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A Comprehensive Review of Map-Matching Techniques:

Empirical Analysis, Taxonomy, and Emerging Research Trends

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ABSTRACT

The map matching method gets simpler with higher precision positioning systems, but because the positioning framework is still not sufficiently precise or too costly for marginal map matching in practice, it is still a hot research domain. Several researchers have worked on map-matching methods and reported their finding of in-depth studies of domain. This literature review provides extensive information on the above map-matching methods related to digital maps with respect to convergence and outline the problems, information sources, as well as future demands identified by industry/society. It focuses on past research work approaches, implementations, capabilities, and their weaknesses using linear search and citation chaining. Finally, this work concludes with recommendations of the future direction of research and ideas to develop new algorithms for advanced applications.

KEYWORDS

Global Positioning System, Internet of Things, Location-Based Services, Map Matching, Pervasive Computing, Road Network, Trajectory, Ubiquitous Computing

1. INTRODUCTION

Real-time positional data (Gupta & Shanker, 2020d) is used by navigational applications to give direction or location-relevant information. The major services include navigation assistance such as fleet management and path planning. Fleet management is a service that helps businesses that rely on transport to eliminate or reduce the costs associated with vehicle investment while increasing productivity, efficiency and lowering total transportation and other costs. The majority of other navigational services are classified as location-based services (LBS). The role of MM in intelligent vehicles systems and other context-aware services is depicted in Figure 1. Since1990, when the global positioning system first became available, MM seems to have been a hot topic of research

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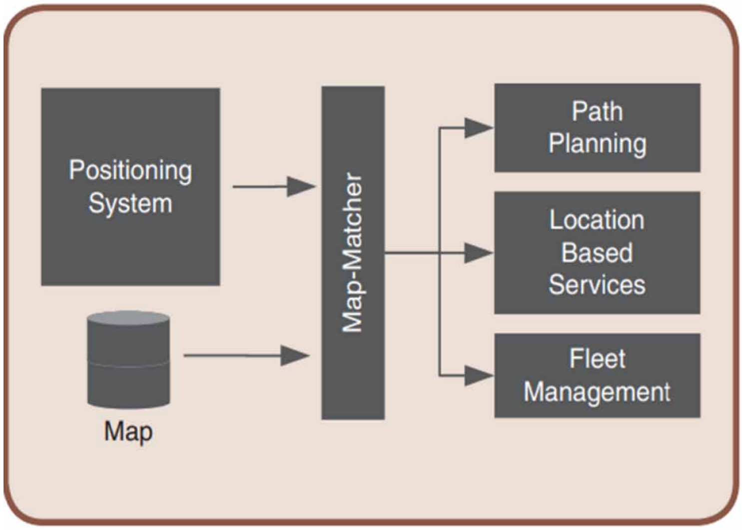
Figure 1. Relation of MM In Intelligent Vehicles Systems and Other Context-Aware Services



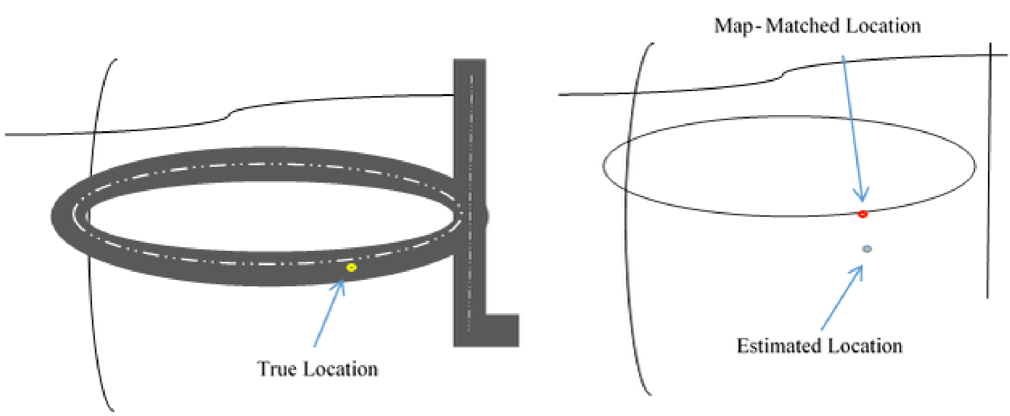
(Buxton et al., 1991) (Alegiani et al., 1989). Initially, there was lot of interest in navigation aids, but as the mobile internet became available, a completely new world of applications emerged in the communication world. If the location and map data are precise enough, the problem can be solved quickly and MM may appear to be a simple task (Gupta, A. K., & Shanker, U., 2022a) (Gupta, A. K., & Shanker, U., 2021a).

Now-a-days, we are having highly précised satellite navigation systems with comprehensive maps with millimetre-scale resolutions. However, none of those is guaranteed yet and can contain complex flaws. Satellite-based location systems are unreliable particularly in urban regions wherein satellite observation is constrained, and signals are frequently deflected. When the satellite signal is poor, this results in missing samples and outliers in positioning data. This can make accurate MM difficult in some circumstances. The map, on the other hand, might be out of its current state (lack of certain roads), or the MM method itself could cause ambiguity in the matching process. Directed graphs, in which junctions are symbolized by their centre points and highways are symbolized by polygonal curves, are often used in any maps. Accurate matching can be a challenge with such a simplified depiction of an otherwise complicated road network. As a result, MM isn't always straightforward. In the past two decades, hundreds of alternative approaches have been developed. These are based on a variety of methodologies and approaches ranging from basic topology and geometry to sophisticated ideas such as ant colony optimization, genetic algorithms, neural networks, Kalman filtering, conditional random fields, particle filtering, belief theory, and fuzzy logic.

Due to the growing need for precision for autonomous vehicles and lane determination, MM methods has been studied a lot in recent decades and is still an active field (Gupta & Shanker, 2020e). The MM is the phase layer between incorrect positioning systems and software that uses the positioning system (Yeh et al., 2017).

Figure 2 illustrates the MM dilemma. It is a pre-processing step in an information system depending on some position. For the two reasons, the need for a MM algorithm is important. The first reason is the errors in the GPS that lead to the incorrect location of a car. Second, sampling rates are not necessarily at a high level due to transfer, storage, and other costs making it difficult to estimate the path. It is, therefore, a critical activity for data recording device spending, data monitoring for traffic analysis, daily route finder, and the preferred framework for a taxi pickup. The observations may be placed with additional detail based on the measurements and chosen MM methodology. The global

Figure 2. Map Matching Problem



navigation satellite system (GNSS)-location heading, velocity, arc position, and output containing the map-matched arc may be used as measuring information. The term road in the figure denotes a portion between two intersections or between a dead-end and an intersection.

1.1 Motivation and Survey Contributions

It is not intuitively clear how the performance should be judged when looking at the outcomes of the MM issue. As a result of this reality, several researchers have offered various assessment techniques. Unfortunately, they are incompatible. Some researchers measure MM accuracy as a percentage of properly matched places to the entire sample, while others look at the degree of overlap between the matched and right routes. Because the two approaches do not share a similar foundation, a direct comparison appears to be impossible. Our survey work separates itself from prior studies by concentrating on real-time MM publishing platforms, carefully reviewing the MM implementation issues, and highlighting the developments identified in enhancing the accuracy of real-time MM methods. Furthermore, by observing stringent standards and performance evaluation, we employ a more comprehensive methodology than any of the previous reviews (Hashemi & Karimi, 2014) (Chao et al., 2020). Section 3 offers an aspect-wise analysis of our sample with current surveys. The current survey works do not seem to be covering all features relevant to various types of MM methods. The purpose of the document is to evaluate the following research questions:

RQ1: What are the data pre-processing challenges that could increase the difficulty of MM?
RQ2: What are the various directions that need an attention to be used in recent MM methods?
RQ3: How the performance of different MM methods should be measured?
RQ4: How the map matching Integrity could be monitored for reporting the reliability of its output.
RQ5: What approaches a researcher should take while selecting a MM method?

1.2 Outline of Paper

The structure of the paper is as follows. The preliminaries, and key terms associated with MM methods are detailed in Section 2. The methodology of the comprehensive literature review is given in Section 3. We are presenting a critical review of recent works by classifying the various category of MM in Section 4. The assessment of the research question identified are detailed in Section 5. The research challenges in full depth, and open issues of the domain are listed in Section 6. Finally, the conclusions of the review paper are given in Section 7 which, further outlines the extent of future contributions to the different themes.

