A Review of Techniques to Extract Road Network Features from Global Positioning System Data for Transport Modelling

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With the spread of smartphones and mobile internet, Global Positioning System (GPS) data from vehicles has become widely available. This data represents a unique opportunity to automatically extract road network features and generate detailed maps that can be used in the creation of transport network models, while minimizing the quantity of resources usually invested in that task. Accurate transport network models can be used in a variety of applications either in transport simulation models or autonomous vehicles navigation. Although two relevant literature reviews were performed during the last decade, they were not systematic and did not explore the road network inference methods from a transport network modelling point of view. The objective of this research is to perform a systematic and reproducible literature review on the use GPS data in transport network modelling and provide limitations and future work to extract a road network representation for transport models and autonomous vehicles navigation. This was done by systematically examining the studies' different approaches with respect to relevant criteria. Most studies produced a simple representation of the road network, not detailed enough for transport models. Other limitations were the bias introduced by the GPS sample and the reproducibility of the different methods.

Keywords: map inference; GPS data; transport model; road network; intersection movements.

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1. Introduction

Data and knowledge of detailed transport network features are important for multiple fields such as traditional and autonomous vehicle navigation, traffic safety, urban planning, and transport modelling. Although a basic road centreline network representation is sufficient for certain applications, other applications can require additional and more detailed information which is the case for transport models. In fact, transport models are tools developed by transport engineers and planners to help in the decision-making process of transport infrastructure planning. This type of model can be divided into three main components: supply, demand, and performance where the supply component is mainly represented by a detailed digital road network. It represents road segments as directional links and intersections as nodes. It also contains additional attributes used to describe road segments and intersection' properties. For example, each link has a specific number of lanes, a road type, and a link performance function. Intersection properties are also required to indicate permitted movements, turn penalty functions, and traffic control type. Additionally, the road network is dynamic in nature, since traffic rules can prohibit a subset of road users from using a specific road lane or making a specific movement at an intersection, depending on a temporal criteria. Therefore, the modelled road network should also represent this characteristic. The digital road network representation is usually obtained through manual extraction or inference using other data sources such as satellite imagery, lidar, and vehicle imagery (Banqiao et al., 2020). The high cost and labour associated to these methods is the main limiting factor to data quality and update frequency.

To improve the transport network modelling process, transport modelling software providers have provided tools to automatically construct transport networks based on digital maps. While improving some aspects of the network modelling process, achieving a satisfactory network model quality still relies on a manual intervention and additional data sources to validate and input some of the essential attributes. For example, traffic control information at intersections, permitted intersection movements, and number of lanes are usually unavailable in digital maps. In addition, digital maps require continuous maintenance and update, which also requires important resources.

Thanks to location-based services, global positioning systems (GPS) data has become widely available in terms of spatial coverage and sample size, providing an immense potential for transport network modelling. This potential lies in the possibility to automatically extract road network features from GPS trajectory information. GPS trajectory data is defined as a set of chronological location points data where each point is described using longitude and latitude coordinates, a timestamp, and a trip ID. Depending on the parameters of the GPS device recording the points, the sampling rate or frequency can be set in terms of time or distance. For example, the sampling rate can be set to record the location point every 1 sec which is equivalent to a frequency of 1 Hz, or to record a location point every 10 meters.

This systematic literature review explores research that used large-sample GPS data to automate the network construction process, by extracting road shape, topology, number of lanes, and permitted intersection movements. A special focus is placed on transport network features extraction usable for large scale transport model development.

In the geography and computer science fields, extracting a road map from GPS data, also known as map inference, has been explored since the 1990s. Within the last decade, two literature reviews were published on map inference techniques using GPS data by Ahmed et al. (2015a) and Chao et al. (2022). Map inference can be defined as the process of constructing the digital road map (roads location, intersections, topology, connectivity, etc.) based on specific data sources such as aerial images or GPS trajectories. In contrast, transport network modelling requires the construction of digital road network model that describes the road network in detail to enable its use in transport modelling and simulation.

The work by Ahmed et al. (2015a) benchmarks map inference algorithms by performing a comparison and evaluation using multiple GPS datasets and various quality measures. These algorithms have a common objective; to use GPS data points or trajectories as an input to create directional links and nodes representing the road network. The output is usually compared to a ground truth map. The algorithms were classified under three distinct categories based on the technique used: 1. Point Clustering, 2. Incremental track insertion, and 3. Intersection linking. In addition, algorithm performances were evaluated using four quality measures: 1. Directed Hausdorff distance, 2. Path based distance, 3. Shortest path-based distance and graph-based sampling distance. This work is complemented by the book authored by Ahmed et al. (2015b). Although the review is insightful and comprehensive in terms of map inference techniques, it is not systematic and does not approach the question from the transport modelling point of view, which requires specific road network features to be included in the network model. In fact, the review does not assess if the examined papers are extracting network features usable for transport network modelling, such as turning movement permissions, intersection controls, or the number of lanes available for traffic. In addition, it does not discuss the reproducibility of the different works reviewed. Furthermore, the review does not present the necessary future work to improve on the techniques and extract more detailed information from GPS data.

