

## A Structural Approach to the Model Generalisation of an Urban Street Network

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**Abstract.** This paper proposes a novel generalisation model for selecting characteristic streets in an urban street network. This model retains the central structure of a street network. It relies on a structural representation of a street network using graph principles where vertices represent named streets and links represent street intersections. Based on this representation, so-called connectivity graph, centrality measures are introduced to qualify the status of each individual vertex within the graph. We show that these measures can be used for characterizing the structural properties of an urban street network, and for the selection of important streets. The proposed approach is validated by a case study applied to a middle-sized Swedish city.

**Keywords :** model generalisation, structural analysis, space syntax, graph modelling, urban modelling

### 1. Introduction

Within Geographic Information Systems (GIS), two types of generalisation have been developed over the past years, namely cartographical and model-based generalisations (Muller et al. 1995). Cartographical generalisation can be defined as a geometrical simplification in a scale reduction process while model generalisation is mainly oriented to a structural-based filtering (Weibel 1995). These two generalisation approaches are closely related, often model generalisation being a pre-process of cartographic generalisation.

Cartographic generalisation is a constraint-based process used by cartographers to reduce the complexity of a map in a scale reduction process. It involves intensive human knowledge obtained through professional cartographic expertise and practise. Since the seminal Douglas-Peucker algorithm for line simplification (Douglas and Peucker 1973), automatic generalisation has long been a research effort by both scientific researchers and cartographic practitioners (Buttenfield and McMaster 1991, Muller et al. 1995, AGENT 1998). In particular the idea of one single master database used to automatically derive maps at different scales has been a dilemma faced by many national mapping agencies. Graph-based approaches have been investigated for linear object generalisation such as street and hydrological networks where the objective is to reduce the complexity of a network in a scale reduction process while retaining its general structure. Mackaness and Beard (1993) discussed

the potential of graph theory principles for derivation of information at the topological level to support generalisation of linear objects. They applied weighted graph, directed graph, and minimum spanning trees in the description of street and drainage networks, and derived some preliminary rules for generalisation process. In particular, Mackaness and Machechnie (1999) developed an algorithm for the generalization of road junctions using some graph theory principles. Thomson and Richardson (1995) used the concept of minimum spanning trees in road network generalisation. A three-step approach to automated road networks has been proposed (Krevelde and Peschier, 1998) by considering basic geometric, topological and semantic requirements in the generalization of road networks.

Although the generalisation of an urban street network is often applied as a cartographical task, it can be also considered as an operation where the objective is to understand the structure, function and organisation of the city. Model-based generalisation is of interest for many application areas as a street network can be considered as a structuring element for many other cartographic objects (e.g. built environment, electricity and gas networks) and socio-economical activities in the city. This is an important aim of many urban studies that focus on the understanding of urban structures and configurations. Amongst many domains of research and study, space syntax (Hillier and Hanson 1984) has developed graph-based measures to analyse and understand the complexity of urban street networks. These principles support the belief that spatial layout or structure has great impact on human social activities. The application of space syntax covers many urban studies such as modelling pedestrian movement, vehicle flows, crime mapping, and human wayfinding process in complex built environments (Penn 1993, Hillier 1996). Many empirical studies have demonstrated the interest of the space syntax for modelling and understanding of urban patterns and structures (Hillier 1997, Holanda 1999, Peponis et al. 2001).

Cartographical and model-based generalisations are often considered independently although a combined approach might be beneficial to both cartographers and urban planners. In particular, model-based generalisations can provide a complementary view of the structure and patterns of the city to a cartographer involved in cartographical-based generalisation task. Also, there is still a need for an exploration of model-based generalisation algorithms that retain the main structural properties of an urban network while combining functional and geometrical views. This paper proposes a model generalisation approach, based on a computational application of graph modelling principles, whose objective is to retain the main characteristic elements of a given urban street network. On the one hand, this should help to observe and analyse the functional structure of the city. On the other hand, the approach can also be used as a preliminary and exploratory process prior to a cartographical generalisation process. The modelling approach (Jiang and Claramunt 2003) uses vertices to represent named streets and edges to represent street intersections, so a dual representation of a given street network. Integrating named streets (e.g. Kennedy avenue, 45th avenue) as a basic modelling unit gives a form of functional representation of the city that complements the structural view of the urban street network given by the graph-based approach (let us remark that this approach applies to cities where streets are labelled using either names or identifiers). This functional component comes from the observed fact that named streets often denote a logical flow unit or commercial environment that is often perceived as a whole by people acting in the city. The computational process is based on the application of three centrality measures derived from graph theory principles. Those support a structural qualification of each vertex in the graph at local and global levels. Selection of characteristic streets can be progressively and recursively achieved through a filtering algorithm based on these structural

measures. The proposed approach is validated with a case study applied to a middle-sized Swedish city.

The remainder of this paper is organised as follows. Section 2 briefly introduces graph theory principles and measures relevant to the context of our work. Section 3 describes the structural representation of a street network and related measures. Section 4 develops the principles of the selection algorithms and illustrates their application to a case study. Section 5 reviews related work on the application of graph-based methods for the model generalization of street networks. Finally section 6 draws some conclusions.