2. PRELIMINARIES AND KEY TERMS

The MM method is a comprehensive procedure that includes mobile user trajectory data preparation, pre-processing of road data, and the process for identifying the best algorithm. The selection of algorithms phase focuses on picking the best algorithm out of several other options based on the scenario. On the gathered experimental data, MM aims to build acceptable MM algorithms (Gupta & Shanker, 2018).

Figure 3 depicts the complete process of the general MM methods. The formal description of the matching map as defined by Kubička et al. (Kubicka et al., 2015) can be found below:

Definition 1: The trajectory Ţ is a GPS point sequence created by a vehicle during a drive. Formally, Ţ =p(1) → p(2) → … → p(n), where n is the cumulative number of GPS trajectory sampling points. The begin and end points are given by the symbols p(1) and p(n) respectively. The latitude, longitude, and duration are the triplets used to describe a GPS point in form of ⟨lat, long., ⟩. Let D denote the N trajectory set. Figure 4 depicts a map-aligned trajectory for given GPS value.

Definition 2: A trip Ť is a two-tuple <r_s, r_e>, where starting and ending points of road are represented by r_s and r_e respectively. If two journeys, $Ť_X$, and $Ť_Y$ have the same path of origin and destination, i.e., $Ť_X = Ť_Y$ then trip may be called tenable.

Definition 3: The path Ṕ is a series of road segments traversed in a single trip by a mobile object. It is represented in the form of Ṕ =*rs* → *r*2 → … → *r*e(*T*), where r_s and r_e denote the starting road and ending roads respectively. A path is said to be a complete path if there are two separate and topologically related adjacent road segments of a path. A road segment in a path is illustrated in Figure 5.

Figure 3. Complete Process of General MM Method

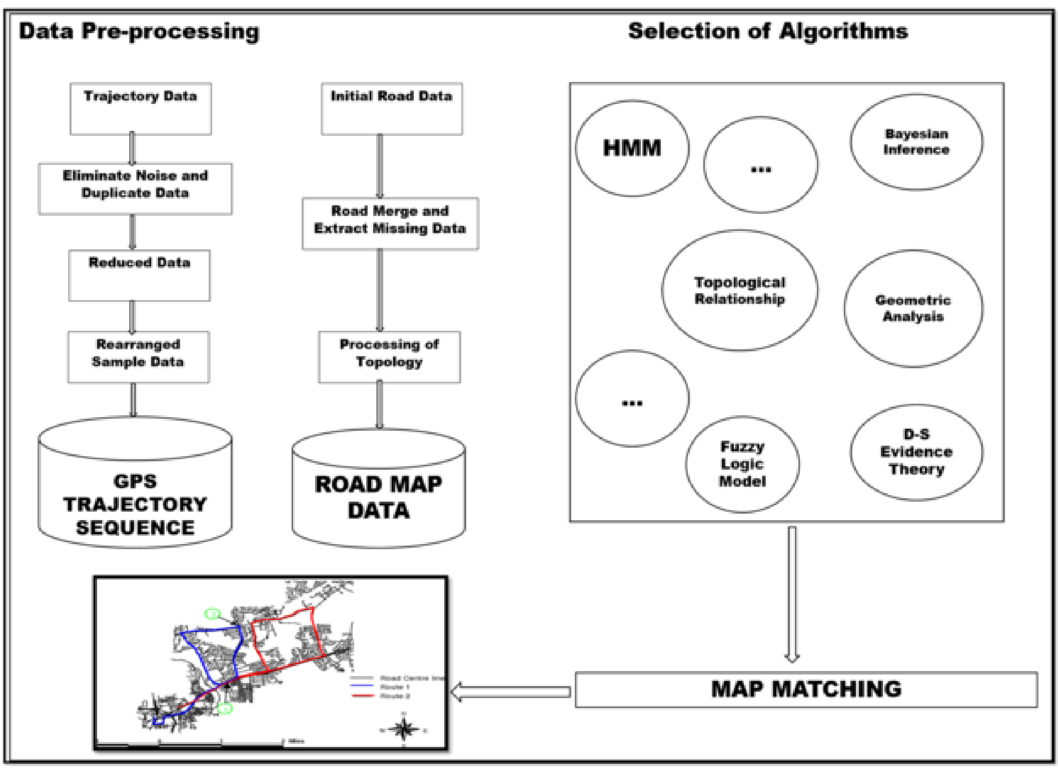


Figure 4. Log & Trajectory for Client Movement

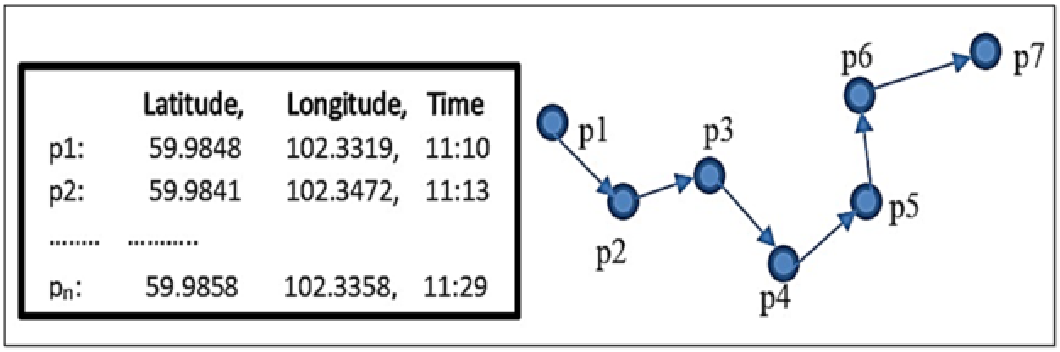
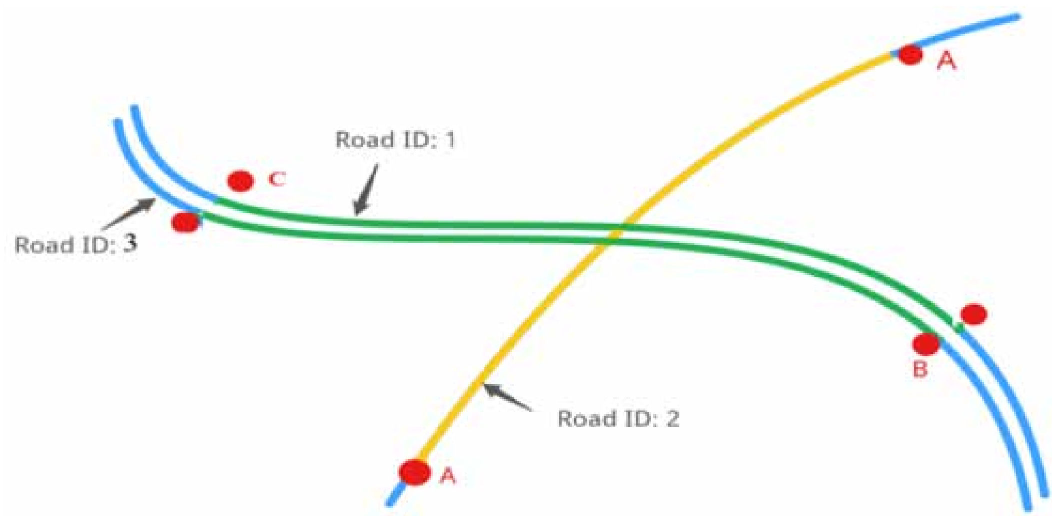


Figure 5. Illustration of Road Segments in a Path



Definition 4: Let the set M = (m_1, ..., m_n) be a series of measurements m_t sampled at times t for a given map, and G = (V, E) be a graph of mobile object movement, where V is a collection of nodes and E is a collection of arcs. A map matcher with G and M gives a map-matched result MM_{Result} = (r_1, .., r_n), where r_t is a map-matched result for m_t.

With a certain interval of position information called GPS trajectory T, the GPS gives us an approximation of the position of the car. Let P_t signifies the real location of the vehicle and P_e is the approximate location at time t. The objective is to discover the road A from G that corresponds to T with its real direction. By generating a guided and annotated street map from GPS lines, the chain of discovered user locations is aligned on the virtual map (or traces).

