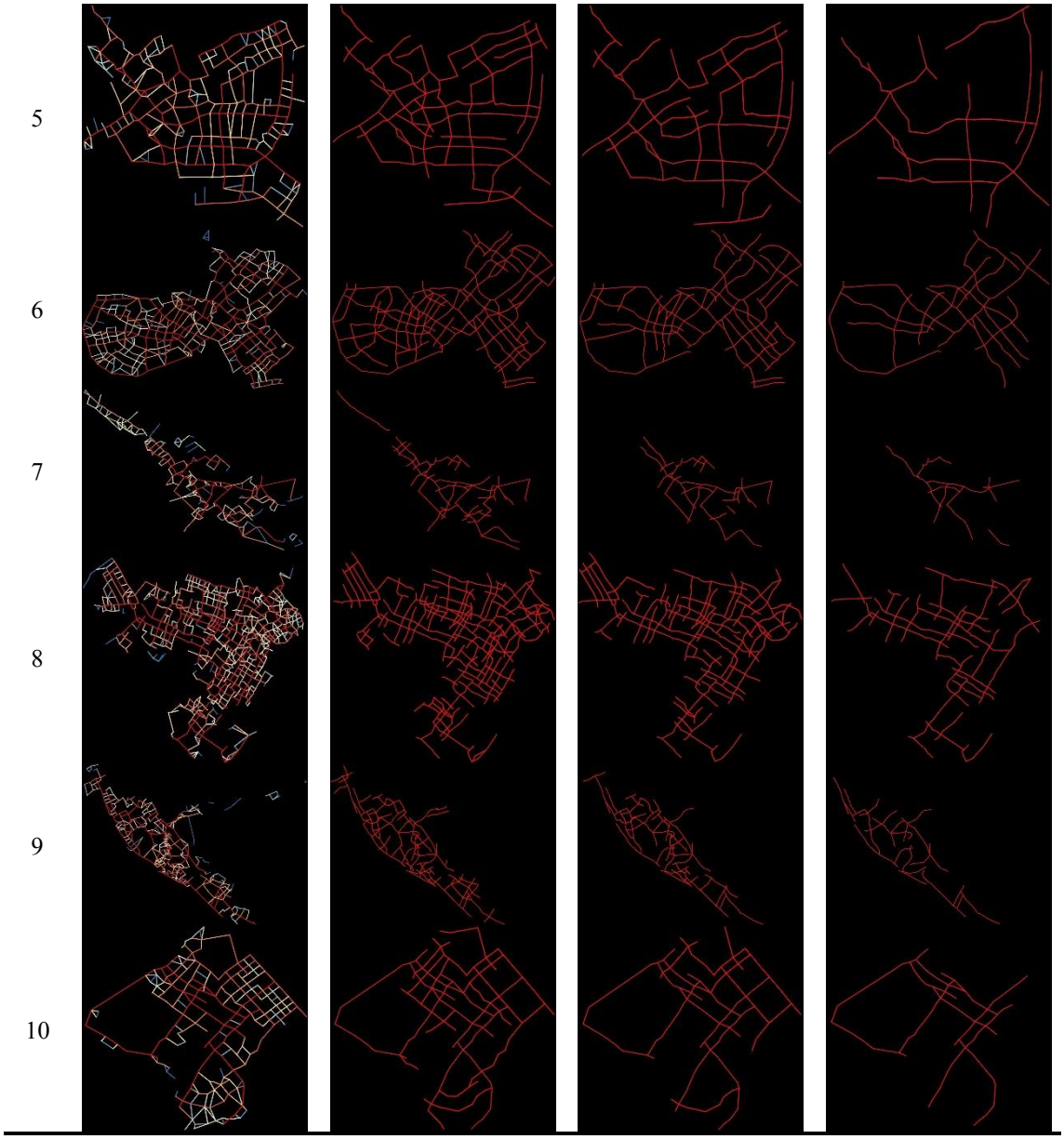
6.7.2 Experimental results

(1) Hierarchical skeleton structures

Based on the proposed methods, by forming the proximity graph and measuring the stroke with the integrated factor, the hierarchical skeleton structures were obtained. Correspondingly, the buildings related by the strokes are also organized hierarchically. Table 6.4 lists the hierarchical skeleton structures derived from the proximity graph network in the ten test regions. By observation, the hierarchical skeleton structures are more obvious below the selection rate of 0.3. From Table 6.4, the main structure of the whole region is reflected within different hierarchical skeleton structures. The extracted skeleton structures can keep the whole original structure as well as the density. When the select rate is reduced, the eliminated strokes are reasonable so that the hierarchy of the original region can be presented by the hierarchical skeleton structures.