## 2. Graph theory principles

Before develop a structural representation of a street network, let us first introduce some basic graph concepts (cf. Gross and Yellen 1999 for an example of comprehensive introduction on graph theory). A *graph*  $G(V,E)$  is defined as a pair of a finite set of vertices  $V = \{v_1, v_2, \dots, v_n\}$  and a finite set of edges  $E = \{v_i v_j\}$  (note that in this paper we use the terms vertices and nodes, and edges and links interchangeably). For computational purposes we represent a connected, undirected and unweighted (i.e. all links with a unit distance) graph by an adjacency matrix  $R(G)$  as follows

$$R(G) = [r_{ij}]_{n \times n} \quad \text{where } r_{ij} = \begin{cases} 1 & \text{if } v_i v_j \in E \\ 0 & \text{otherwise} \end{cases} \quad [1]$$

It should be noted that an adjacency matrix  $R(G)$  is symmetric, i.e.  $\forall r_{ij} \Rightarrow r_{ij} = r_{ji}$ . Also all diagonal elements of  $R(G)$  are equal to zero thus either the lower or upper triangular matrix of  $R(G)$  are sufficient for a complete description of the graph  $G$ .

A graph  $H$  is denoted as a subgraph of a graph  $G$  if the vertices of  $H$  give a subset of the vertices of  $G$ . Conversely, if  $H$  is a subgraph of  $G$ , we say that  $G$  is a supergraph of  $H$ . For a vertex subset  $U$  of a given graph  $G$ , a subgraph whose vertices belong to  $U$  is said to be *induced* on the vertex subset  $U$ . Any two adjacent vertices  $v_i, v_j$  of  $G$  (i.e.,  $v_i, v_j \in E$ ) are said to be neighbours. The *neighbourhood* of a vertex  $v_i$  of a graph  $G$ , denoted  $N_G(v_i)$ , is the subgraph induced by the set of vertices consisting of  $v_i$  and all its neighbours, i.e.,  $N_G(v_i) = \{v_j \mid v_i v_j \in E, i \neq j\}$ .

First developed in the field of social network study (Freeman 1979), centrality measures support the description of a node status within a graph. The degree centrality, also called connectivity, measures the number of nodes that interconnect a given node. In a graph, the degree is the number of nodes that link a given node. Formally the degree centrality for a given node  $v_i$  is defined by:

$$C_D(v_i) = \sum_{k=1}^n r(v_i, v_k) \quad [2]$$

where  $n$  is the total number of vertices of the graph  $G$ .

Closeness centrality measures the smallest number of links from a node to all other nodes. In a graph, it is the shortest distance from a given node to all other nodes. It is defined by:

$$C_C(v_i) = \frac{n-1}{\sum_{k=1}^n d(v_i, v_k)}, \quad [3]$$

where  $d(v_i, v_k)$  is the shortest distance between nodes  $v_i$  and  $v_k$ .

It should be noted that closeness centrality is also called status in graph theory (Buckley and Harary 1990), and integration in space syntax (Hillier and Hanson 1984). It is the reciprocal of the average path length, another term often used in small-world networks (Watts and Strogatz 1998).

Betweenness centrality measures to what extent a node is located in between the paths that connect pairs of nodes. In a graph, it reflects the intermediary location of a node along indirect relationships linking other nodes. Formally it is defined by:

$$C_B(v_i) = \sum_{j=1}^n \sum_{k=1}^{j-1} \frac{p_{ikj}}{p_{ij}}, \quad [4]$$

where  $p_{ij}$  is the number of shortest paths from  $i$  to  $j$ , and  $p_{ikj}$  is the number of shortest paths from  $i$  to  $j$  that pass through  $k$ , so  $\frac{p_{ikj}}{p_{ij}}$  is the proportion of shortest paths from  $i$  to  $j$  that pass through  $k$ .

These centrality measures describe a node status from a graph and topological perspective. We can remark that the degree value reflects the topological relationship between a node and its immediate neighbouring node(s), while closeness exhibits a structural relationship between a node and all other nodes. They can be characterized as local and global measures respectively. Note that a node with high connectivity does not guarantee that it is well connected to all other nodes. Also a node with few direct connections does not mean that it is less important, since it can play a 'bridge' role, which means that without it a network may be broken into two sub-graphs. This property is controlled by betweenness.

### 3. Structural representation of street networks

A street network has its own intrinsic logical and spatial structures that must be represented and retained in generalisation process. As previously mentioned we represent a street network using a graph where named streets are represented as vertices and street intersections as links of the graph (note that a named street is not a street segment but the entire named street as a basic modelling unit). One can remark that any graph derived using such an approach is connected, i.e., one can reach every vertex of the graph from every other vertex.

To illustrate this approach, let us consider the example of a district of the Swedish city Gävle as shown in figure 1. To the left of the figure is the street network of the district Sättra; while to the right is the corresponding connectivity graph. One can remark that this district is a relatively closed one: a bell-shaped street Sättrahöjden constitutes a form of boundary, and it is internally connected by two streets (Norrbägen, Nyöstervägen) that form an internal

communication link. These three main streets form the main structure of this district to which other short streets are connected.