2.1 Map Matching Pre-Processing

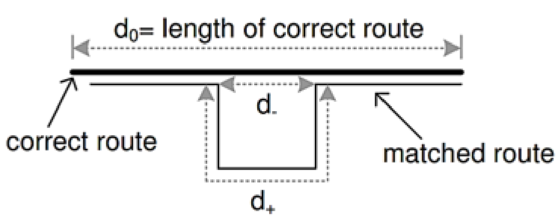
GPS suffers from the issue of line-of-sight, low-visibility area of sensors such as near-fly-overs, highly tree-lined streets, caves, and urban canyons (Grejner-brzezinska et al., 2004). Stand-alone GPS for many location-based applications (Gupta & Shanker, 2020a)(Gupta & Shanker, 2020b)(Gupta & Shanker, 2020c) will not achieve the necessary navigation efficiency in some comparatively harsh operating environments. GPS must be combined with the other sensors to compensate for this limitation such as Dead Reckoning (DR) and road maps utilizing Geographic Information System (GIS) to include horizontal orientation support and a Digital Elevation Model (DEM) to minimize the complexity in the vertical direction.

Digital elevation models are digital images of points on the surface region of a landscape with x, y, and z coordinates of locations. Depending on the spatial precision required, these coordinates are obtained from either a GPS receiver, satellite stereo photography, or aerial or survey instruments. The algorithms in the GIS program use these digital files of x, y, and z locations to translate them into either three-dimensional surfaces or elevation contours. It is the GIS framework that makes use of this “spatial information”. Further, analysis and simulations are carried out using the performance of these algorithms.

A positional approximation is taken by a map matcher through electromagnetic (EM) signal or dead-reckoning types (DR) and converted to a road network. These are the minimum sensor required by the machine, where it may give required positional estimate measurements. The Global Navigation Satellite Framework uses mainly electromagnetic signals for positioning, although other mechanisms can also be used depending on the requirement. E.g. GSM or other forms of telecommunications networks may be used in phones to collect position information. Indoor positioning is also popular for wireless LAN signals. EM-systems operate by providing reference artifacts transmitting EM-signals obtained by a receiver, and the EM-signals provide the information necessary to approximate the location. The plus side of EM-systems is that, relative to its equivalent DR (Ahmad et al., 2017), the error did not increase over time. However, it comes with the issue that scattering & shading are present in all EM signals. The position of Dead-reckoning estimates the location and uses it as the first estimated position. Provided the observations from various types of sensors (Mohamed et al., 2017), the predicted location is changed over time. For this, several different types of sensors can be used, for example, accelerometer and odometer. Many cars are fitted with an inertial measurement unit (IMU) which could be used for DR by combining the multiple accelerations or by using the commercially available wheel speed sensors. Due to the slight inaccuracies of the sensors that will become greater with time, Dead-reckoning is constrained by its addition of error.

2.2 Measuring Correctness of Map Matcher

Map matches are assessed in terms of implementation execution time and accuracy in terms of some precision measurement. The precision may be calculated in various ways. However, it is necessary to provide an estimate of how good the measurements matched by the map relative to other ground-truth results. Accuracy was specified by Newson et al. (Newson & Krumm, 2009) as the total of the length of the path added erroneously and length deducted erroneously in comparison to correctly identified route divided by the length of the correctly identified route (see below).



d_-= length erroneously subtracted
d_+= length erroneously added
$(d_- + d_+)/d_0$ = reported error

Therefore, the precision identified in conjunction with Newson et al. is defined by function given below:

$$\text{Accuracy}_{\text{Newson}} = \frac{d_+ + d_-}{d_o}$$

where:

d+ = length of the path added erroneously
d_ = length of path deducted erroneously
d_o = Length of ground-truth route

Some authors define position accuracy as the ratio of the number of positions properly mapped to the direction of ground truth relative to the overall number of positions, which is given by the below equation [6]:

$$Accuracy_{position} = \frac{\left|L_{correct}\right|}{\left|L\right|}$$

where, L is the list of all positions and $L_{correct}$ is the set of matched positions that are correctly mapped. The number of accurately aligned roads relative to ground-truth roads (Ren, 2012) is another measurement defined as the below equation:

$$Accuracy_{Road} = \frac{\left|R_{correct}\right|}{\left|R\right|}$$

where, in the ground-truth trajectory, R is the set of paths and $R_{correct} \in R$ is the set of roads that leads to the direction in both the map matched trajectories as well as ground-truth trajectory. Finally, according to the number of roads, the calculation of the entirely correct map-aligned routes could be assessed. For the spatial precision used by Kubicka et al. (Chatterjee & Russell, 2012), it would be more appropriate to get the metric applied to accurately map matched measurements to the path from which they were taken.

3. RESEARCH METHODOLOGY

The methodology of the comprehensive literature review is classified into two-part namely research area and research context. The research area is on MM. For studying the research area, the article presents the categorization and structured comparison of different MM methods for GPS trajectories in LBS. The research context describes scientific evidence by describing application, algorithms, techniques, findings, limits, strengths, and future research directions utilizing various research papers. Applying linear and citation chaining search, three categories of publications were evaluated in online libraries namely mathematical modelling, empirical research, and literature reviews.

A comprehensive literature review is a compilation of research studies in several areas (Hashemi & Karimi, 2014)(Chao et al., 2020) that shows evidence with a wide range of facts on the fundamental review of information research using a rigorous procedure (Huang et al., 2020). The study utilizes the parameters given by (C. Blazquez et al., 2018)(C A Blazquez et al., 2017) to perform a comprehensive literature review. Planning the review, performing the review, and reporting the review are the three distinct steps. The procedure is broken into numerous phases for each level. To make it easier to understand, we have listed below the activities from each step.

3.1 Review Planning

Review planning involves a set of the task such as Research Question specification, Inclusion and exclusion criteria specification, Digital Database specification, and Evaluation of Review policy. Table 1 contains a comprehensive list of the set of a task associated with review planning.

It is critical to review and assess the policies' quality to support the criteria for exclusion and, inclusion as well as the collection of research data. Indeed, the goal of quality evaluation is to ensure that the study's findings are appropriate and unbiased. To enhance this study, a variety of performance assessment questions were established. The design of this study was influenced by previous extensive literature studies (Hashemi & Karimi, 2014)(Huang et al., 2020)(Chao et al., 2020). The composition of performance assessment questions is an exclusion criterion as shown in Table 2. To guarantee that

Table 1. Set of a task associated with review planning

Research Question	Exclusion Criteria	Inclusion Criteria	Digital Database	Development Of Review Policy	Review Protocol Evaluation
Compile the research findings in terms of technique, applications, algorithms, and then present the findings for MM policies.	The criteria that were utilized to decide which literature should be excluded from the review.	The criterion for selecting the article study for inclusion in the review.	The digital databases were utilized to acquire data for the article review.	Determine the order in which journals can be evaluated for data extraction. Scopus, DBLP, PubMed, ScienceDirect, Sage, Springer, Taylor & Francis, and Emerald are examples of priority sequences followed by citation chaining searches.	To optimize this study, a variety of performance evaluation questions were established to complement the criteria for inclusion and exclusion, as well as selecting the research data.

Table 2. Composition of performance assessment questions

Performance Assessment (PA)	Meaning
PA1	The Performance Assessment includes evidence that has been evaluated statistically or subjectively. "No evidence (+0)", "Qualitative research (+2)," and "Quantitative research (+3)" are the most likely responses.
PA2	The performance question assesses both the benefits and the drawbacks in detail. The most likely responses are "no (0)", "Few (+1)" and "yes (+2)". If just one of the study's benefits or difficulties is mentioned, the score will be partial.
PA3	The performance assessment is used to find the justifiability of the policy. The most likely responses are "no (0)", "Incomplete (+1)" and "yes (+2)". If only a few approaches are mentioned or a few of the methods adopted are not described in detailed way, the score will be reduced.
PA4	The performance question is used to assess, whether the article being reviewed was published in a reputable and well-known journal or not. "Sum(Citation_Count + H_Index) > 100 (**+2**)," "100>Sum(Citation_Count + H_Index) > 50 (**+1.5**)," "50 > Sum(Citation_Count + H_Index) > 0 (**+1.0**)," and "Sum(Citation_Count + H_Index) = 0 (**+0**)."
PA5	The suggested technique is compared to other ways, and the likely results are "no: 0" and "yes: + 1".

the study's findings are as efficient as possible, the quality score is used as a criterion for exclusion. Consequently, only studies that reach or surpass 50% of the ideal score of 10 have been chosen.