Table 6.4 Hierarchical skeleton structures in the ten regions (Part I).

No.	Original stroke	Select rate = 0.3	Select rate = 0.2	Select rate = 0.1
1				
2				
3				
4				



(2) Generalization results

Based on the extracted hierarchical skeleton structures, the buildings are generalized by the proposed generalization strategies. For the aggregation of double buildings group, the tool of "Aggregate polygons" in ArcGIS toolbox is used. For the linear building alignments, the typification tool is created in QGIS by the authors to remove one building in each operation. Table 6.5 lists the threshold of the generalization parameters. The generalization results of Region 1 are shown in Figure 6.16. From the results, it can be found that the hierarchies help to keep the main structure of the region, and the generalization results seem reasonable.

Table 6.5 The thresholds of different generalization operators.

Hierarchy level	Aggregation	Typification	Selective omission
Select rate = 0.20	*D*=20m	*RN*=1	*Minarea*=200m^2
Select rate = 0.15	*D*=25m	*RN* =2	*Minarea* =300m^2
Select rate = 0.10	*D*=30m	*RN* =3	*Minarea* =400m^2

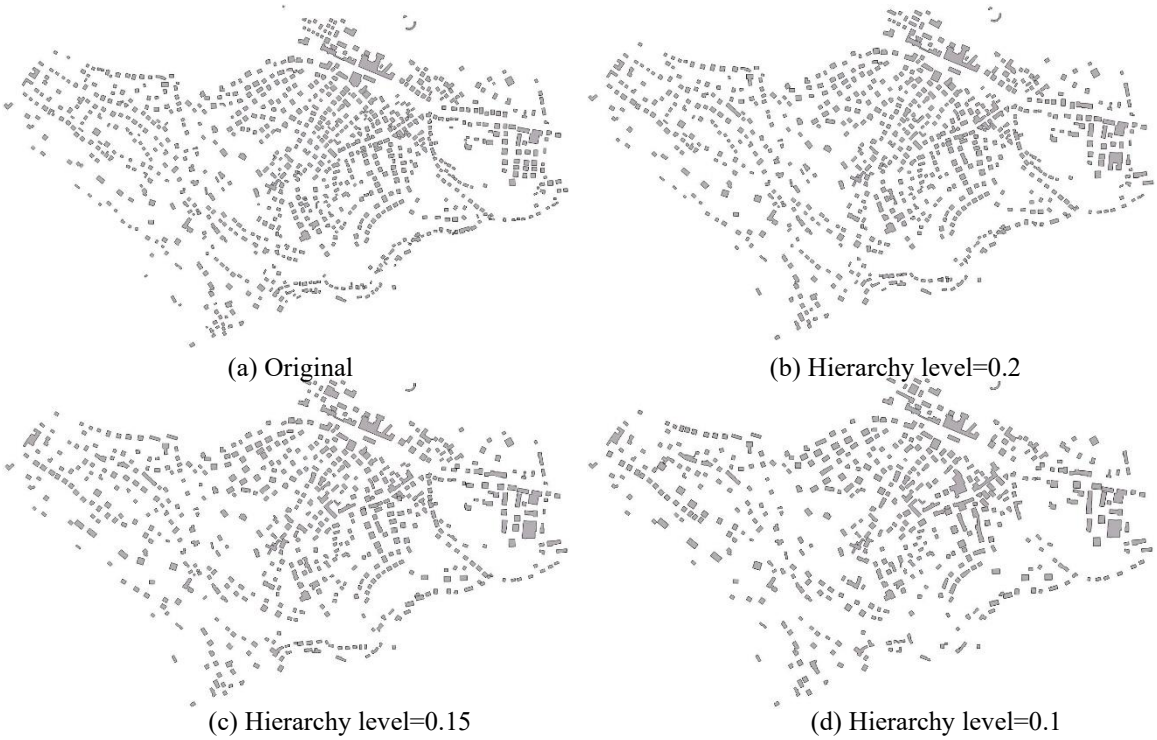


Figure 6.16 Generalization results of Region 1 within different hierarchy levels.

6.7.3 Discussion

(1) Comparison test without using hierarchical skeleton structures

To evaluate the effectiveness of the proposed methods, the aggregation operator is selected to generalize the buildings in Region 1 without using the hierarchical skeleton structures. From the generalization results of Figure 6.17, with the given aggregation distance, the buildings are excessively aggregated which creates a wide range of building blocks with exaggerated sizes. The original distributions of the building dataset have not been preserved and even disrupted by the aggregation. For example, the massive linear patterns in the original buildings are lost. By comparison, with the hierarchical skeleton structures, the buildings are generalized gradually and their original distribution characteristics can be preserved, which can provide good continuous generalization results in the multiple representations.