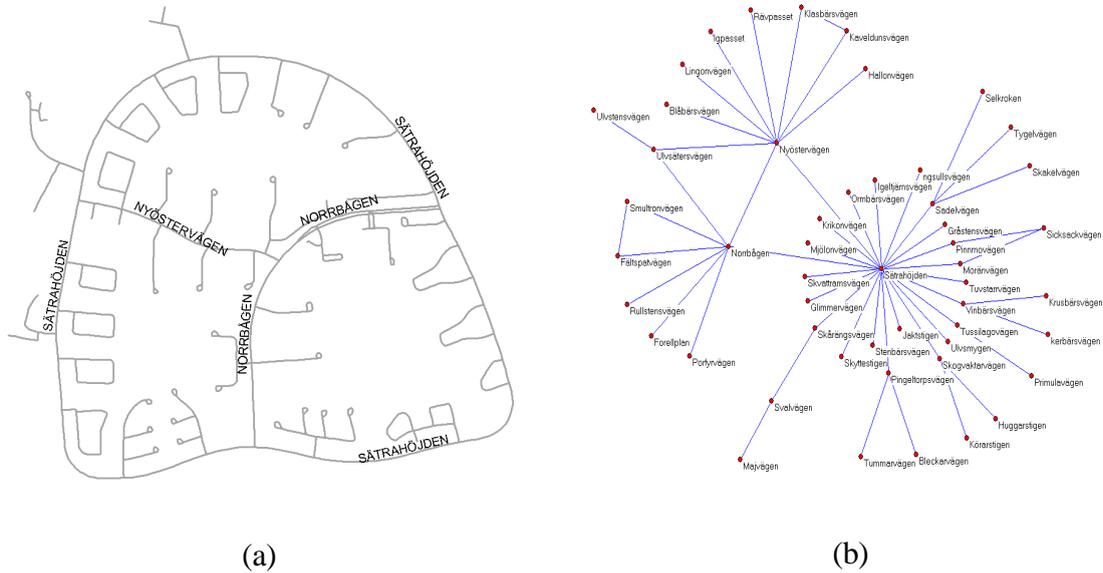


Figure 1: Sättra district network (a) and its connectivity graph (b)  
(Note: every vertex is labeled by the corresponding street name)

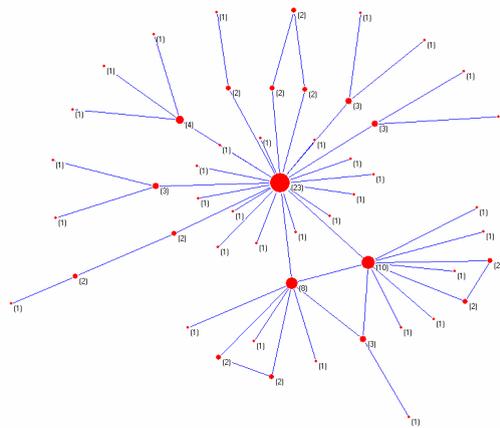
Centrality measures help to analyse the local and global structural patterns of a given network. Table 1 presents a sample of 10 streets (in reverse order of degree) that are relatively well connected thanks to their high values of connectivity among totally 51 named streets of Sättra district. Figure 1 and table 1 show that most streets have a small number of connectivity, while only a few have very high connectivity. We can remark that less connected streets are less important than those well connected from a structural point of view. Figure 2a illustrates degree centralities for the Sättra district network where the node (i.e. named street) sizes increase with degree centrality measures.

Closeness centrality reflects how far a given street to every other is. This gives a sense to what extent a street is integrated or segregated to other streets. The higher the value of closeness centrality for a given street, the more integrated this street is (Figure 2b). For example, we can observe that the street Sättrahöjden is better integrated to the other streets than the street Nyöstervägen. This illustrates the fact that the connectivity structure of the graph should be an important criterion to consider in deriving a series of subgraphs whose objective is to retain the main structure of the initial graph. For instance, the street Sättrahöjden should have a higher possibility than the street Nyöstervägen to be kept during a model-based generalisation process, as it is better integrated to other streets, and also better connected to the other neighbouring streets.

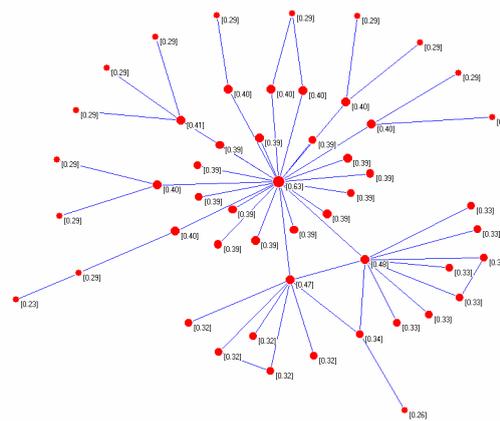
Finally, the betweenness centrality evaluates to what extent a given street is part of the shortest paths that connect any two other streets. For instance, the street Sättrahöjden has the highest value of betweenness which is represented as the largest node in figure 2c. Note the size in figure 2 is not comparable between the three centralities.

Table 1: Centralities for the streets of Sättra district (part)

Street name	Degree	Closeness	Betweenness
Sättrahöjden	23	0.6329	0.8845
Nyöstervägen	10	0.4808	0.2906
Norrbågen	8	0.4717	0.2196
Sadelvägen	4	0.4098	0.1176
Pingeltorpsvägen	3	0.4032	0.0792
Skogvaktarvägen	3	0.4032	0.0792
Ulvsättersvägen	3	0.3448	0.0400
Vinbärsvägen	3	0.4032	0.0792
Fältspatvägen	2	0.3247	0.0000
Kaveldunsvägen	2	0.3289	0.0000



(a)



(b)