3.2 Conducting the Review

Conducting the Review makes advantage of the search syntax's different characteristics. The following are some of the most often used search syntax attributes:

1. TITLE-ABS-KEY: The keywords chosen are looked for the paper's keywords, abstract, and title.
2. OR: One of the terms in the requested item must be present, according to this operator.
3. AND: Both terms in the requested item must be present, according to this operator.
4. LIMIT-TO (EXACTKEYWORD): include publications that match the precise keyword.
5. LIMIT-TO (DOCTYPE): Only journals were examined in this analysis. 'ar' denotes a journal article, 're' denotes a review article, and 'ip' denotes an item in the press.
6. LANGUAGE: This research looks at articles written in English.
7. * is a search syntax that may be used to represent one or more characters.

The Search Syntax for choosing research papers in our literature review is shown in Table 3. An approach for creating a high-quality meta-synthesis that was developed in conjunction with Review planning is used to acquire a thorough knowledge of the application, algorithms, methodologies, findings, limitations, strengths, and research directions.

3.3 Literature Review Reporting

In digital databases, linear and citation chaining searching was conducted for 6 years (2015-2020). These studies were extensively examined to pick just the most relevant publications, and the research ultimately comprised of 130 articles. PAs were used in the research to assess the quality of the articles based on their complete texts. Data from such publications were categorized, sorted, analyzed, and structured in a way that demonstrates the findings.

Table 3. Search syntax for selecting research papers in our literature review

Digital Library	Search Syntax
Scopus	(TITLE-ABS-KEY ("map matching*") OR TITLE-ABS-KEY ("positioning*") OR TITLE-ABS-KEY ("road network*") AND (TITLEABS-KEY ("navigation *") OR TITLE-ABS-KEY ("GPS trajectory *") AND (LIMIT-TO (LANGUAGE, "English") AND (LIMIT-TO (EXACTKEYWORD," map matching *") OR LIMIT-TO (EXACTKEYWORD," positioning") OR LIMIT-TO (EXACTKEYWORD," road network ") OR LIMIT-TO (EXACTKEYWORD, "navigation*") AND(LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,"re") OR LIMIT-TO (DOCTYPE,"ip")
Emerald	("positioning " OR " road network " OR " navigation ") AND map*
Taylor & Francis	("Positioning" OR "Road Network" OR "Cognitive informatics") AND map*
Sage	"Positioning" OR "Road Network" OR "Navigation" AND map*
Springer	(Positioning* OR "Road Network" OR Navigation*) AND (map matching OR map-matching)
ScienceDirect	("Positioning" OR "Road Network" OR "Navigation") AND (map-matching OR "map matching")
PubMed	(Positioning[Title/Abstract] OR Road Network[Title/Abstract] OR Navigation[Title/Abstract]) AND (map-matching[Title/Abstract] OR map matching[Title/Abstract])
DBLP	Map* and "Road Network" type:Journal_Articles: Positioning* and healthcare type:Journal_Articles: Navigation and map-matching type:Journal_Articles:

Figure 6 depicts a word cloud based on the title of a few research. The article title word cloud gives an outline of the title of the selected article.

Figure 7 shows the papers distribution by digital databases, and year of publication. The graph indicates that the year 2020 had the highest number of quality articles.

Figure 8 shows the number of citations for the papers published throughout the publication year, indicating that 2018 is the year with the highest quality citation. The quality citations in 2020 and later years, on the other hand, may contribute to future growth.

Figure 6. Word Cloud based on Title of Articles

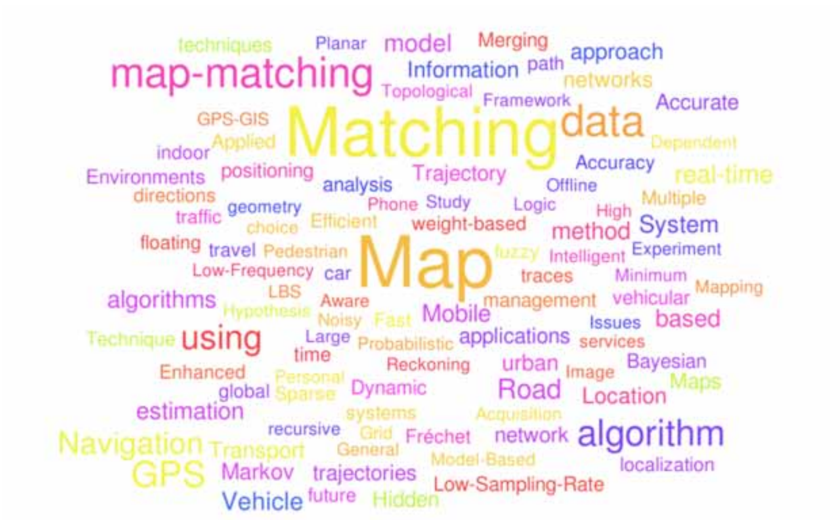


Figure 7. Papers distribution by digital databases, and year of publication

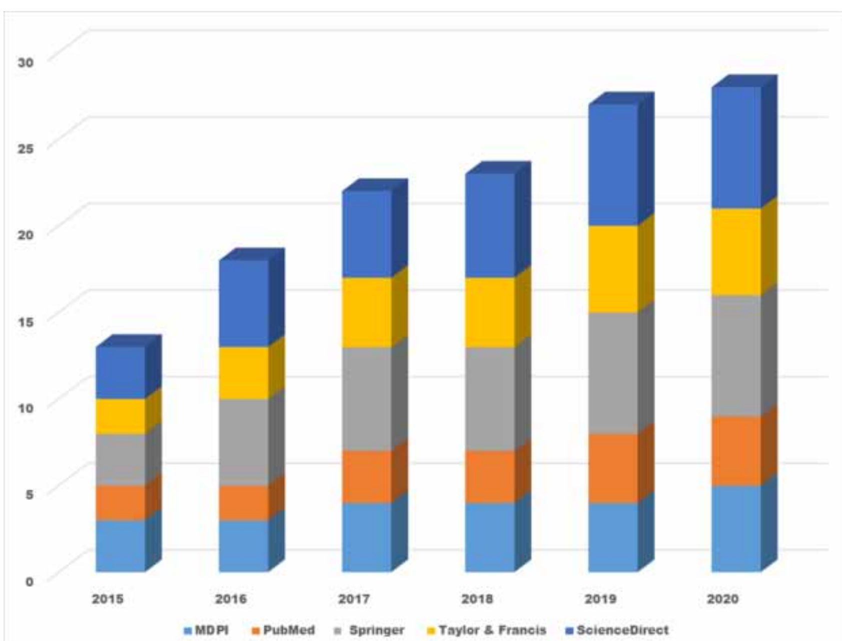
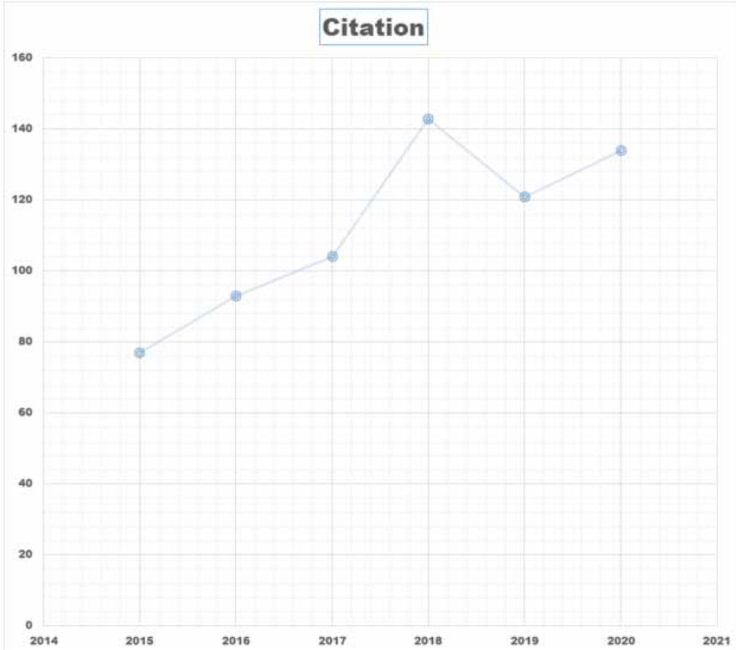


Figure 8. Quality Citations Count for the Papers Published (2014-2020)

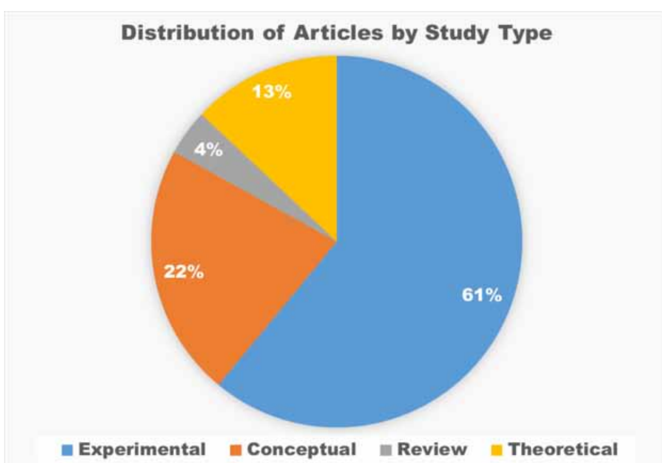


The distribution of publications by research type is seen in Figure 9. The papers are classified into four categories of studies, i.e., theoretical, review, conceptual, and experimental.