Finally, Given the time elapsed since 2015 and the increasing availability of GPS data in recent years, an updated review of the work is beneficial to explore new work.

More Recently, the literature review by Chao et al. (2022) explored more recent studies in the map inference context. Their focus was placed on the proposition of a new categorization of algorithms while assessing the existing map inference quality measures and the effect of GPS errors on the inference results. They proposed to classify map inference algorithms as: 1. Road abstraction, 2. Intersection linking and 3. incremental branching. Despite a minor change in the category names, these categories are not significantly different from the ones proposed by Ahmed et al. (2015a) and do not change the classification of the different algorithms. In addition, the work identifies the best algorithms in terms of scalability, accuracy, and suitability to update. This review is not systematic and does not discuss map inference from the transport modelling point of view. Thus, it cannot assist in determining which technique is preferred to extract network features for transport modelling. In fact, the review focuses on the performance of the available algorithms and does not present future works required to be able to extract more detailed network features from GPS data.

Although past literature reviews are a good place to explore the work done in map inference, it was usually performed from the optic of the geography and computer science fields. Overall, there was no discussion about the ability of current algorithms to extract more detailed network features or the necessary research towards this objective. The literature review method performed in both works was not systematic, thus not reproducible. Finally, past literature reviews provide limited guidance for transport modelers in selecting the best techniques to model road networks or in determining future work. Therefore, the contribution of this work is to build on previous research by developing a systematic and reproducible literature review that informs the reader of the work done in the map inference field and the additional work required to be able to extract detailed road network features to support in transport network modelling.

2. Methods

To systematically review all relevant research while ensuring a high level of reproducibility of this research effort, this work was inspired by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA, 2015). This technique requires the presentation of the study identification process, clearly indicating the sources and the screening steps and justifications. The research scope design, including objective, input and output data, and inclusion and exclusion criteria are presented below.

2.1 Search criteria

The objective of the studies had to be development of inference techniques of road network features based on regular / commodity GPS data. This excludes the use of high precision GPS or differential GPS, which is not feasible for large scale applications. Studies in the fields of geography, computer science, and transport planning and engineering using GPS points or trajectories as the main input regardless of the data collection device (in-vehicle, smartphone, etc.) were included. All studies aiming to construct (infer) a road network were included. The final output had to be a map of the road network. Only English and French publications were selected given the authors' language abilities. If an author produced multiple publications, only the most recent was selected. In addition, only publications from the last 10 years were included (2012-2022). Publications without full texts were discarded.

2.2 Search strategy

The search strategy was developed by the authors in consultation with the librarian associated to the Civil Engineering department. Multiple trial searches were conducted to determine all synonyms. These trials were critical to the keyword selection as this research effort included different fields of research that do not use the same terminology. For example, the main research objective could be called network modelling, map inference, map generation, map construction, or map extraction depending on the research field (computer science, geography, or transportation engineering and planning). The chosen keywords were then selected and searched in the following bibliographic databases: Scopus, Web of Science, Compendex, and Transport Research International Documentation (TRID). The searches were performed on February 24th, 2022. The exact keyword specification is presented below:

> ("GPS") AND ("network inference" OR "inference of network" OR "network extraction" OR “extraction of network” OR "network mining" OR “mining of network” OR "network generation" OR “Generation of network” OR "Road extraction" OR “Extraction of Road” OR "Road inference" OR “Inference of road” OR "Road Mining" OR “mining of road” OR "map extraction" OR “extraction of map” OR "map inference" OR “Inference of map” OR "Map mining" OR “mining of map” OR "lane reconstruction" OR “reconstruction of lane” OR "intersection reconstruction" OR “Reconstruction of intersection” OR "lane mining" OR “mining of lane” OR "intersection mining" OR “Mining of intersection” OR "lane inference" OR “inference of lane” or "intersection inference" OR “Inference of intersection” OR "intersection detection" OR “detection of intersection”)

2.3 Selection of studies

Following the removal of duplicates, the titles and abstracts were screened systematically by the author using the Rayyan web platform (Ouzzani et al., 2016). The full texts of the remaining publications were retrieved for an in-depth selection assessment. Finally, all studies respecting the inclusion criteria stated above were selected for data extraction and further analysis.

2.4 Data Extraction

A global extraction form was developed and used to systematically extract all relevant information from the publications. The form was then used to analyse all studies on the same standardized basis. This form was completed by the author and contained, when available, the following information: author, year, title, journal / conference, study setting (country, city), field of study, research question, sample description, comparative methods, techniques used, detailed output, coverage, validation, comprehensibility, reproducibility, and limitations.