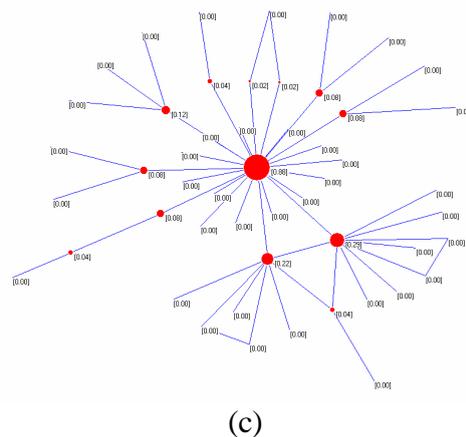


Figure 2: Visualization of degree (a), closeness (b) betweenness (c) centralities for streets of Sättra district (every node is labelled by the corresponding street centralities)

The above example illustrates how *degree centrality* gives a sense of each street's integration with respect to its neighbouring streets, how the *closeness centrality* reflects the way a street is integrated to all other streets, and how the *betweenness centrality* shows a bridge role of a street between other streets. Overall a relevant structural approach to the model generalization of an urban street network should keep streets that have higher value of centralities. This is related to the fact that streets of higher centralities tend to be more important from a structural point of view, e.g. they tend to attract more pedestrian flows in urban systems (Hillier 1996).

#### 4. Case study: Centralities and hierarchical-based selection of characteristic streets

In order to illustrate how our approach can be used for analysis of urban street networks and model-based generalisation process, we conducted a case study applied to a city network of Gävle, Sweden. This network involves 565 named streets, so 565 nodes in the connectivity graph (figure 3). It is composed of street central lines topologically interconnected, i.e. no isolated streets. The case study is based on an implementation that combines the capabilities of a GIS-based package with those of network analysis software. An Avenue script of the ArcView GIS transforms the street network to the connectivity graph. The connectivity graph is further imported into a network analysis software package Pajek (Batagelj and Mrvar 1997) for computation of centrality measures. The computing results are assigned to corresponding streets in ArcView for presentation purpose.

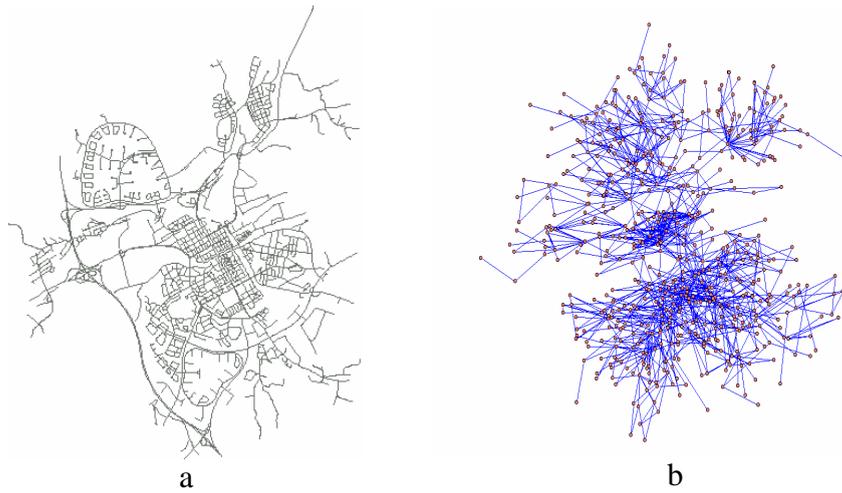


Figure 3: Gävle street network (a), and its connectivity graph (b)

#### 4.1 Structure of an urban street network

Based on the connectivity graph, three centrality measures have been computed and mapped as shown in figure 4, where dark grey shows high value of centralities and light grey shows low value of centralities. One can remark that the distribution reflects the different roles of a street within the network in terms of connectivity, closeness and betweenness centralities.

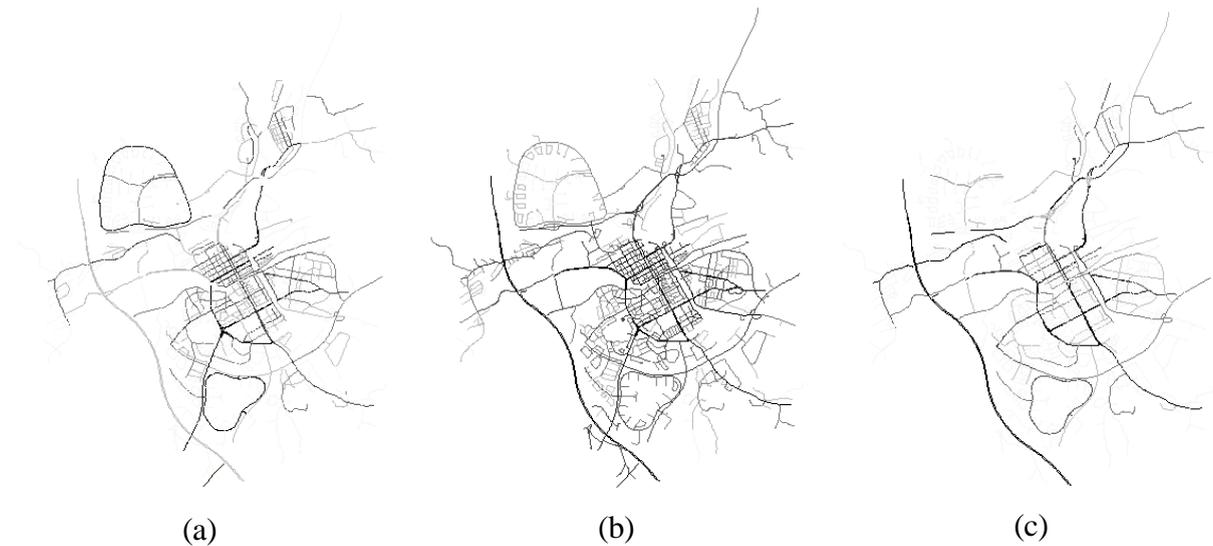


Figure 4: Distribution of street centralities (a) degree (b) closeness and (c) betweenness

The patterns illustrated in figure 4 can be used to guide the selection of characteristic streets for a model-based generalisation purpose. For instance, figure 5 shows a series of selections with a threshold for connectivity values respectively equal to 1, 2, 3 and 4.