4. CATEGORIZATION AND STRUCTURED COMPARISON OF DIFFERENT MM METHODS FOR GPS TRAJECTORIES IN LBS

MM methods do the job of locating a moving car on a road utilizing map data in digital form with GPS receiver knowledge. MM implementations serve many functions such as route selection

Figure 9. Distribution of Articles by Study Type



parameter estimation (Oyama & Hato, 2018), travel time estimation (Rahmani et al., 2017)(Tang et al., 2018), motion anomaly identification (Qin et al., 2019), and gridlock network analysis (Oyama & Hato, 2017). There are several common use cases and configurations for MM Algorithms. There are several common use cases and configurations for MM Algorithms. Based on use cases, there are many algorithm categorizations. Some of the basis of categorization used in this paper are Use of Road Network and Trajectory Details, Range of Used Trajectory, Type of Algorithm, Type of Sensors, Type of Environment, Type of Tracked object, Type of Sampling, and Processing of Algorithm, etc. Table 4 provides an overview of different categorizations.

In the MM methods, geometric map matches make use of geometric closeness. Topological map matches use topological details as well as geometrical knowledge (e.g. links between roads).

Table 4. Different Categories of MM Methods

Basis of Classification	Classes	Policies/ Papers
Based on Use of Road Network and Trajectory Details	Topological, Geometrical	Topological (Greenfeld, 2002)(Liu et al., 2017)(Schwertfeger & Yu, 2016)(Velaga et al., 2009) Geometrical (Abdallah et al., 2011)
Based On Range of Used Trajectory	Incremental (online, real-time), Global (post-process, offline)	Incremental (White et al., 2000) (J. Yang et al., 2005) (Carola A Blazquez & Vonderohe, 2005) (Li et al., 2008) (Greenfeld, 2002) (M. A. Quddus et al., 2003) (Velaga et al., 2009) (M. Quddus & Washington, 2015) (Griffin et al., 2011) (Mazhelis, 2010), Global (Marchal et al., 2005) (Lou et al., 2009) (Oliver Pink & Hummel, 2008) (Thiagarajan et al., 2009) (Newson & Krumm, 2009)
Based On Type of Algorithm	Weighted-algorithms, fuzzy-logic, Machine-Learning, HMM, Fuzzy-Logic, Particle-Filter, Kalman	Weighted-algorithms (Carpin, 2008)(Abdallah et al., 2011) fuzzy-logic (Gupta & Shanker, 2020d) (Gupta & Shanker, 2022b) (Gupta & Shanker, 2021b) Smoothing (Hsueh & Chen, 2018)(Cao & Krumm, 2009) ARIMA (Yan, 2010) Kalman Filter (O Pink & Hummel, 2008)(Cho & Choi, 2014) (M. A. Quddus et al., 2003) Non-Para Metric Regression (Nagaraj & Mohanraj, 2020) (Sharath et al., 2019) Neural Network (K. Zheng et al., 2012)
Based on Type of Sensors	GPS, DR, DEM	GPS (Greenfeld, 2002) (M. Quddus & Washington, 2015) (Hashemi & Karimi, 2014) (Wu & Wu, 2003) DR (M. A. Quddus et al., 2003) (Velaga et al., 2009)(Pyo et al., 2001) (M. A. Quddus et al., 2006) DEM (Ahmad et al., 2017)
Based on Type of Environment	Outdoor, Indoor	Outdoor (Y. Zheng et al., 2011)(Abowd et al., 1997) Indoor (Tian et al., 2015)(Petrou et al., 2014)
Based on the Type of Tracked object	Wheelchair, Vehicle, Pedestrian	Wheelchair (Ren & Karimi, 2009)(Ren, 2012) Vehicle (Jagadeesh et al., 2004)(M. Quddus & Washington, 2015) Pedestrian (Shin et al., 2010)(Ren, 2012)
Based on Type of Sampling	Low-Sampling, High-Sampling	Low-Sampling (M. Quddus & Washington, 2015)(Lou et al., 2009)(K. Zheng et al., 2012) High-Sampling
Based on Processing of Algorithm	Post-processing, Real-Time	Post-processing (Knapen et al., 2018)(Rappos et al., 2018) Real Time (Algizawy et al., 2017)(Goh et al., 2012)

The links of roads can be used by topological map matches to build an arc which can be contrasted against a generated trajectory through measurement. Many algorithms that have been released belong to the topological category (Schwertfeger & Yu, 2016). But geometrical implementations are still being investigated for better estimation functions for distance metrics. The incremental and global classification published by Wei et al. (Wei et al., 2013) was later taken up by other researchers (Kubicka et al., 2018). Until giving an output, global algorithms consider the entire position trace, while incremental methodology calculates the output for each position estimation before going on to the subsequent position. Other terms used by many researchers are real-time and online/offline (Goh et al., 2012)(Wang et al., 2017)(Pereira et al., 2009). It is possible to see these as the same class as incremental and global (Kubicka et al., 2018). The accuracy of these algorithms may become a secondary factor in performance as outputs can need to be produced rapidly instead of accurately.

Another way to categorize the algorithms is using sampling rate. Intervals for sampling will vary from seconds to several minutes. Many researchers have explicitly opted to concentrate on low sampling (Newson & Krumm, 2009)(Lou et al., 2009). The precision can be useful for both high and low sampling depending on the algorithm. The researchers normally sub-sample a high-sampled trajectory to validate their algorithm at several different rates of sampling.

Another form of categorization is vehicle/pedestrian and outdoor/indoor which can be seen as two distinct categorizations as tracked entity and environment. Since, Simultaneous Localization and Mapping (SLAM) can be used by indoor structures, the MM methods can only be used to decide whether the loop is closed (Williams et al., 2008) or not. Such use cases may be taken where the system has limitations to the positioning system, keeping it within some limits. Since pedestrians can travel indoors and outdoors, while vehicles were regarded outdoors alone, pedestrian MM is highly tied to indoor MM.

The accessible sensor/positioning data is also a classification system for algorithms that fits the map. Basic vehicle MM normally depends only on GNSS positioning, while gyroscope, accelerometer, and Wi-Fi positioning can be used by pedestrians. It is an issue to differentiate the part of the MM algorithm and sensor fusion for the positioning system as multiple sensors are used and tightly combined with a map matcher and positioning system. Georgiou et al. (Georgiou et al., 2017) reported that it is desired to enhance the efficacy of human-robot cooperation by measuring the correspondence between abstract human-readable maps with a map that is built from sensors of a robot. In a topological map, path matching is a similar subject, which can then be used to align maps (Schwertfeger & Yu, 2016). The last grouping will be to categorize the MM algorithms based on what optimization methods they are based on. Weighted-algorithms, fuzzy-logic, Smoothing, ARIMA, Kalman Filter, Non-Para Metric Regression, Neural Network (Kubicka et al., 2018) are common methods to base map matches on. The area of using various types of AI algorithms to solve the MM problem has also extended in recent years (Algizawy et al., 2017).