3. Results

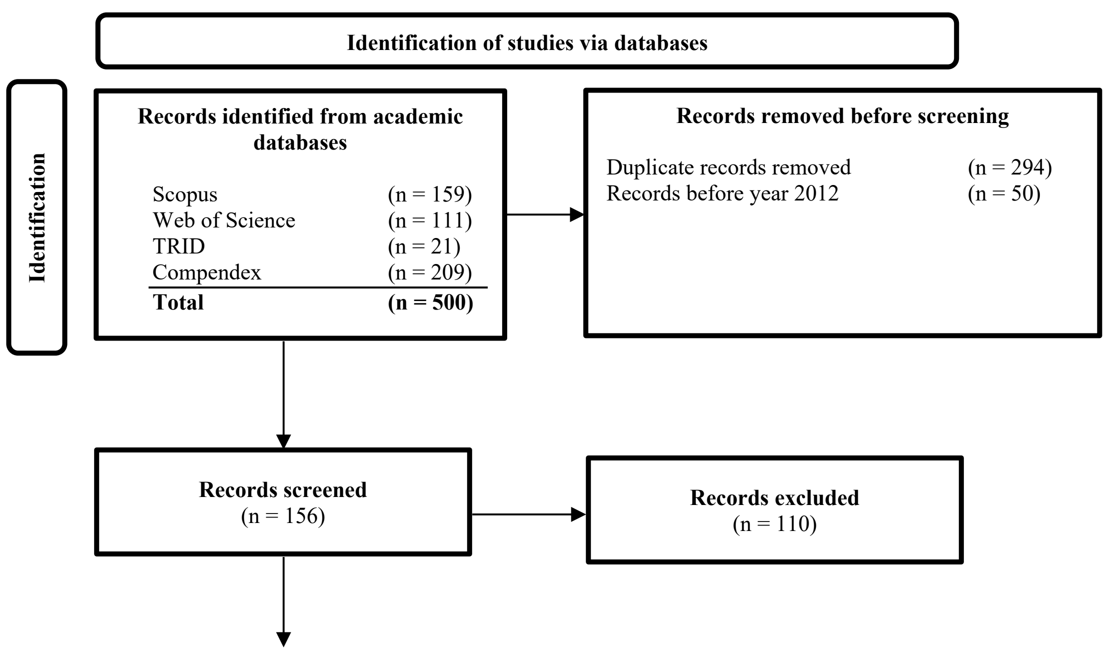
Following the keywords' selection, the database search identified 500 publications. Duplicate articles and publications before 2012 were removed. The title and abstract of the remaining 158 articles were screened, resulting in the exclusion of 110 articles. The final screening step was the full report retrieval and examination of the 48 publications. Following the screening process, 17 articles were included in this literature review. Reports were excluded when the research paper was a literature review, a book, not building a road network, requiring additional resources such aerial images, newer work was published by the same author, or the GPS sampling frequency was greater than one minute. Figure 1 presents a breakdown of the search and screening process.

A summary of the selected papers is presented in Table 1. It can be noted in the Journal/Conference column that most of the work done is in the field of geography and computer science. As for the experimental data that was tested, it was mainly collected in the United States and China. The main research question for all the studies was the construction of a road network using GPS points or trajectories as input, by developing different algorithms and methodologies that can outperform previous research efforts.

Out of the 17 studies, the most popular approach is clustering (n = 11). The intersection linking approach is the most recent to be explored by researchers (n = 4). Finally, the least popular approach is track alignment (n = 2).

This work presents the different publications by approach as in Ahmed et al. (2015a). The selected studies are summarized in the following section under each of these approaches. The summarized information relates to the following elements: a) road network definition (network components, directionality, number of lanes, and turning movement permissions), b) output quality (if and how the output quality was evaluated), c) experimental data characteristics (sample size, sampling rate, collection method, and coverage), d) method clarity and reproducibility (if the article is sufficient to understand the method and be able to reproduce it.).

The discussion goes further by analysing the results from a transport network model point of view and presenting the opportunities for further research to extract road network features.