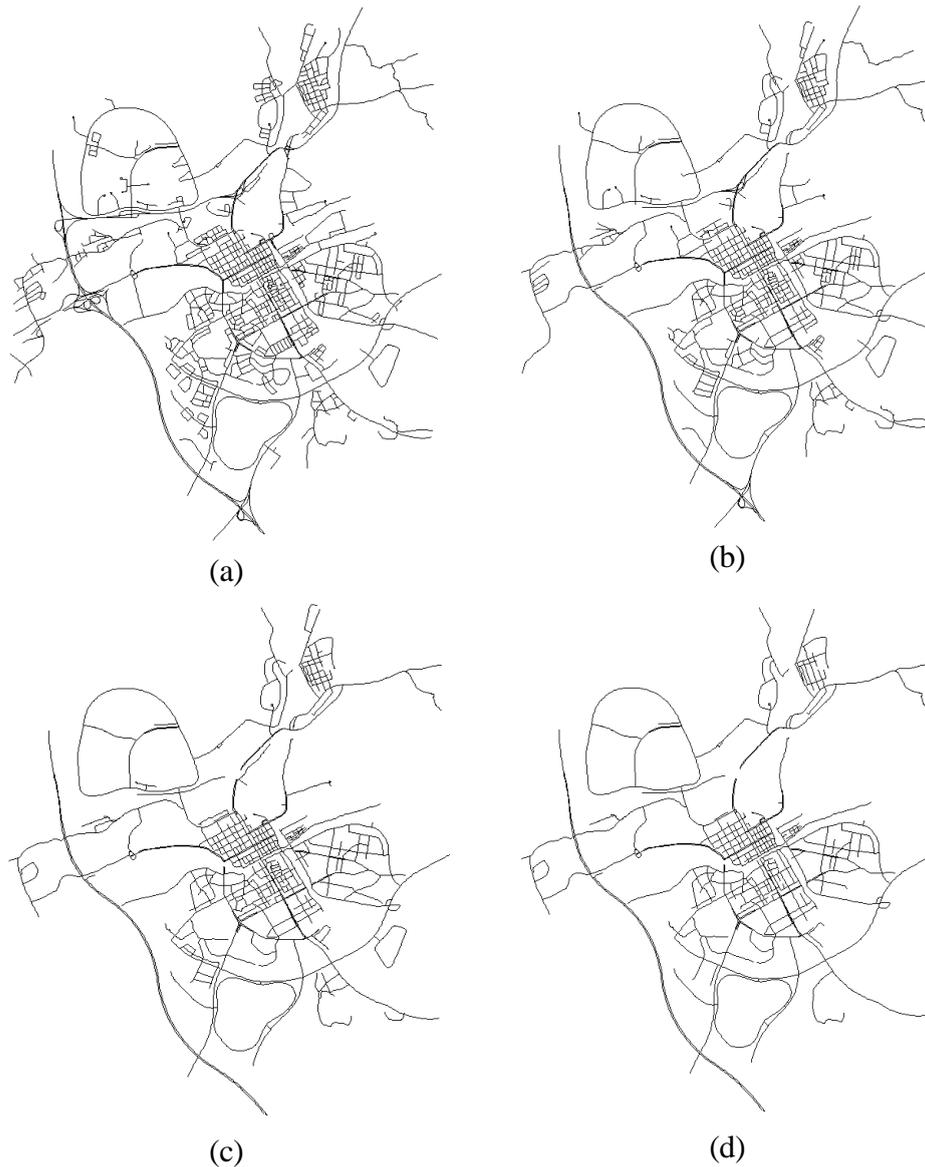


Figure 5: Selection of streets with degree values 1 (a), 2 (b), 3 (c) and 4 (d)

Degree centrality considers 1-neighbourhoods of a given street, which are streets within a range of one step. On the other hand, closeness centrality considers all the streets with respect to a given street, and this reflects how a given street is integrated to every other within an urban street network. Figure 6 illustrates a series of selections with the threshold values of closeness centrality equal to 0.154, 0.160, 0.174, and 0.182 (respectively figures (a) (b) (c) and (d)).