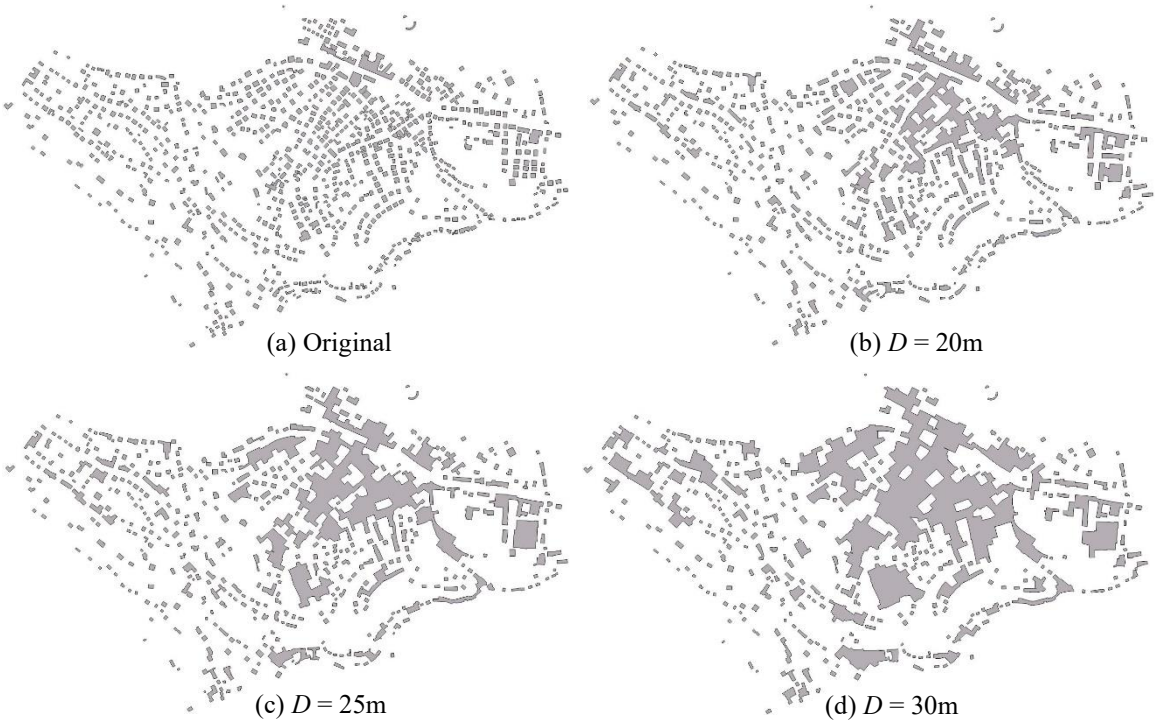


Figure 6.17 Aggregation results of Region 1 without using hierarchical skeleton.

(2) Advantages of the proposed method

The advantages of the proposed method lie in the following aspects: the main idea of the proposed method is to use hierarchical skeleton structures to control the building generalization process. As is well-known, generalization should keep the main structures of the original distributions. The hierarchical skeleton structures can catch and reveal the main framework of the building datasets. The global characteristics of the buildings can be reflected on the skeleton structures. With the extracted hierarchical skeleton structures, the original buildings are generalized into different results. The generalization results have good continuous property, which is beneficial for the multiple representations.

The generation of proximity graph network builds the mapping relationships between the network nodes and buildings. The operation to the nodes can be equivalently transferred to their corresponding buildings. The network theory and analysis methods enrich the techniques of building generalization. In the formation process of hierarchical skeleton structures, the betweenness and degree centrality indices are used, which considers both the local and global effects of the stroke. Therefore, the stroke grade is more reasonable so that the extracted hierarchical skeleton structures can reflect the main structure. The introduction of stroke idea can also preserve the local linear building patterns which largely appearing in the suburban and rural areas. Based on the above advantages, the original building distributions can be preserved in the generalization results in the global level as well as the local level.