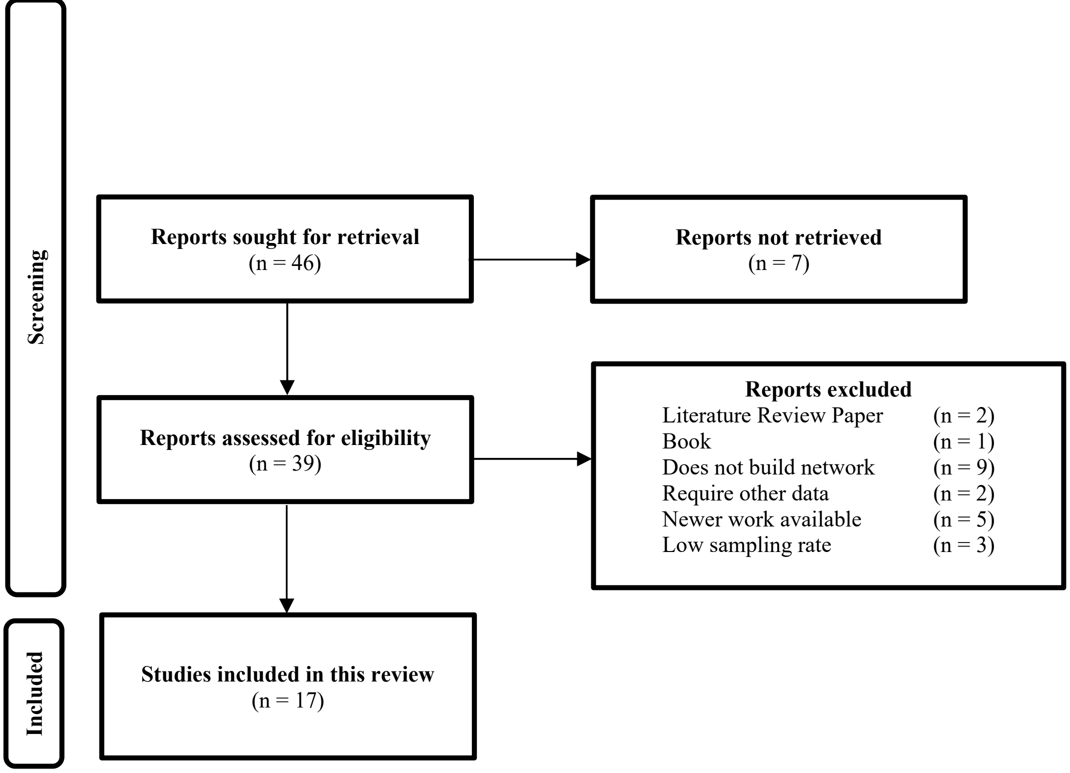


Figure 1. PRISMA diagram - Study identification process

Paper	Journal / Conference	Data Location	Research question(s)	Approach
Guo (2021)	Geo-spatial Information Science	Wuhan, China	Develop a novel method of extracting road maps from floating car data.	Clustering
Chen (2021)	ISPRS International Journal of Geo-Information	Shenzhen, China	Automatically generate road maps.	Clustering
Zhang (2020)	ISPRS International Journal of Geo-Information	Shenzhen, China	Incrementally extract urban road networks from spatio-temporal trajectory data.	Clustering
Arman (2020)	Procedia Computer Science	Antwerp, Belgium	Identify lanes on highway segments based on Mobile Phone GPS.	Map inference: Intersection Linking Lane detection: Gaussian Mixture Model
Zhang (2019)	ISPRS International Journal of Geo-Information	Chicago, USA and Wuhan, China	Intersection-first approach for road network generation based on low-frequency taxi trajectories.	Intersection Linking
Leichter (2019)	Applied Sciences-Basel	Joensuu, Chicago, Berlin, Athens	Fast and straightforward method for the extraction of road segment shapes from trajectories of vehicles.	Track alignment
Hashemi (2019)	IEEE Transactions on Intelligent Transportation Systems	Cary, USA, and Beijing China	Automatic inference of road and pedestrian networks from spatial-temporal trajectories.	Clustering
Daigang (2019)	ISPRS International Journal of Geo-Information	Chicago, USA and Dongguan, China	Two-stage approach for inferring road networks from trajectory points and capturing road geometry with better accuracy.	Clustering
Zhongyi (2018)	ISPRS International Journal of Geo-Information	Nanning, China	A road network generation method based on the incremental learning of vehicle trajectories.	Track alignment
Stanojevic (2018)	SIAM International Conference on Data Mining	Doha, Qatar and Chicago, USA	Inferring the road network of a city from crowd-sourced GPS traces.	Clustering
Ezzat (2018)	Journal of Computational Science	Cairo, Egypt	A clustering-based technique to extract the road map from GPS tracks.	Clustering
Dorum (2017)	ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems	San Francisco and Knoxville, USA	A comprehensive end-to-end unsupervised method based on principal curves for creating bi-directional road geometry from sparse probe data yielding a complete double-digitized road network from raw probe sources without prior map information.	Clustering
Li (2016)	ACM International on Conference on Information and Knowledge Management	Chicago, USA and Porto, Portugal	A Spatial-Linear Clustering (SLC) technique to infer road segments from GPS traces.	Clustering
Jia (2016)	ISPRS International Journal of Geo-Information	Chicago, USA and Wuhan, China	A new segmentation and grouping framework for road map inference from GPS traces.	Clustering
Xingzhe (2016)	ISPRS International Journal of Geo-Information	Chicago, USA	A method to infer the topology of the road network through intersection identification, and to extract the geometric representation of each road segment by track alignment.	Intersection Linking
Elleuch (2015)	INNS Conference on Big Data	Tunisia	Infer the geometry of road maps in Tunisia and the connectivity between them.	Clustering
Karagiorgou (2012)	International Conference on Advances in Geographic Information Systems	Athens, Greece,	Automatic road network generation algorithm that takes vehicle tracking data in the form of trajectories as input and produces a road network graph.	Intersection Linking

