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The Potential of VGI and Traffic Flow Generation Model for Solving the Traffic Sensor Location Problem

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Abstract:

Traffic flow data is central to transportation planning and operational activities, and is also crucial for various traffic applications and intelligent transportation systems (ITS) (Liu et al., 2014, Owais, 2022). It is mainly captured by means of traffic sensors. However, limited budgets do not allow for a dense installation of traffic sensors throughout the road network, apart from other concerns related to privacy protection. The demand for a small number of traffic sensors increases when using expensive traffic sensors, such as the increasingly popular LiDAR sensors and high-definition cameras. The smaller the number, the more critical the traffic sensor location problem (TSLP) becomes (Owais, 2022). TSLP aims to identify the minimum set of particular traffic sensors to be installed in links or nodes in a road traffic network to obtain pre-specified traffic flow data, usually of the whole network. It is usually treated as a mathematical optimization problem. Some heuristic algorithms such as genetic algorithm (GA) are used to address this problem (Castillo et al., 2015).

In order to solve TSLP, historical traffic flow data and other prior information, including the network topology are usually required. The historical traffic flow data can either be collected from the existing traffic sensors or be generated from the trajectory data acquired by the onboard sensors. Unfortunately, these data are not easy to obtain, nor is it necessarily reliable, apart from high economic costs. They may not provide enough information for the whole deployment area. And the situation gets even more difficult without an existing traffic sensor system.

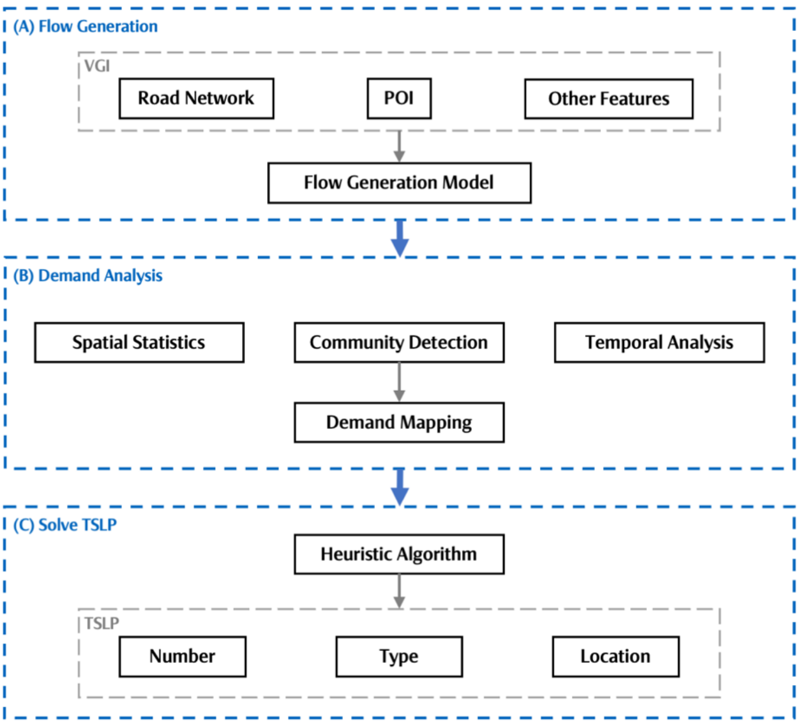

Figure 1. The Workflow Proposed in this Abstract.

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However, the booming flow generation model based on the artificial neural network may provide a solution without requiring historical traffic flow data. The flow generation method uses Volunteered Geographic Information (VGI), for example, OpenStreetMap, including road network data, POI data, and other geographic features, such as land use data, to train a deep neural network to generate traffic flows between a set of locations without relying on historical data (Simini et al., 2021). Rich geographical semantics, neighborhood effects, and the topological nature of the network are considered to train the model (Yin et al., 2022). We believe that the flow generation model is a promising alternative to generating traffic flows for addressing the TSLP. Meanwhile, the community detection method (Fortunato, 2010) can be used to detect different traffic communities with different traffic characteristics, which may even change over time. By formulating different location strategies for different communities, we may more reasonably solve TSLP.

Hereby, we propose a novel low-cost and universal workflow on how to address TSLP. The workflow is illustrated in Figure 1. It comprises three steps: (A) Flow Generation: VGI, especially road network data and POI data, are fed into the flow generation model based on neural networks so that generated traffic flow can be gotten; (B) Demand Analysis: with the generated traffic flow, community detection, spatial statistics, and temporal analysis are carried out to finish demand mapping; (C) Solve TSLP: using the extracted demand information, heuristic algorithms are used to finally solve TSLP, answering the three most basic questions, namely, how many sensors, which types, and which locations in a given road network. Preliminary results for selected urban scenarios will be reported.

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