(3) Limitations and further improvements

The formation of hierarchical skeleton structures is largely dependent on the proximity graph network, in other words, the quality of the proximity graph network largely determines the subsequent formation process of hierarchical skeleton structures. Although the facing ratio can remove the visual conflict proximal edges, there are still some edges that cannot well reflect the proximal relationships among buildings. For example, some visually distant buildings are still connected by the proximal edges. If new factors are used in the refinement, such as distance, the proximity graph may be over-refined so that the completeness and connectedness of the proximity graph network may be affected a lot. Actually, in the current refinement results, there are few buildings that are not included by the proximity graph. The hierarchical skeleton structures of the building datasets are only visually evaluated, which lack quantitative assessment. In the next step, the more objective methods should be applied to evaluate the similarities in the different hierarchical skeleton structures. The proposed method also needs to be further improved, for example, considering the road network around the buildings, optimizing the parameterization process.

6.8 Conclusions

This paper presents the idea of hierarchical skeleton structures to control the generalization process of building datasets. The hierarchical skeleton structures are formed based on the proximity graph network and centrality analysis on the stroke level. With the extracted skeleton structures, buildings are classified into different categories whereby different operators are selected to execute the generalization process. The main contribution of the proposed work lies in three aspects: (1) centrality measures are introduced into the study of building generalization; (2) hierarchical skeleton structures are formed and used as a control in the generalization process, which can preserve the global structures of the original building distributions; (3) the buildings are generalized based on different hierarchical skeleton structures; and in the generalization process, the buildings are classified into different categories, which enables the application of suitable generalization operations. For further study of the research, through the bridge of proximity graph network, more concepts and methods in network theory, network analysis, and even spatial syntax are expected to be introduced and applied in building pattern detection, building structure analysis and building generalization.

Chapter 7

Discussion

In the preceding chapters, the author presented different methods and results to detect building patterns and generalize building groups. This chapter gives an integrated discussion of the work presented in the four individual papers. First, the problems proposed in the previous Chapter 2.2.3 and Chapter 2.3.4 are recalled. Then, the strengths and limitations of the proposed methodology are evaluated.

7.1 Revisiting the research problems

(1) ***How can we summarize the terminology and typology of building patterns from the previous researches?***

We addressed this problem in Research Paper 1. The terminology and typology concerning building patterns varies in previous different researches. Some similar studies are described with different terminologies while some different research topics are named by the same words. To give a more explicit description in the study of building pattern detection, the frequently mentioned terminologies in the previous studies have been summarized and listed in this dissertation. The literal definitions of the mentioned terminologies (i.e. group, alignment, cluster, and pattern) are looked up in the professional English dictionary. The original meaning of the words helps us understand the implications of the terminologies. Based on the definitions, a relatively reasonable and complete typology of building patterns is proposed.

In the typology, the affiliation relationship of different words has been established. The dimension concept is considered to differentiate the building group into building alignment (one-dimensional group) and building cluster (two-dimensional group). Thus, the various usage of the terminology in the previous researches is clarified. Hopefully, the proposed typology can help further studies.

Building pattern is a quite complex topic. In this thesis, although a relatively complete and detailed building pattern typology has been proposed, it cannot enumerate all the possible building patterns. The author just takes the very typical building patterns into consideration. For the letter-like building patterns, such as T-like, E-like, L-like, H-like, etc., although they are also regular patterns and frequently appear on maps, the author does not include them in the typology. Because

the number of letters is quite a lot, and the specific letter shape can vary differently in detail, it is hard to find a standard to measure.

(2) ***How can we detect the building group with grid patterns?***

Grid patterns frequently appear in the buildings from the residential areas. Comparing with linear pattern, the grid pattern is more complex because of its two-dimensional characteristics. Moreover, the layout of the grid pattern is more flexible than the linear pattern. Because it is hard to form the perfect grids in the real building datasets, this study extends the grid pattern into the grid-like pattern which reveals more regular patterns in the building datasets. With the help of the proximity graph and mesh, the grid-like patterns are successfully detected from the building datasets. Mesh is a data structure formed among the building groups. If the building group belongs to the grid pattern, their meshes should also belong to the grid pattern, and vice versa. By using this idea, the grid pattern can be detected by judging the rectangular degree of their meshes.

(3) ***How can we combine the building grouping and pattern detection into an integrated process?***

Building grouping and building pattern detection are two separate processes. In Research Paper 1, the dimension of the building groups is firstly discussed. The conclusion is obtained that building alignment and building cluster belong to one-dimensional (linear) and two-dimensional (areal) building group, respectively. Then, the stroke and mesh are used as the tool to recognize the linear and grid building patterns. The stroke belongs to linear feature while mesh belongs to the areal feature, thus, very naturally, their related building groups should belong to the linear pattern and grid pattern. Based on this strategy, it can combine the building grouping and pattern detecting process together.