4.1 MM Strategies Based on Range of Used Trajectory

Current MM methods may be divided into two groups based on the range of trajectories employed:

1. Local/Incremental MM Methods
2. Global MM Methods

The first type (Liang et al., 2016)(Goh et al., 2012) is based on a greedy method in which the starting point in MM is determined by the current trajectory point, which is then followed by subsequent points. It uses turn-by-turn navigation in practical systems. With a faster rate of sampling, the local/incremental approach provides improved accuracy. When the sample rate decreases, the problem of arc-skipping (Lou et al., 2009) occurs. In this case, the automobile shifts from one highway segment to another while it is farther from the intersection, which is absurd. It results in a significant loss of accuracy. Because of the greater rate of sampling, the local/incremental approach would have a relatively high energy consumption. During this whole scenario, the author (Fang &

Zimmermann, 2011) introduces a GPS trajectory data Acquisition based method namely EnAcq for efficient utilization of energy resources, which seeks to reduce energy consumption while maintaining precision. The notion of dynamic sampling is initially proposed in EnAcq, which may be characterized as dividing data into three groups and applying sample rates to the vehicle's speed throughout each group. Even yet, this approach is not effective, and there is still a need for more research.

The global mapping approach (Liu et al., 2017) aims to identify a curve as close to the vehicle route as feasible within a network of roadways. It entails gathering of all track points before determining the far more frequent trajectory path on the road system. The precision of Global techniques grew due to the scarcity of additional information; nevertheless, was also constrained by the long computation time. In (M. Quddus & Washington, 2015), the authors combine the path-searching techniques such as A * shortest-path procedure (Hart et al., 1968), quadtrees (Marchal et al., 2004), and t-d tree (Bentley, 1975) to reduce the processing time. Fréchet distance (D. Chen et al., 2011)(Shigezumi et al., 2015) is commonly used to calculate the similarity between the direction of the vehicles and the street. Empirically, the global MM method is appropriate for matching in offline cases because it includes all trajectories as data input. The local trajectories contain a very low amount of valid information, and if only these are available for MM then the accuracy of the matching will be significantly reduced. To produce correct mapping results within a fairly short period, Ant Mapper-matching (Gong et al., 2018) using the Ant colony synthesis method has been discussed for local and global geometric/topological information. Many global methods use the segment-wise matching technique (Chawathe, 2007) and candidate path technique (Yuan et al., 2010)(Marchal et al., 2004)(Schuessler et al., 2009) to effectively manage a huge quantity of trajectory data that have recently been published. The difficulty in evaluating the segmentation schema scale and segment is a major drawback of these sorts of segment, and candidate path mapping techniques. Such techniques employ a set of segment width that is not customizable but will not be optimum. An additional downside of segment-wise, and candidate path mapping techniques is that they build a candidate pathway for every point or point segment. The potential routes are compiled exhaustively (Yuan et al., 2010)(Marchal et al., 2004)(Schuessler et al., 2009). Path-searching and candidate path-maintaining processes degrade the techniques' performance in terms of running time.

A non-real-time corresponding method was introduced in (Lowe, 2004). This method is different than the matching of curve-to-curve types and works by Fre'chet distance measurement between the vehicle trajectory curve and the curve of the road. Nevertheless, because the purpose of this algorithm is also geometrical analysis, the defects of the process of geometric analysis cannot be fully eliminated. In (Baker et al., 2003)(Lucas & Kanade, 1981), a matching model consists of two stages namely initial & subsequent matching using Fuzzy theory reasoning. This method first measures the input values of the navigation scheme utilizing the topology of the road network, and geometric evaluation then transforms into fuzzy memberships from the input values and later completes by imposing the rules of fuzzy to the fuzzy member. The critical feature of this policy is to decide the rules and memberships that include several variables. The values of these variables are decided through neural network training. The downside of this technique is a longer amount of time required by the initial matching requirement and can repeat if the subsequent match is incorrect.

The Hidden Markov Model (HMM)-based methods are ideal for balancing both real-time and non-real-time MM because it is indifferent to noise and sampling rate (Gupta, A. K., & Shanker, U., 2021c) (Gupta, A. K., & Shanker, U., 2021d). This algorithm computation is less difficult than the Fre'chet distance-based algorithms due to historical errors of non-real-time matches being fixed. Low sample rate and non-real-time matching are the focus of recent HMM-based technique research (Carpin & Birk, 2005)(Carpin et al., 2005). This approach may be used to build a sophisticated navigation framework for vehicle routes and traffic movement tracking. Nonetheless, a navigation device client requires a real-time matching function which is ideal for a fast-sampling rate. Since the matching methodology based on HMM adapts to this criterion unlike the non-real-time matching, these matching steps do not increase the precision by fixing historical errors. Using a subset of features, Table 5 summarises recent incremental methods and global MM methods.

Table 5. A Summary of Recent Incremental and Global MM Methods

Policy		GPS Points Functions		Segment Edge Functions			
Paper	**Incremental Or Global**	**Features used in Policy (Distance or Bearing)**	**The function of used feature/s**	**Features used in Policy**	**The function of used feature/s**	**Aggregation used in GPS Local / Global**	**Drawback**
(White et al., 2000)	Incremental	Both	Distance d, and Bearing $\Delta\theta$	connectivity	1 or 0	Threshold	Sensitive to noise, and connectivity problems exist during link transitions
(J. Yang et al., 2005)	Incremental	Distance	Distance d	shortest-path	ℓ	Rules	Fails to find the exact position of the vehicles.
(Carola A Blazquez & Vonderohe, 2005)	Incremental	Distance	Distance d	Speed	$v - \frac{v_i + v_{i-1}}{2}$	Threshold	Increases the complexity, especially for the intersection.
(Li et al., 2008)	Incremental	Both	Distance d and Bearing $\Delta\theta$	None		Tie-breaker	Not feasible in the different context and environment having hardware limitations.
(Greenfeld, 2002)	Incremental	Distance	Distance $C - w_d d^{n_d}$	Direction	$w_\alpha \cos\left(\Delta\alpha\right)^{n_\alpha}$	Sum	Inferior for lower sampling frequency cases.
(M. A. Quddus et al., 2003)	Incremental	Both	Distance $w_d \frac{1}{d}$, and Bearing $w_\theta \cos(\Delta\theta)$	None		Sum	Inferior for lower sampling frequency cases.
(Velaga et al., 2009)	Incremental	Both	Distance $w_d\left(1 - \frac{d}{80}\right)$, and Bearing $w_\theta \cos(\Delta\theta)$	connectivity	w_c or $-w_c$	Sum	Lack of dynamic coefficient of the weights on road network analysis.
(M. Quddus & Washington, 2015)	Incremental	Both	Distance $w_d\left(1 - \frac{d}{80}\right)$, and Bearing $w_\theta \left\lvert\cos(\Delta\theta)\right\rvert$	shortest-path and direction	shortest-path , and direction	Sum	Face the problem of data sparsity in prediction of a road network

continued on following page

Table 5. Continued

Policy		GPS Points Functions		Segment Edge Functions			Drawback
Paper	Incremental Or Global	Features used in Policy (Distance or Bearing)	The function of used feature/s	Features used in Policy	The function of used feature/s	Aggregation used in GPS Local / Global	
(Griffin et al., 2011)	Incremental	Both	Distance d and Bearing $\Delta\theta$	Shortest-path	$\frac{l_0}{l}$	Decision tree Gupta, A. K., & Shanker, U. (2020f)	Inferior for lower sampling frequency cases.
(Mazhelis, 2010)	Incremental	Distance	Distance $\frac{1}{d+\delta}$	Direction and Length	Direction $1-2k\frac{\Delta\alpha}{\pi}$, and Length $\frac{1}{\left(d'+\xi\right)^2}$	Bayes filter	Highly dependent on the availability and performance of the GPS positioning.
(Marchal et al., 2005)	Global	Distance	Distance d	None		Sum as Global	Highly time consuming and computationally costly.
(Lou et al., 2009)	Global	Distance	Distance $\frac{1}{\sqrt{2\pi}\,\sigma}e^{-\frac{d^2}{2\sigma^2}}$	shortest-path, and Speed	shortest-path $\frac{l_0}{l}$, and Speed $\frac{v'.v}{v'.\ v}$	Multiply as Local, and Sum as Global	It cannot handle the matching error well at junctions.
(Oliver Pink & Hummel, 2008)	Global	Distance	Mahalanobis Distance	Connectivity	$\frac{1}{n+0}$ or 0	Multiply for Local and Global Both	Inferior for lower sampling frequency cases. Data collection process is expensive
(Thiagarajan et al., 2009)	Global	Distance	Distance $\frac{1}{\sqrt{2\pi}\,\sigma}e^{-\frac{d^2}{2\sigma^2}}$	Connectivity	ε or 0	Multiply for Local and Global	High energy consumption on mobile devices and overhead in terms of communication and processing.
(Newson & Krumm, 2009)	Global	Distance	Distance $\frac{1}{\sqrt{2\pi}\,\sigma}e^{-\frac{d^2}{2\sigma^2}}$	Shortest-path	$\frac{1}{\beta}e^{-\frac{l-l_0}{\beta}}$	Multiply for Local and Global Both	Time taking process and is not suitable for real-time map matching.