Table 1. Summary of findings

3.1 Clustering approach

This method uses GPS points or segments to fit the road centreline according to the data density distribution. Two main methods are used to cluster GPS data. The first covers the entire region with a grid and computes the GPS data density for each grid cell. Based on that information, it is possible to infer road segment or intersection locations. An example of density-based clustering is the Kernel Density Estimation (KDE) method used by Chen et al. (2021).

The second method clusters the GPS data by averaging it based on proximity and direction criteria to determine road segments and intersections. Examples of this method are the k-means algorithm used by Stanojevic et al. (2018) and the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) used by Ezzat et al. (2018). Eleven publications are classified under this approach of map inference. A summary of the experimental data description and validation results of these papers is presented in Table 2. The data collection method provides information regarding how the GPS trajectory data was collected, for example, it could be collected using GPS-enabled smartphones, commercially available GPS devices, or in-vehicle GPS trackers. Moreover, the GPS trajectory data sample size, which is the number of collected GPS points, is also presented in the table to give an idea about the scale of the sample. Finally, it is important to mention that sampling rate, or the frequency at which GPS points are collected during a trip, has a direct influence on the resolution of the GPS trajectory data and it is also reported in Table 2.

In network modelling, a detailed network model is essential to ensure the correct connectivity, topology, and capacity of roads and intersections. Therefore, road direction, turning movement permissions at intersections, and number of lanes are essential features to know. Research effort by Elleuch et al. (2015) has simply created an undirected road network without formally creating road segment and intersection representations. The produced shape of the road network is insufficient for use in road network modelling since it is missing most of the basic essential details, such as connectivity and topology. Meanwhile, several research efforts go further by generating directional road segments and intersection location (Chen et al., 2021; Ezzat et al., 2018; Guo et al., 2021; Y. F. Zhang et al., 2020). However, none of the studies implementing a clustering approach extract an explicit representation of intersection

Paper	**Sample Description (Location, Collection Method, Sample Size, Sampling Rate)**	**Validation Results**	
Guo (2021)	Wuhan, China, GPS device by researchers, 1.4 million points, 20 to 60 seconds	Intersection Detection: Road centerline extraction:	Precision: 0.914 - 0.929 Recall: 0.787 - 0.975 F-score: 0.846 - 0.951 Precision: 0.754 - 0.802 Recall: 0.805 - 0.812
Chen (2021)	Shenzhen, China, Taxi GPS, 75 million points, 26 seconds	Road centerline extraction:	Precision: 0.966 Recall: 0.943 F-score: 0.850
Zhang (2020)	Shenzhen, China, Taxi GPS, 1.2 million points, 60 to 100 seconds	96% of extracted road length fell within 15m buffer w.r.t. ground truth	
Hashemi (2019)	Cary, USA, and Beijing China, N/A, Multiple datasets, 9 to 40 seconds,	Completeness, Precision, and Topology Correctness Variable results reported for 33 datasets	
Daigang (2019)	Chicago, USA and Dongguan, China, University Campus Shuttles and taxis, respectively, 118364 and 280253 points, respectively, 3.61 and 50.13 respectively	Length of extracted road: 83.6% - 87.4% Precision: 0.78 Recall: 0.6 F-score: 0.68	
Stanojevic (2018)	Doha, Qatar and Chicago, USA, Fleet of vehicles with GPS-enabled devices. 5.5 million and 200 000 points, respectively, N/A	Geometry: F-score: 0.53 - 0.60 Topology: F-score: 0.80 to 0.85	
Ezzat (2018)	Cairo, Egypt, Two user contributed datasets, 302 000 and 12.7 million points, 11 to 15 seconds and 1 to 3 seconds	Precision: 0.92 Recall: 0.68 F-score: 0.79	
Dorum (2017)	San Francisco and Knoxville, USA, Commercial fleets and consumer devices, 43 million and 850 million points, respectively, N/A	Link Count % (reported per road type) 65% - 98.6% Link Length % (reported per road type) 71.9% - 99.4%	
Li (2016)	Chicago, USA and Porto, Portugal, University Shuttles and Taxis, respectively, 118 000 and 296 573 points respectively,	Precision: 0.68 - 0.98 Recall: 0.45 - 0.65 F-Score: 0.56 - 0.78	

Paper	Sample Description (Location, Collection Method, Sample Size, Sampling Rate)	Validation Results
	3.6 seconds and more than 15 seconds, respectively	
Jia (2016)	Chicago, USA and Wuhan, China, University Shuttles and Taxis, respectively, 118 000 and 350 000 points respectively, 3.6 seconds and more than 37.4 seconds, respectively	Precision: 0.902 - 0.975 Recall: 0.679 - 0.734 F-Score: 0.775 - 0.838
Elleuch (2015)	Tunisia, GPS receivers in 10 000 vehicles, > 100 Gb, N/A	N/A

Table 2. Clustering approach - sample description and validation results

movements nor have they developed a lane-level road network, essential in determining the network's vehicular capacity.