(4) ***How can we typify linear building groups based on the shape?***

Linear patterns have two specific forms, i.e. collinear and curvilinear. The previous study of linear pattern typification did not consider these two specific forms. In Research Paper 2, the typification of linear building groups considers the shape characteristics, which obtains more satisfying results. Through extracting the stroke from the linear building group, the shape of the original linear pattern can be well reflected by its related stroke. The analogy between line simplification and linear building pattern typification reduces the difficulty in the building group generalization. The line feature can better display the straightness and tortuosity of the original building group. Therefore, the collinear and curvilinear patterns can be well distinguished in the process of typification. Different strategies have been adopted in the determination of the newly created buildings: for the collinear pattern, the importance is to keep the orientation homogeneity of each building, by comparison, for the curvilinear pattern, preserving the integrated orientation homogeneity of the curvilinear patterns is more crucial. Based on the two solutions, the linear building group can achieve satisfying typification results considering their original shapes.

(5) ***How can we generalize building groups with grid patterns?***

As the representative research of *m*:*n* objects generalization, the generalization of grid pattern needs to meet two rules that reducing the number of buildings while preserving the original grid shape in the generalized buildings. Like linear patterns, this objective is just what the typification operator can solve. Thus, the author considers that typification is an appropriate operator to generalize building groups with grid patterns. The difficulty of typifying grid patterns lies in that the determination of the typified building number while preserving the original grid-like distribution. To solve this problem, the mesh is used as the bridge to balance the two requirements. The original grid patterns can be regarded as a "matrix" with a specific $m \times n$ formation. Mesh is derived from the grid buildings and it is located in the central position of the grid pattern, which can reduce the dimension of the "matrix" and still keep it as a "matrix". Based on this strategy, the typification of the grid-like pattern is achieved. After the typification, the typified buildings are still presented as a grid-like pattern while the building number is reduced. The specific distribution characteristics of different grid-like patterns can be also transferred and reflected by the newly created buildings.

7.2 Evaluation of the presented methodology

In the following paragraphs, the strengths and limitations of the proposed methodology for building pattern detection and building group generalization are examined.

7.2.1 Strengths

(1) Building pattern detection

The previous studies often treated building grouping and pattern detection as separate parts, which potentially results in that the patterns expected to be identified may be disrupted by the grouping process. In this thesis, the proposed stroke and mesh strategy combines the building grouping and pattern detection, which ensures the completeness of the patterns expected to be identified. In the proposed approaches, stroke and mesh are used to group buildings into building alignments and building clusters, respectively, which will not disrupt the original patterns. Strokes and meshes have the natural ability to form building alignments and building clusters. In essence, stroke belongs to the linear entity (one-dimensional) and mesh is an areal entity (two-dimensional). Because strokes are linear objects, the buildings grouped by the stroke are naturally and inevitably presented as the linear pattern. Similarly, meshes are grouped into clusters so that their related buildings are also grouped into clusters. With the help of mesh clusters, the issue of recognizing the grid pattern in buildings is transformed into recognizing the grid pattern in the network. This transformation simplifies the original issue and reduces the difficulty. The six-constraints refinement strategy makes the grouping process more controllable. In different datasets and

generalization requirements, there are different situations in the grouping process. The six constraints provide more possibilities and flexibility.

(2) Building typification

Typification belongs to *m*:*n* generalization problem. The difficulty of building typification lies in how to create a general rule to determine the remaining number of newly typified buildings, as well as keeping the original patterns. We have to face the problems of reorganizing the newly typified buildings, and well keep the balance between the number, position, and representation.

- Number

For the typification of linear building patterns, the method only removes one building in each typification process, which makes the building number reducing progressively so that the buildings are gradually generalized. For the typification of grid building patterns, the number of remained buildings is determined by their related meshes. Specifically, the number of newly typified buildings is equal to the number of meshes. Because the meshes are derived from the building group, the number reduces mildly. For a similar original number of buildings, the reducing rate of building number remains consistent, which demonstrates that the proposed mesh-based typification method performs steadily in different building groups.

- Position

For the typification of linear building patterns, the positions of the newly created buildings are determined by the nodes of simplified stroke. The proposed simplification method of stroke can preserve the original curve characteristics as well as guarantee the new nodes are evenly distributed. For the typification of grid building patterns, the positions of the newly created buildings are determined by their related mesh. The mesh is located within the original building groups so that the typified buildings can keep their similar original locations.