4.2 MM Strategies Dependent on Use of Road Network and Trajectory Details

The map matching strategies are classified into four groups (Table 6), depending upon how the trajectory details and road network are used:

1. Geometric Approach (e.g. curve-to-curve, point-to-curve, and point-to-point).
2. Topological Approach (e.g. containment & connectivity of the entity in the road network, and adjacency).

Table 6. Map Matching Strategies Depending Upon Use of Road System & Trajectory Details

Category	Definition	Used Parameters	Papers/ Policies
Geometric Algorithms	Using defined geometry it derives the requisite information for matching the edge segments	Euclidean, Hausdorff, Frechet´, Area, overlap, etc. function used for a curve to curve, point to curve or point to point matching	Geometrical (Abdallah et al., 2011)
Topological Algorithms	These methods use information from defined map topological knowledge	Node-degree, Valid traffic directions, speed, prohibited manoeuvres, distance, connected segments, etc.	Topological (Greenfeld, 2002) (Liu et al., 2017)(Schwertfeger & Yu, 2016)(Velaga et al., 2009)
Probabilistic Algorithms	Around the points, estimation of the confidence value is achieved through probabilities calculation	Use the confidence region around the trajectory points with closeness, heading, and connectivity to estimate the best matching segment.	Probabilistic (M. A. Quddus et al., 2007)(Jagadeesh & Srikanthan, 2015)

3. Probabilistic Approach (e.g. Bayesian inference, Fuzzy logic model, Kalman filter and its derivatives).
4. Other Advanced Strategies.

A very simple MM strategy is the geometric MM approach; however, very few matching strategies concentrated on the method of geometric analysis were presented in the literature (Greenfeld, 2002) (White et al., 2000). In point-to-point matching of the geometric approach, points of GPS are located at the closest nodes on the road network. In point-to-curve match, GPS points are located at the closest path segments. In curve-to-curve match, GPS trajectory is compared to the closest continuous path segments. Bernstein et al. (Brakatsoulas et al., 2005) provided a geometric matching technique that mainly included point-to-curve and point-to-point matching. The foundation for the MM algorithm is a geometric matching algorithm. Taylor (Pyo et al., 2001) suggested a road curtailment filter method designed to match the map to the GPS positioning machine that can enhance curve-to-curve and point-to-curve matching precision with differential GPS correction. The geometric strategy based MM relies on the distance between the candidate road connections & the location. It also depends on the projective deviation similarity between road links and trajectory (Oliver Pink & Hummel, 2008)(Jagadeesh et al., 2004). In the map, the algorithms consider connections between the point of orientation and projective points. It also uses multiple sequential ties to bind the route. Such algorithms reveal their drawbacks when the topology of traffic routes is complicated. Greenfeld et al. (Greenfeld, 2002) published a seminal study for MM on road network space by considering the spatial details. This policy is simple to apply; however, it has low matching precision because it does not find the link details between the road networks.

Apart from the basic geometric methodology, few of the studies in (Greenfeld, 2002)(White et al., 2000) used road network analysis or topology MM approach. From a separate viewpoint, the topology of MM approach (Jagadeesh et al., 2004)(Schweizer et al., 2016)(G. Hu et al., 2017) (Jagadeesh & Srikanthan, 2015)(Taylor et al., 2006) makes better use of road network continuity and connectivity and greatly increases the MM precision. This approach considers both spatial details and route topology relationships through locations and path ties to candidates as the considerations of decision. The topology MM approach steps can be divided into two sections:

1. Initial Matching
2. Subsequent Matching.

Initial matching is the first step that decides the section of the path to be matched by geometrical analysis. In the second step, subsequent matching chooses segments of candidates according to previous matching outcomes by both the analyses of the road network and geometric analysis. The candidate links are assigned a value in this step. The value is based on the three components:

1. Alignment Angle in Direct Link and “Axis” Across Next Locations.
2. Relation Link and Orientation of Successive Points.
3. Closeness of Direct Link to Positioning Point.

After defining the segments of candidates, the best candidate suited can be chosen by topological & geometric-based calculations and candidates, which earn the highest score called the true position of the vehicle. The topological approach dependent MM utilizes the geometric strategy; however, in a more complex situation, such as data with low precision, large-scale positional data or a low sampling rate, it cannot produce satisfactory results. The MM methods based on the topological weight-based approach depict the simplicity of execution and are better in speed & accuracy efficiency. The studies (Bouju et al., 2002)(Srinivasan et al., 2003) show that topological details such as historical matching information, speed limits, turn restrictions, and each link shape are integrated into the location deriving. Thus, the efficiency of the MM algorithm is improved. Quddus et al. (M. A. Quddus et al., 2003) have established and empirically calculated the weight coefficients and efficiency dependency in MM policy. They developed a MM method relying upon A* method and weight-based approach using Expanded Kalman Filter (EKF) to evaluate the shortest route between consecutive GPS location fixes and to combine the Inertial Navigation System with GPS respectively. However, almost all implementations require a high-frequency localization of vehicles. Yeh et al. (Yeh et al., 2017) attempted to address this problem using the MM algorithm with necessary modifications. The analysis demonstrates the influence of weight coefficients on the complexity of the road network.

Besides, probabilistic strategy based MM methods (Y. Yin et al., 2018)(Tian et al., 2015)(Hashemi & Karimi, 2014)(Alonso et al., 2016)(Y. Yin et al., 2016) are designed to deal with complicated road or junction segments, and they use a lot of math to improve matching precision. Multiple hypotheses are included in a probabilistic technique based on MM (Yuan et al., 2010)(Toledo-Moreo et al., 2010)(Shin et al., 2010), and HMM-dependent MM for GPS positioning (Ren & Karimi, 2009)(B. Y. Chen et al., 2014). These methods rely on a holistic assessment of the situation for all prospective road linkages as well as all geographical information rather than estimating particular places and possible road linkages in the vicinity (Tian et al., 2015)(Raymond et al., 2012)(H. Yin & Wolfson, 2004). The accuracy of the location data is frequently influenced by the sample size (J. Hu et al., 2009)(M. A. Quddus et al., 2007). Small sample rate and mapping for cell phone positioning in terms of precision and dependability, GPS mapping requires gradual improvements. Several advanced MM methods are used with Hidden Markov Models (HMM) (Mohamed et al., 2017)(C. Yang & Gidófalvi, 2017), fuzzy logic model (M. A. Quddus et al., 2006), Kalman filtering (Cho & Choi, 2014), etc. to deal with difficult road markings. When dealing with noise and sparse location details, HMM (Mohamed et al., 2017)(C. Yang & Gidófalvi, 2017) is utilised to determine the best matching path. All these techniques, on average, required three stages:

1. The direct link must be extracted first with soft constraints closing the distance to the positioning point. This procedure ensures the selection of correct trajectories as well as a high level of duplicity.
2. The next step is to assign a practical attribute to each link. The accuracy is based on topological MM practicability attributes such as topology connection, angle intersection, direction similarity, and projective deviations.
3. The third stage is to calculate all the ties that have accrued throughout time.

4.3 MM Approaches Based on Processing of Algorithm

It is possible to apply the matching position obtained from GPS or other sensors in either on-road segments in real-time or post-processing mode. When MM is performed in real-time mode, then MM problems like road section exploration, where the consumer is going, etc. need to be resolved in the GPS coordinates that are visible and updated in real-time. Whereas if MM is performed in segment post-processing mode, a large portion of the GPS points is collected. Discovering a path that perfectly matches a raw GPS trajectory on a road network is the difficulty of matching post-processing maps. The major differences between MM algorithms in real-time and post-processing are defined in Table 7.