Although researchers are continuously improving map inference techniques to obtain higher quality results, input data characteristics remain a main determinant of output quality. The variety of data sources used in the 11 studies makes it difficult to compare them and determine the best map inference method. This is caused by the differences in GPS data collection devices (in-vehicle, GPS enabled smartphone, GPS tracker, etc.), differences in sampling rates, differences in the number of points or trajectories available, and differences in collection environments (various levels of GPS signal interference and availability). For Example, Chen et al. (2021) uses a dataset of 75 million points collected by taxi GPS devices in Shenzhen, China with an average sampling rate of 26 seconds, while one of the two datasets used by Daigang et al. (2019) is composed of 118 000 points collected by university shuttles in Chicago, United States at an average sampling rate of 3.6 seconds. The same algorithm applied to both datasets can result in different output quality levels. GPS data used in most of the studies was obtained using GPS-equipped taxis or shuttles, which introduces bias by not representing an average motorist's behavior. In the case of shuttles, this bias can be in terms on spatial coverage since they have fixed routes and might also be permitted to drive on private roads such as campuses. Thus, the inferred map based on this data might not reflect the whole network available to all motorists. Additionally, shuttles usually have a fixed schedule and cannot provide a good temporal coverage of all periods of the day. On the other hand, GPS-equipped taxis can have an adequate temporal coverage, however, some road networks have dedicated lanes and turning permissions for taxis to encourage their use. Therefore, this introduces some spatial bias if the extracted network is to be used by a private motorist.

In the study by Elleuch et al. (2015), insufficient information was provided regarding the experimental data. In parallel, some researchers have used well known benchmark datasets to enable the comparability of their algorithm's performance. For example, some researchers have evaluated the execution of their algorithms on the Chicago dataset (Daigang et al., 2019; Jia & Ruisheng, 2016; Li et al., 2016; Stanojevic et al., 2018). However, this dataset is obtained from university shuttles and has spatial and temporal limitations.

The most common evaluation method, initially introduced by Biagioni and Eriksson (2012), was the harmonic mean of precision and recall, also known as F-score or F-value. It is calculated as follows:

$$Precision = \frac{Correctly\ Extracted}{Correctly\ Extracted + Incorrectly\ Extracted}$$

$$Recall = \frac{Correctly\ Extracted}{Correctly\ Extracted + Not\ Extracted}$$

$$F - score = 2 * \frac{Precision * \ Recall}{Precision + Recall}$$

where *Correctly Extracted* + *Incorrectly Extracted* = *Extracted* or inferred network elements and *Correctly Extracted* + *Not Extracted* = *Ground Truth*. A higher F-score (closer to one) indicates a better inference and match to the ground truth. Typically, the ground truth was selected to be an open-source map from Open Street Maps, a road map that relies on the public for update. Using it as the ground truth assumes that does not contain errors, which is not always true. Therefore, this introduces a bias in the output quality measurement.

Distance and direction angle thresholds are used to determine if two elements (road segments or intersections) match. In addition, the sampling can be in terms of points or entire segments. For example, Li et al. (2016) samples every segment (or link) while Biagioni and Eriksson (2012) sample points throughout the inferred and ground truth networks. Eight papers out of eleven use this indicator to quantify the output network quality, while Dorum (2017) and Y. F. Zhang et al. (2020) only report recall values. Recall values are unable to quantify the number of network elements that were incorrectly extracted. The study by Elleuch et al. (2015) does not report any quantitative measures, which does not allow the author to assess the output quality.

The output quality assessment was also reported for different threshold values with lower thresholds making the ground truth matching stricter. This explains the different values presented for precision, recall, and F-score for a given method.

As presented in Table 2, the method proposed by Chen et al. (2021) for centerline extraction achieved the highest F-score (0.850), followed closely by Jia and Ruisheng (2016) (0.838). Meanwhile, the method proposed by Daigang et al. (2019) resulted with the lowest F-score (0.68).

Overall, F-score is found to be the best indicator method output quality since it takes into account the number of correctly extracted, incorrectly extracted, and not extracted network features.