- Representation

The geometric characteristic (i.e. size, shape and elongation, orientation) of the newly typified buildings are calculated from their original surrounded buildings. Therefore, local geometry information can be inherited. This can keep the typified buildings meeting the visual consistency. Moreover, the mesh-based typification method preserves the global characteristics of the building group as well as the local details, such as the local convex and concave characteristics and the difference between the number of rows and columns in grid patterns. Not only the grid patterns but also some special local characteristics of the original patterns can be preserved and reflected on the newly typified buildings, which keeps the visual consistency.

- Iterative typification process

Both the typification methods for linear and grid patterns are modeled as an iterative process, which creates progressive typification results. With several iterative typification processes, the

hierarchical typification results of the building groups can be obtained, which is useful for continuous generalization. With the scale reducing, the hierarchical typification results can give supports to the mapmakers when generalizing building groups on maps. The hierarchical typification results can also avoid large and sudden changes in the generalized maps, thereby improving the quality of the multiple representations.

(3) Hierarchical skeleton structures of buildings

As well-known, generalization should keep the main structures of the original distributions. The extracted hierarchical skeleton structures can be used to preserve the global distribution the same as the original ones. The hierarchical skeleton structures can catch and reveal the main framework of the building datasets. The global characteristics of the buildings can be reflected on the skeleton structures. With the extracted hierarchical skeleton structures, the original buildings are generalized into different results. The generalization results have good continuous property, which is beneficial for the multiple representations.

In the formation process of hierarchical skeleton structures, the betweenness and degree centrality indices are used, which considers both the local and global effects of the stroke. Therefore, the stroke grade is more reasonable so that the extracted hierarchical skeleton structures can reflect the main structure of the region. The introduction of the stroke idea can also preserve the local linear building patterns which largely appearing in the suburban and rural areas.

7.2.2 Limitations

The limitation of the proposed methods mainly lies in the following aspects, correspondingly, the potential future works are also given hope to solve or improve these limitations.

(1) As mentioned in Chapter 3.7.2, building patterns have the ambiguity property, the same building presentation can be detected as different patterns in different standards. Therefore, it is not suitable to give a single answer to a building group. In further steps, the fuzzy patterns can be proposed which aims at just recognizing the regular and irregular patterns.

(2) In the proposed pattern detection methods, there are many parameters that should be specified before executing the process. The given values of the parameters largely affect the results. Only appropriate values can achieve satisfying results, and the values are normally obtained by trial and error, which reduces the efficiency of the methods. Future work will focus on automatically calibrate the parameter and threshold values involved in the proposed methods.

(3) The proposed typification methods consider less about the contextual information, which may cause conflicts between the newly typified buildings and other features, such as other non-typified buildings and roads. Thus, the improvements of the current typification methods could focus on the development of algorithms that can consider the interchanges with other feature

classes. The future work could also be done on the collaborative generalization with other operators, such as aggregation, displacement.

(4) The results of the pattern detection and building typification are only visually evaluated, which lack of quantitative evaluation. More evaluation indicators should be created to measure the effectiveness of the given methods. The evaluation could be done by the experts in cartography with the context of zoomable web maps.

(5) The extracted hierarchical skeleton structures have the defection on building type. It only validates on the discrete buildings in suburban or rural areas. For the buildings in the city center, because of their dense and connected distribution, it cannot extract the satisfying hierarchical skeleton structures based on the proposed method. For future work, the corresponding theories and algorithms in Graph theory and network analysis can be introduced to the study of building hierarchy researches.

(6) Future works should also be carried out on the buildings with irregular patterns, for their generalization, the algorithms for operators like aggregation, simplification can be developed.

(7) This thesis only provides the methods and algorithms about how to recognize and generalize the building groups with special patterns, however, it does not provide the specific application situations. For example, it does not provide in which specific scale that the special building patterns should be preserved. Therefore, in the future work, the study should focus on the scale issue, such as the study of pattern preservation in the transitions between scales and continuous zooming.

Chapter 8

Conclusions

This thesis presents researches about automated detection and generalization of building patterns. In this concluding chapter, the author highlights the main contributions of the thesis and gives an outlook on the further research directions.

8.1 Main contributions

Building patterns are important local characteristics so that in the process of building generalization, the building patterns should be carefully generalized. In this dissertation, the author proposes a framework that can automatically detect building patterns from building datasets, and develops the corresponding operator (typification) for the generalization of the building groups with special patterns. With the help of different data structures, such as proximity graph, stroke, network mesh, etc., the building patterns are detected from the building datasets. By proposing the stroke- simplification-based and mesh-based idea, the building groups with the detected linear and grid patterns are generalized by the new typification methods. The dissertation also proposes method for extracting the hierarchical skeleton structures, which can consider the global distribution of the buildings in the process of generalization. The main contribution of this dissertation lies in the following five aspects:

(1) A detailed and complete typology of building patterns is proposed. In the previous work, several researchers have given their typologies of building patterns, which has overlap and difference parts. This makes the pattern typology more complex than it is to be. By referring to the existing typologies and analyzing the definition of the terminologies, the typology of building patterns is extended and completed. The typology is more complete which includes almost all the types of building patterns, especially linear and grid patterns. The proposal of the typology gives a standard to detect different building patterns, which have the benefits for the subsequent generalization process.