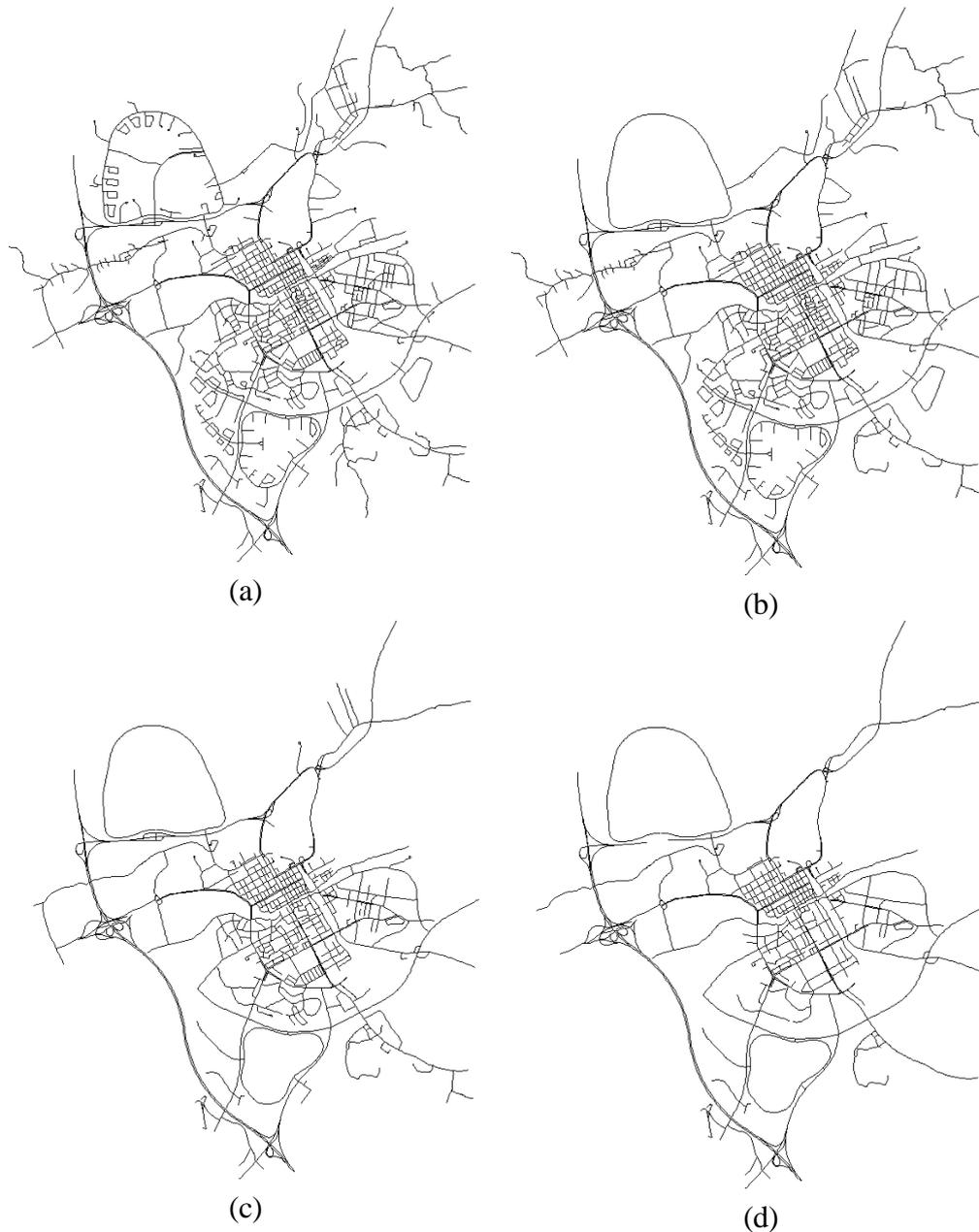


Figure 6: Selections of streets with threshold values of closeness equal to 0.154 (a), 0.160 (b), 0.174 (c) and 0.182 (d)

It should be noted that in figures 5 and 6, thresholds for the centralities are defined for illustration purpose. End users can choose appropriate thresholds according to their particular objectives in applying such a selection (this might be an exploratory and interactive process). It is important to note that other thresholds may lead the network to separated pieces which are not supposed to be expected in model generalisation process (although this may help to identify local clusters and isolated parts in the urban street network cf. figure 7d). However, this should not be considered as disadvantage of the centrality measures. Instead it supports our belief that these centralities must be considered with other geometric and semantic properties in the course of selection. It is also important to note the so called “edge effect” in the computation of centrality measures, i.e. those streets at the edge of a network will get

biased values. To get rid of this effect, we could choose a larger network to include more streets than actually needed.

#### 4.2 Hierarchy-based filtering

Centrality measures applied to an urban streets network denote a form of hierarchical structure. Let us consider the connectivity graph whose nodes are represented by different sizes that reflect the corresponding street's degree values (figure 7). These figures display well-connected streets using larger node sizes, and less connected streets using smaller node sizes. These patterns illustrate the fact that these nodes are arranged at different levels of the hierarchy derived from those centrality measures.

We introduce a model generalisation process based on this hierarchy that reflects high vs. lower values of centrality, from the root to the leaf of the hierarchy. For example, if we set a connectivity threshold of 2, then in the generalised graph the minimum connectivity of nodes is equal to 2 as shown in figure 7(b) (so no nodes with a connectivity value of 1 are left). Similarly, we can then filter this resulting graph (using connectivity values derived from this new graph) with a connectivity threshold being equal to 3 (171 nodes left as in figure 7c), and then 4 (65 nodes left as in figure 7d), and then 5 (19 nodes left as in figure 7e) and then 6 (18 nodes left as in figure 7f). It should be noted that from this stage, an additional iteration of the process gives no nodes left at all.