Most studies are easy to read and understand and graphics, tables, and GIS components are relatively well presented (Dorum, 2017; Ezzat et al., 2018; Guo et al., 2021; Jia & Ruisheng, 2016; Y. F. Zhang et al., 2020). However, only the works by Hashemi (2019) and Ezzat et al. (2018) are presented in a reproducible fashion.

3.2 Intersection linking approach

This approach divides the network inference process into two main steps: 1) detecting intersections using the GPS data, for example, based on turning angles, 2) using GPS trajectories to link the intersections together and form a network.

This technique can be seen in (Karagiorgou & Pfoser, 2012; Xingzhe et al., 2016; C. Zhang et al., 2019). A variation is presented by Arman and Tampere (2020) where intersections are determined by finding merge and diverge locations. In fact, this paper also uses the Gaussian Mixture Method to estimate the number of lanes based on the distribution of GPS points within a road segment.

Four publications are classified under this approach of map inference. A summary of the experimental data description and validation results of these papers is presented in Table 3.

Paper	**Sample Description (Location, Collection Method, Sample Size, Sampling Rate)**	**Validation Results**
Arman (2020)	Antwerp, Belgium, Mobilis smartphone app, 21 100 trajectories, 1 second	On average within 4% in term of speed and 14% in term of lane share w.r.t ground truth
Zhang (2019)	Chicago, USA and Wuhan, China, University Shuttles and Taxis, respectively, 118 364 and 800 000 points respectively, 3.6 seconds and more than 40 seconds, respectively	Intersection Detection: more than 90% Road centerline extraction: Precision: 0.932-0.980 Recall: 0.704 - 0.886 F-score: 0.820 - 0.908
Xingzhe (2015)	Chicago, USA, University Shuttles, 118 000 points, 3.6 seconds	Intersection Accuracy: F-Score: 0.02 - 0.91 Connectivity Accuracy: F-Score: 0.19-0.95
Karagiorgou (2012)	Athens, Greece, GPS devices, N/A, 30 seconds	Shortest paths comparison

Table 3. Intersection linking approach - sample description and validation results

The intersection linking approach has the advantage of explicitly defining intersections by default, since it is the first step of the method. The four papers produce a directional road network. While three of the methods infer road centerlines, the work by Arman and Tampere (2020) is the only one to propose a method that determines the number of lanes. Intersection movements are only determined using the methods proposed by Karagiorgou and Pfoser (2012) and Xingzhe et al. (2016).

Different GPS data sources were used to propose intersection linking map inference methods. The Sampling rate varies between one second and thirty second in the works by Arman and Tampere (2020) and Karagiorgou and Pfoser (2012), respectively. Meanwhile, Xingzhe et al. (2016) and C. Zhang et al. (2019) use the same benchmark dataset, which enables their comparability. It is important to note that the work by Arman and Tampere (2020) limits the experiment to a small section of a highway corridor. This is insufficient to determine if the proposed method will perform well in more complex environments.

Network inference quality was evaluated using three different methods. Arman and Tampere (2020) compared the results with speed and count data while Karagiorgou and Pfoser (2012) used a shortest path based distance. In fact, this measure computes the shortest path distance for a set of OD pairs for both inferred and ground truth maps. The similarity between these distances indicates a similarity between the two maps in terms of geometry and connectivity. This method is not deterministic and can lead to false similarity conclusions. The final two papers by Xingzhe et al. (2016) and C. Zhang et al. (2019) use the harmonic mean of precision and recall, to assess the output quality. Both methods produce a very good F-score (>0.90), however, the method proposed by Xingzhe et al. (2016) has a high variability in the output quality. In terms of clarity, methods proposed by Karagiorgou and Pfoser (2012) and C. Zhang et al. (2019) are well explained. However, only the work by Karagiorgou and Pfoser (2012) contains sufficient details to be deemed reproducible.

3.3 Track alignment approach

Map inference using track alignment incrementally adds GPS tracks to an initially empty map. This approach can also be seen as an incremental averaging of the GPS tracks. Two publications are classified under this approach of map inference. A summary of the experimental data description and validation results of these papers is presented in Table 4.

The proposed methods focus on extracting a directional road network, represented by the centerline of the road. Therefore, intersections are not formally defined, and the number of lanes information is not determined.

In Zhongyi et al. (2018), experimental GPS data is obtained from a logistics company trucks. The use of truck GPS data can introduce a bias in terms of road coverage, as trucks are usually limited to drive on a subset of the entire road network due to their size, nuisance, and material they transport. The work by Leichter and Werner (2019) does not specify the experimental data details. In fact, this paper was written as part of competition oriented towards map inference algorithms efficiency and speed.