(2) The building patterns are detected based on stroke and mesh data structure, which is derived from the proximity graph of the buildings. The proximity graph is refined by six constraints which can make the grouping process more controllable. The stroke and mesh-based methods can combine the grouping and detecting process together. The buildings related by the

stroke and mesh are naturally detected as building alignments (linear pattern) and building clusters (grid pattern).

(3) A stroke simplification based typification method is proposed to generalize the building groups with linear patterns. In this method, the analogy between the typification of linear buildings and line feature simplification has been made, which gives a new strategy for building typification. With the line simplification idea, the stroke is regarded as an auxiliary structure for building typification. By simplifying the stroke, the remained and new positioned nodes of the stork are regarded as the new centroid positions of the typified buildings. The new representations of the typified buildings are also reasonably calculated.

(4) Mesh-based typification method is developed to generalize building groups with grid patterns. The typification of grid patterns can be regarded as a *m*:*n* problem, which has to decide the new distribution of the newly typified buildings. With the help of mesh derived from buildings, the original grid pattern can be kept in the newly typified buildings with the building number reducing.

(5) The hierarchical skeleton structures of the buildings are extracted. The hierarchical skeleton structures can represent the global pattern of the building dataset. In the generalization process, the buildings within the skeleton structures are largely preserved by enhancing their patterns, which preserves the main structure of the original area.

The corresponding experiments were designed and conducted to validate the effectiveness of the above-proposed methods. The experiments achieved reasonable and satisfying results.

8.2 Outlook

(1) Deep learning methods with building pattern detection and generalization

Whereas lots of algorithms have been developed for different sub-problems of map generalization, and some existing generalization models can already perform very well on individual buildings, there are still cases, which are not generalized adequately or in a satisfying way, for example, the interplay between different operators, the generalization of blocks or building groups, the generalization of a complete map with all features, etc. As mentioned the limitations of the presented typification methodology, the results of building typification may have conflicts with the non-typified buildings or other features, such as road networks. If the building generalization process could be considered within a holistic way, the generalization processes would perform better.

Therefore, new techniques, particularly, deep learning methods, are expected to be introduced into the research field of building pattern detection and generalization. In recent years, with the advancements in computing power and the advent of the big-data ear, deep learning methods have achieved great improvements and have been applied to many research fields. Deep learning

methods have shown impressive success for interpretation problems while algorithmic methods are difficult (Feng et al., 2019). Currently, only a few studies have been done by deep learning methods in the research fields of map generalization. Touya et al. (2019) discussed the usage possibility of deep learning in cartographic generalization. For applications, Feng et al. (2019) employed deep convolutional neural networks (specifically, three network architectures, U-net, residual U-net, and generative adversarial network) for building generalization.

There are also many challenges to overcome by introducing deep learning methods into map generalization, for instance, the current deep learning networks are designed mainly for images (raster datasets), and building generalization is mostly implemented with vector datasets. Hopefully, the deep learning methods could be the new agent to make the generalization research bridge the gap to fully automated generalization processes.

For the detection of building patterns, deep learning methods could also be helpful to further improve the performance. As far as the author's knowledge, currently, there is only one study about using deep learning methods to detect building patterns. A novel graph convolution neural network was proposed by Yan et al. (2019) for the classification of building patterns. By considering the ambiguity characteristic of building patterns, a deep learning method could be a better solution to detect the ambiguity features because of their strong ability in fuzzy recognition. Thus, deep learning methods could be a good way to enhance the research field of data enrichment.

(2) Semantic grouping and pattern detection in the central area

In this thesis, the proposed detection methods of building patterns only consider geometry information of buildings, namely, in the grouping process, only geometric indices, such as size, shape, orientation, etc., are used to measure whether buildings should be grouped. However, in the generalization process, semantic information is also important. Thus, in the further study, the semantic information of the buildings should also be considered in the detection process. On the other hand, in this study, the attention has been mainly paid on the building patterns which have regular distribution. These patterns are normally located in suburban or rural areas where the building density is normally lower than city center. For the buildings in the city center, they normally present in the city blocks so that they have very dense distribution, which results in that the building patterns are quite different in the central area of a city. How to detect these patterns and give a reasonable typology should be further studied. Moreover, after the pattern detection, which generalization strategy and operations should be executed to these patterns is also a study issue.