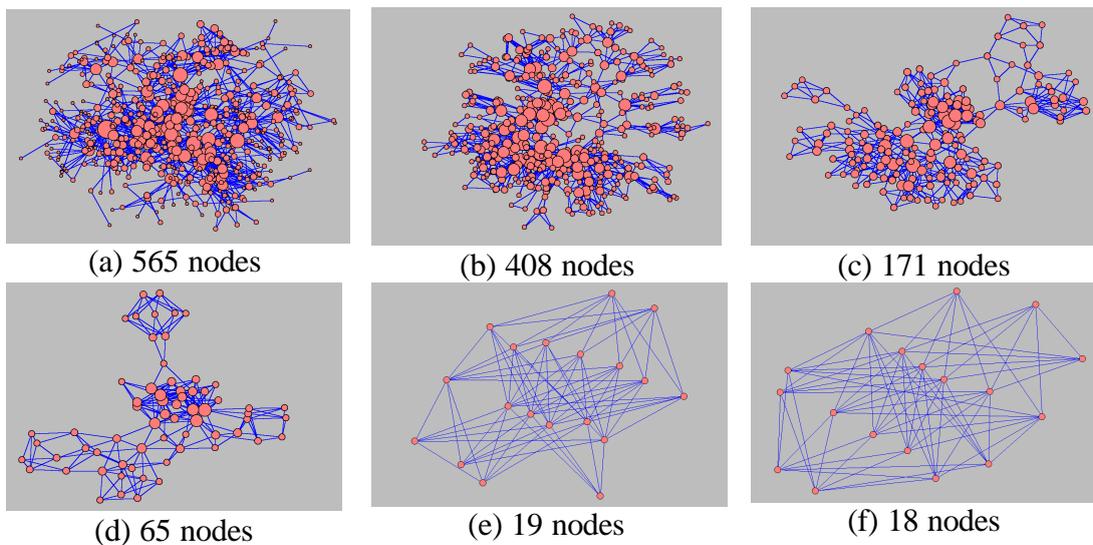


Figure 7: A hierarchy-based filtering

Let us map the schematic graph in figure 7f into the street network. Figure 8 shows the corresponding network derived from the 18 resulting nodes based on the model generalisation process. A cross-check of the roles of those resulting streets in the city of Gävle shows that these streets constitute the central structuring part of the city, and are most accessible in terms of transportation and commercial activities allocation. For example, the four streets labelled in figure 8 namely Nygatan, Drottningatan, Norra Kungsgatan and Norra Rådmanngatan are most important commercial streets. Important landmarks such as central station, theatre, city hall, and central shopping mall are also located within this generalised street network. The analysis based on the structural representation of street networks appears to illustrate the relationship between space and social activities. This result confirms the general observed

trend that structural properties of the city reflect the functional/historical component of the city (Hillier 1996).

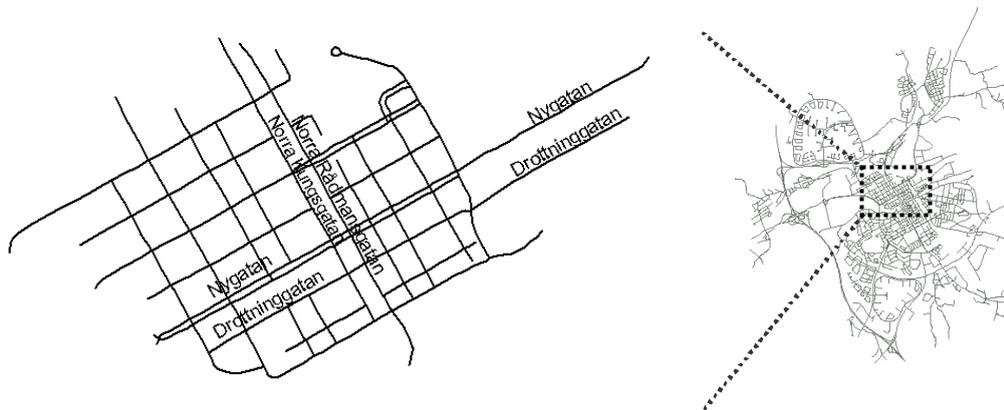


Figure 8: A final filtered map with 18 major streets in the centre of Gävle

## 5. Related work

This section reviews related work in model-based generalisation of urban street networks. Space syntax has developed many computational solutions to the analysis of an urban street network through defining some quantitative measures for a given urban network (Hillier and Hanson 1984, Hillier 1996). It is essentially a graph-theoretic method that is developed for analysis of the spatial configuration of a given street network or the internal distribution of a built environment (Batty et al. 1998). Those analyses are based on a range of graphic representations, dependent on the nature of spatial configurations. For instance, space syntax adopts a so-called axial line representation that partitions a street network into a finite set of intersected axial line, the longest visibility line from a standing point. Based on the intersection of axial lines, a connected graph is derived and a range of quantitative measures is defined for analytical purpose. However, as indicated by a previous study (Jiang and Claramunt 2002), the axial line representation has some serious limitations, i.e. there is no simple transformation from a street network to the axial line representation or *vice versa*. Instead our structural representation of street networks takes a street-centred view and provides an alternative graph representation that is functionally plausible and of interest for both analysis and a model-based generalisation process.

In a recent work, Richardson (2000) developed an approach based on human's spontaneously perceptual organisation (or grouping) of linear streets. She used a term 'stroke' to define the elementary units of a network based on movement continuity. Each stroke is actually a basic modelling unit, a similar concept to the one we adopt by considering named street as vertices of the connectivity graph. However, and at the exception of regular and orthogonal networks, street networks may not appear to have such immediate and structuring visual properties. Her approach, which considers a cognitive-based graphic representation, is also different in essence from the structural and model-based generalisation proposed in this paper, and it is also not directly computable. Mackaness (1995) applied space syntax principles and elaborated how they can be used to derive hierarchies of urban road networks. His study shows that street segment inter-connections (note herein street segments rather than named streets) and space syntax parameters can be used to illustrate the structure of an urban street

network. However, no implementation of these principles achieved due to the lack of transformation from a street network to the axial line representation.