The inferred map quality was not evaluated by Zhongyi et al. (2018) since no ground truth was available. Meanwhile, Leichter and Werner (2019) evaluated the quality of inferred map using the HC-SIM, which measures the overlap of two lines (inferred and ground truth). An HC-SIM measure of 0.612 was obtained which ranked this method among the best in the competition. The explained methods lack some details to be fully understandable. The work by Leichter and Werner (2019) does not present the algorithm, while Zhongyi et al. (2018) does not present sufficient description, figures, and diagrams. Therefore, none of the two works is reproducible.

Paper	Sample Description (Location, Collection Method, Sample Size, Sampling Rate)	Validation Results
Leichter (2019)	Joensuu, Chicago, Berlin, Athens, N/A, Multiple datasets, N/A	HC-SIM of around 0.66

Zhongyi (2018)	Nanning, China, Logistics company trucks, 451 537 points, 10 seconds	N/A (no ground truth)

Table 4. Track alignment approach - sample description and validation results

4. Discussion

A detailed road network representation is essential for multiple tasks such as traditional navigation, autonomous vehicle navigation, and transport modelling. A transport model relies on the road network model as one of its main components. In more detail, the road network representation needs to accurately depict the road's geographic location, direction, type, number of lanes, connectivity, and intersection control type, and permitted turning movements. Additionally, the actual road network is dynamic in nature, since traffic rules can prohibit a subset of road users from using a specific road lane or segment or making a specific movement at an intersection, depending on the temporal criteria. Therefore, the modelled road network should also consider this characteristic.

The reviewed studies demonstrate that research has been carried out on the topic of road network feature extraction. This review found that two main approaches are the most popular: clustering and intersection linking, as can be seen in tables 3 and 4. They can reconstruct a road network model from GPS data with high accuracy (Guo et al., 2021). However, it is not possible to conclude if one approach is better than the other since within one approach, different methods achieve different accuracies. Moreover, different methods have used GPS data from different sources and different validation methods which makes them not directly comparable. Although this study allowed the identification of limitations in current methods towards building transport models usable in transportation engineering, it can be said that methods are available to use large spatiotemporal coverage GPS trajectory dataset to extract road network centreline and topology.

The reviewed research used multiple measures to evaluate the accuracy of the constructed networks in comparison to ground truth maps. The most relevant and common measure was the F-score introduced by Biagioni and Eriksson (2012). It evaluates the similarity between the extracted network and the ground truth by relating the number of correctly extracted features, with the number of incorrectly extracted features and the number of unextracted features. Although these findings are a good basis for road network features extraction from GPS, the following limitations were noted and need to be addressed in future research to be able to extract road network models usable in transport modelling and autonomous vehicle navigation:

- The constructed network is only a representation of directed road centrelines, and intersection locations. This level of detail is insufficient for road network model requirements as described above.
- Given the multitude of GPS data sources used in past research to extract network features, it is impossible to select the best method simply based on the F-score. In fact, GPS data used in the studies was obtained via shuttles, taxis, trucks, fleets, researcher initiative, or crowdsourcing. This results in variable spatiotemporal sampling characteristics rendering a direct comparison of the results impossible. Ideally, all methods should be evaluated using the same GPS sample and compared to the same ground truth.
- Not all GPS data sources provide the same level of road network representativity. For example, using GPS data collected by a specific fleet such as trucks, transit vehicles, or shuttles introduces bias with respect to the type of roads or routes that are permitted for them. Multiple studies used university

shuttles to extract road network features, the most recent being the effort by Daigang et al. (2019). This limits the coverage of the extracted network features to fixed routes or road types.

- Several studies were found to be irreproducible since the method is not clearly detailed or due to data unavailability.

These limitations need to be addressed to extract road network features with sufficient detail for use in transport simulation models. The following steps can help achieving this goal and contribute to the current research:

- The use of large GPS datasets collected by light private vehicles to reduce the road network coverage bias.
- The development of methods to extract road segment related features from GPS data such as road type, posted speed, and number of lanes.
- The development of methods to extract intersection related features from GPS data such as turning movement permissions and control type.
- The consideration of the dynamic nature of the road network which affects road segment or intersection related variables.
- Making detailed and reproducible methodology available for future researchers to build on.

5. Conclusion

This paper extends past literature reviews by viewing the map inference problem from the transport network modelling point of view. The search strategy was shared to render the search reproducible. It has been found that two main approaches are popular to extract network features from GPS data. However, the extracted output is limited to the road centreline, including directionality, and intersection locations. It was also found that the main accuracy indicator used to assess the similarity between the extracted network and the ground truth is the F-score. Additionally, some of the reviewed methods achieve high, but improvable accuracy.

GPS data, depending on its sampling coverage and frequency is rich and can be further explored to extract more detailed road network features. For example, future research can explore the extraction of road segment type, posted speed and number of lanes in addition to intersection control type and turning movement permissions. Being able to extract all road network features required for large scale transport modelling from GPS data will be of immense value as it will improve model quality and update frequency while reducing the required resources. Such data will be valuable for accurate navigation systems of automated vehicles.

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