(3) Application in urban studies

The domains of urban and regional planning, land management and urban studies require detailed information about the functional, morphological and socio-economic structure of the

built environment (Hecht et al., 2015). For example, urban morphology studies the form of human settlement areas and the process of their formation and transformation. It seeks to understand the spatial structure and character of a metropolitan area, city, town or village by examining the patterns. Urban modeling aims at understanding the development of urban structures including the understanding of physical and socio-economic distributions for purposes of socio-economic analysis and urban planning.

Among the above urban research fields, buildings play an important role because they determine the physical structure of a region; thus, building patterns are strongly related to urban studies. The discovered building patterns correspond to natural, social and ecological implications, and interpretations. When the properties of the building patterns are analyzed, their implications can be found. Building patterns are also crucial components of urban functions that can be used to evaluate landscape configuration and estimate the urban population. Therefore, the proposed methodologies about building patterns could be extended and applied to a wide range of urban studies and applications, such as urban morphology and urban modeling. For instance, how to extract and interpret the social functions and regionalization from building patterns can be investigated. Based on the extracted urban function information, many social and economic variables can be revealed, for example, people live in residential buildings, and work in industrial and commercial buildings. And the population estimation results in urban areas can benefit for the urban planning and building construction in turn.

(4) Continuous generalization and real-time processing

With the development of web mapping and big geo-data, the goals and methods of map generalization have been changed. The mode of map services should support interactive zooming in and out to arbitrary scales, which asks the cartographic generalization of foreground data has to be achieved in real-time, requiring flexible and on-the-fly generalization algorithms. The pre-generalized datasets cannot meet the requirements of real-time processing, because there are transitional jumps from one scale to the next. Therefore, continuous generalization using hierarchical schemes are required to minimize the discrepancy when the scale is changing. Continuous generalization aims to generate smooth and continuous geographic information at arbitrary scales. Although serval studies have been carried out on continuous generalization, it is still needed to improve the quality of continuous generalization and real-time processing. In this thesis, although the progressive typification results of building groups with linear and grid patterns have been achieved, there still needs to study their representation issue within different scales to give support to continuous generalization.

8.3 Final thoughts

“纸上得来终觉浅，绝知此事要躬行”

—陆游

“What's learned from books is superficial after all.
It's crucial to have it personally tested somehow.” (by Lu You)

This thesis focuses on the topic of building pattern detection and generalization, which is not a very new and hot topic in the current study environment. The ultimate goal, fully automated map generalization, is still at the heart of the cartographers and is still chased from generation to generation. Through the study of this classic cartographic topic, the author hopes that this thesis brings forward the understanding of map generalization and is a contribution to cartography and geo-information science.

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Publications

The list displays the author's publications and unpublished works during his Ph.D. study in TU Dresden until October 2019.

1. Wang, X. and Burghardt, D. (2017): A Stroke-based Approach to Detect Building Pattern for Generalization Purposes. *20th ICA Workshop on Generalisation and Multiple Representation*, 2017, Washington, US. https://generalisation.icaci.org/prevevents/workshop2017program.html

2. Wang, X. and Burghardt, D. (2018): A Generalization Strategy for Discrete Area Feature by Using Stroke Grouping and Polarization Transportation Selection, *Proceedings of 28th International Cartographic Conference*, Washington, US. 1, 122. https://doi.org/10.5194/ica-proc-1-122-2018

3. Wang, X. and Burghardt, D. (2019): Using stroke and mesh to recognize building group patterns, *International Journal of Cartography*. https://doi.org/10.1080/23729333.2019.1574371

4. Wang, X. and Burghardt, D. (2019): A Mesh-Based Typification Method for Building Groups with Grid Patterns. *ISPRS International Journal of GeoInformation Science*, 2019, 8(4), 168. https://doi.org/10.3390/ijgi8040168

5. Wang, X. and Burghardt, D. (2019): Building-network: Concept, generation method and centrality analysis. *Proceedings of 29th International Cartographic Conference*, Tokyo, Japan. 2, 141. https://doi.org/10.5194/ica-proc-2-141-2019

6. Wang, X. and Burghardt, D. (2019): A typification method for linear building groups based on stroke simplification. *Geocarto International*. https://doi.org/10.1080/10106049.2019.1669725

7. Wang, X. and Burghardt, D. (Submitted): Hierarchical extraction of skeleton structures from discrete buildings. *The cartographic Journal*.