

Review of road selection methods for purpose of multiscale mapping

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Abstract:

Cartographic generalization is the process of reducing map details in order to present information at a smaller scale, ensuring the map remains coherent, topologically correct, and legible (Stanislawski et al., 2014; Kraak et al., 2020). Traditionally, cartographers decided which details to keep based on their expertise, making generalization both an art and science (Pawlak, 1971). Road networks are essential on general geographic maps, therefore selecting roads to display at multiple scales is of the key importance. AI techniques, especially machine learning (ML) and deep learning (DL), can assist this process. These methods use decision trees, neural networks, and graph convolutional networks to select road networks by assessing the road importance. Although these models seem promising, they face challenges in processing geographic data, in particular they require a large amount of ground true (reference) data as well as efficient and plausible evaluation measures. This research focuses on the assessment of methods for generalizing road networks treating road selection as a primary step. In this review across the Web of Science and Scopus databases we have identified 44 relevant studies (from 742 initially found using search queries) that demonstrated the effectiveness of different road selection approaches.

Five major approaches to automated road selection were identified. Stroke-based methods that group road segments into longer, continuous sections based on the deflection angles using conceptual grouping principle of the good continuation (Thomson & Brooks, 2000). This approach is considered to effectively maintain connectivity in road networks. The second approach is mesh-based with meshes (Chen et al. 2009) or urban blocks being formed by grouping adjacent road segments, and further retaining segments based on density thresholds. This approach is particularly useful for urban road network elimination. The third group constitutes graph-based methods that convert road networks into graph structures, allowing the use of topological metrics such as centrality measures and shortest path (Zheng et al., 2021). The fourth group includes machine learning-based methods that apply the elements of artificial intelligence to automate selection. This is done by implementing various traditional machine learning algorithms: self-organizing neural networks, genetic algorithms, backpropagation neural networks, decision tree models and support vector machines. This task can be also tackled with use of deep learning methods such as graph convolutional networks, graph attention networks etc. Despite the advancements in AI integration, fully automating high-quality generalization remains difficult due to limitations in capturing visual coherence and spatial complexity. Although AI-driven models (e.g., neural networks, graph-based algorithms) produce impressive results, they still rely on expert oversight to handle unique spatial and contextual variations that automated algorithms struggle to interpret. Lastly, semantic-based methods exist which use the importance of roads based on attribute information, such as road level and road type, road category or any other attribute which can hierarchize this thematic layer. The implementation of this method relies only on what the map designer wants to achieve. Combining the listed methods can enhance road selection results; for example, stroke and mesh combinations help to maintain road density and network connectivity both in urban and rural areas.

The conducted review finds that most researchers design selection methods with particular context in mind, leading to significant variation in the objectives of the referenced studies. However, this diversity should not be viewed negatively; it reflects a clear understanding among authors that no single method can be applied effectively to every selection scenario.

Moreover, the broad range of measures (apart from accuracy which can refer to different objects and baselines set by authors in each research) for the quantitative assessment of results makes it harder to compare results between papers. Quantitative measures are useful for evaluating map generalization methods, but they don't always capture how good the map looks in visual terms. Since visual quality is a key factor for a good map comprehension, researchers often ask experienced cartographers for help to prepare data or review automated generalization results (Karsznia et al. 2024). Although involving experts can slow down the generalization process, their input significantly enhances the evaluation of visual quality, which is often not fully captured by quantitative measures.

The varying strengths and applications of stroke-based, mesh-based, graph-based and machine learning-based methods indicate that no single approach serves all generalization needs, particularly when map purpose, scale and context differ. Even the most advanced methods do not achieve the nuanced decision-making required for high-quality, fully automated map generalization. AI's contribution to automating the process is promising, but it still demands a human-in-the-loop approach to ensure the visual quality and functional accuracy that users expect. While ongoing integration of AI may eventually offer more robust automation, a hybrid approach of automated processes supplemented both by expert and AI input remains essential for achieving cartographic generalization goals and quality across multiple scales and regions.

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