## 6. Conclusion

An urban street network is a structuring component of the city so defining and implementing filtering algorithms that keep the main and central structure of an urban street network is of much interest for many urban applications and studies. This paper proposes a model generalisation approach for the selection of characteristic streets in an urban street network. It is based on the application of centrality measures that consider both local and global structuring properties of named streets that correspond to basic functional elements in the city. A major advantage of our approach when compared to other geometric approaches is that a named street is never truncated at one end or broken into separate pieces in the course of selection.

The case study presented in the paper shows how the structure of a street network is retained with subsequent filtering of streets. The street centred representation extends Mackaness' (1995) proposal by qualifying topological status of individual streets within a network. The alternative graph representation can be well adopted for illustrating structure of an urban street network and further be used for a model-based generalisation process. Although the centrality measures identified for a network can be used for model-based generalisation purpose, it might be combined with other geometric and semantic properties. This will be considered in our future work.

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## References

- AGENT (1998), *Constraint Analysis*, ESPRIT report, Department of Geography, University of Zurich.
- Batagelj V. and Mrvar A. (1997), *Networks/Pajek: Program for Large Networks Analysis*, available at <http://vlado.fmf.uni-lj.si/pub/networks/pajek/> (access on 2002-03-20)
- Batty M., Conroy R., Hillier B., Jiang B., Desyllas J. Mottram C. Penn A. Smith A. and Turner A. (1998), *The Virtual Tate*, CASA working paper available at [http://www.casa.ucl.ac.uk/publications/working\\_papers01.htm](http://www.casa.ucl.ac.uk/publications/working_papers01.htm) (access on 2003-05-18)
- Buttenfield B. P. and McMaster R. B. (1991), *Map Generalisation: Making Rules for Knowledge Representation*, Longman Scientific & Technical.
- Douglas D. and Peucker T. (1973), Algorithms for the Reduction of the Number of Points Required to Represent a Digital Line or its Caricature, *The Canadian Cartographer*, Vol. 10, pp. 112 – 22.
- Freeman L. C. (1979), Centrality in Social Networks: Conceptual Clarification, *Social Networks*, 1, pp. 215 – 239.
- Gross J. and Yellen J. (1999), *Graph Theory and Its Application*, CRC Press: London.

Hillier B. (1996), *Space is the Machine: A Configurational Theory of Architecture*, Cambridge University Press, Cambridge, UK.

Hillier B. and Hanson J. (1984), *The Social Logic of Space*, Cambridge University Press: Cambridge.

Hillier, B. (editor, 1997), *Proceedings, First International Symposium on Space Syntax*, University College London, London, 16-18 April, 1997.

Holanda F. (editor, 1999), *Proceedings, Second International Symposium on Space Syntax*, Universidade de Brasilia, Brasilia, 29 March-2 April 1999.

Jiang B. and Claramunt C. (2002), Integration of Space Syntax into GIS: New Perspectives for Urban Morphology, *Transactions in GIS*, Vol. 6, no. 3, pp. 295-309.

Jiang B. and Claramunt C. (2003), Topological Analysis of Urban Street Networks, *Environment and Planning B: Planning and Design* (forthcoming), Pion Ltd.

Kreveld M. V. and Peschier J. (1998), On the Automated Generalization of Road Network Maps, *GeoComputation'98*, available at <http://divcom.otago.ac.nz/SIRC/webpages/Conferences/GeoComp/GeoComp98/geocomp98.htm> (access on 2002-03-20)

Mackanness W. A. and Beard M. K. (1993), Use of Graph Theory to Support Map Generalisation, *Cartography and Geographic Information Systems*, Vol. 20, pp. 210 – 221.

Mackanness W. A. (1995), Analysis of Urban Road Networks to Support Cartographic Generalization, *Cartography and Geographic Information Systems*, Vol. 22, pp. 306 – 316.

Mackanness W. A. and Mackechnie G. A. (1999), Automating the Detection and Simplification of Junctions in Road Networks, *GeoInformatica*, 3:2, pp. 185- 200.

Muller J. C., Lagrange J. P. and Weibel R. (1995, eds.), *GIS and Generalization: Methodology and Practice*, Taylor and Francis: London.

Penn A. (1993), Intelligent Analysis of Urban Space Patterns: Graphical Interface to Precedent Databases for Urban Design, *Auto Carto 11 Proceedings*, ACSM-ASPRS, Minneapolis, pp. 53 – 62.

Peponis J., Wineman J. and Bafna S. (editors, 2001), *Proceedings, Third International Symposium on Space Syntax*, Georgia Institute of Technology Atlanta, May 7-11, 2001.

Richardson D. (2000), Generalization of Road Networks, available at <http://www.ccrs.nrcan.gc.ca/ccrs/tekrd/rd/apps/map/current/genrne.html> (access on 2002-03-20)

Thomson R. C. and Richardson D. E. (1995), A Graph Theory Approach to Road Network Generalisation, in: *Proceeding of the 17<sup>th</sup> International Cartographic Conference*, pp. 1871 – 1880.

Watts D. J. and Strogatz S. H. (1998), Collective Dynamics of 'Small-World' Networks, *Nature*, 393, 440 – 442.

Weibel R. (1995), Three Essential Building Blocks for Automated Generalisation, in: Muller J. C., Lagrange J. P. and Weibel R. (eds.), *GIS and Generalization: Methodology and Practice*, Taylor and Francis: London, pp. 56 - 69.