4.4 Algorithmic Approach Based MM Procedures

In the early stages of this field of study, optimization is among the most prevalent methodologies. MM is a crucial and demanding challenge for item recognition in robot mapping utilizing feature-based and optimization techniques presented as image registration. Table 8 details the comparative study of various algorithmic approaches which have been used by researchers in MM procedure with their pros and cons.

Table 7. A Comparative Study of Real-Time & Post-Processing MM Methods

Basis	Real-time	Post-processing
Response	Fast	Accurate
Live Updates	Not Assured	Conditional
Polling Interval Time	1–10 s	1–5 min
Subsequent points	Not Required	Required
Required Information	Heading, speed, accuracy, position, and timestamp	Timestamp and position
Uses	Real-time navigation applications	Moving vehicle large-scale trajectory data mapping, fleet monitoring, surveillance of traffic
Problem	Assign road segment using current GPS point	Use of comprehensive points to find out real path

Table 8. A comparison of Different Algorithmic Approaches in MM Procedure

Algorithm Used In MM	Quality Of Data	Accuracy	Nature of Prediction	Advantage	Disadvantage	Papers/Policies
Smoothing	Short Series	Low	Static	Short Series Needed	Low Accuracy	(Hsueh & Chen, 2018) (Cao & Krumm, 2009)
ARIMA	Extensive	Low	Recursive	Theoretical Back Ground Needed	Low Accuracy Slow Data Processing	(Yan, 2010)
Kalman Filter	Extensive	Medium	Static	Multivariate Nature	Gaussian Hypothesis	(O Pink & Hummel, 2008)(Cho & Choi, 2014)(M. A. Quddus et al., 2003)
Non-Para Metric Regression	Extensive	High	Dynamic	Simple Model Structure	Intensive Data	(Nagaraj & Mohanraj, 2020)(Sharath et al., 2019)
Neural Network	Extensive	High	Dynamic	Wide Mapping Capability	Intensive Data Complex Internal Structure	(K. Zheng et al., 2012)

Scale Invariant Feature Transform (SIFT) (Lowe, 2004), and Lucas Kanade (Baker et al., 2003) (Lucas & Kanade, 1981) algorithm suggested that maps may be viewed as an image, and MM may be regarded as image registration. However, owing to the self-similarity of the indoor condition, it provides characteristics less distinguishable than general digital pictures. These methods are likely to be influenced to local minimal especially when there is no initial estimate.

Carpin (Carpin & Birk, 2005) and Birk (Birk & Carpin, 2006) discussed the issues of MM and used a stochastic search methodology to resolve as an optimization concern. His later research increases the efficiency of their past work by utilizing fault detection systems and a much more seasoned approach to direct the search. To decompose the transition of search space into rotation and translation computations, Carpin (Carpin, 2008) suggested the framework for integrating occupancy maps into multi-robot structures using the Hough transform. These approaches are also deterministic, non-iterative, and fast because of the decomposition; however, they are restricted to certain assumptions. The combined input maps performed best only on and same modality maps due to the use of common scaling. These approaches are still restrictive to static transformations and in a large-scale context will not fulfil matching due to the distortions effect.

A decomposition-oriented method is suggested by Shahbandi et al. (Gholami Shahbandi & Magnusson, 2019) to align 2D spatial maps to find the right relation between the various map modalities. They abstract maps into 2D configurations by area decomposition, which specifically reflect both the open-space field and borders. It allows the system able to view maps in different scales and modalities.

4.5 Different MM Algorithm Based on Type of Sensors Used

Here, as seen in Table 9, we study the performance of the current Real-Time MM Algorithms in Urban Roads based on the sensor used in the system. In columns two, three, four, five, and six, respectively, we reviewed the recent studies based on user navigation sensors, the model used for segment identification, segment identification parameters, the percentage of accurate relation identification, and the data set. Either GPS or GPS/DR is the most used navigation sensor. The percentage of proper identification of ties ranges from 86 to 97. Particularly in dense urban areas, where the total distance among roads is very short, accurate link identification is critical. The probability of errors can be minimized by taking into consideration all the available data from digital maps and navigation sensors. The speed and heading information can be collected as a by-product of the positioning solution when the navigation information is retrieved from GPS. In identifying the appropriate link, the speed and heading of the vehicle may play a vital role, particularly at junctions in which the vehicle speed is relatively low. It must be remembered that GPS measurements of vehicle headings appear to be unreliable at low speeds (Taylor et al., 2001)(Ochieng et al., 2003). However, it can be enhanced when the heading is measured with the DR gyro sensor. None of the existing techniques considered velocity details using GPS observable headings during the identification of a valid link.

Several techniques in this section are reviewed according to their scientific foundations and structure in such a way that each one's contribution is acknowledged and discussed. Each approach is categorized and associated with its intended use. Approaches based on multiple hypotheses, geometric approach, conditional random field, and hidden Markov model are described. The geometric approaches are appropriate for mapping applications that need a high sampling frequency from an uninterrupted GPS module. Their susceptibility to outliers is one of their flaws. They can be utilized for tracking with reduced sampling frequencies on trajectories. Their performance, however, is likely to be inferior to that of other modern techniques. Algorithms that rely on the multiple hypothesis methodology are ideal for online MM, and therefore for navigational apps. Literature reveals that recent techniques might provide a decent trade-off in matching precision and computing need. Another benefit is that, as compared to approaches based on belief theory or fuzzy logic, they need a relatively little tuning. Both offline as well as online MM were effectively implemented using hidden Markov models. They are utilised generally in tracking software. They have high precision across a wide

Table 9. A Comparison of Different Sensor-Based Real-Time MM Algorithms in Urban Roads

Paper/Policies	Positioning Sensors	Segment Identification Model (Weight Based or Other Advanced)	Segment Estimation Criteria	Correct Segment Estimation (%)	Map Scale and Place
Pyo et al. (2001) (Pyo et al., 2001)	GPS, DR	Multiple hypothesis technique	Closeness, Heading difference, Segment connectivity	89	Taejon
Greenfeld, 2002 (Greenfeld, 2002)	GPS	Weighted method	Intersecting angle between segment and GPS points connecting line, Segment connectivity, Direction difference, Closeness	85.6	New York
Yang et al. (2003) (Wu & Wu, 2003)	GPS	Dempster-Shafer theory	Closeness	96	Beijing
(Quddus et al., 2003) (M. A. Quddus et al., 2003)	GPS DR	Weighted method	Segment connectivity, Relative to segment point position, Heading difference, Closeness,	80.1	1:2500 London
Jagadeesh, Srikanthan, and Zhang (2004) (Jagadeesh et al., 2004)	Simulated	Fuzzy logic	The closeness Heading difference, Segment, connectivity	89.57	Singapore city
Syed and Cannon (2004)	GPS (high sensitivity) Gyroscope	Fuzzy logic	Closeness Heading difference	92.8	Calgary
(Quddus, Noland et al. 2006) (M. A. Quddus et al., 2006)	GPS DR	Fuzzy logic	Closeness, Heading difference, Direction difference, Segment connectivity	93.1	London
(Velaga et al., 2009) (Velaga et al., 2009)	GPS, DR	Weighted method	Closeness, Heading difference, Turn-restrictions, Segment connectivity	96.36	1:2500 London and Washington D.C.
Li et al. (2013)	GPS DR DEM	Weighted method	Closeness, Heading difference, Segment connectivity,	97.7	Nottingham, London
(M. Quddus & Washington, 2015) (M. Quddus & Washington, 2015)	Standalone GPS	Weighted method	Closeness, Heading difference, Direction difference, Segment connectivity	97.2	London
(Hashemi, & Karimi, 2016) (Hashemi & Karimi, 2014)	Standalone GPS	Weighted method	Closeness, Heading difference, Turn-restrictions, Segment connectivity	93.5	Washington
Present Study (Huang et al., 2020) (Chao et al., 2020)	Standalone GPS	Advanced Methods	-	-	-

sample frequency range. Overall, route inference filtering appears to be a potential approach over hidden Markov model-based techniques' limitations. The authors claim that when Markov model-based techniques are employed in MM, then it has a selection bias problem, and therefore a route inference filter is required to prevent it.

5. ASSESSMENT OF RESEARCH QUESTIONS [RQ] AND EVALUATIONS

To strengthen the framework and reasoning behind the survey, we have introduced standards of categorization for separate literature review policies/papers here. We used comparative analysis tables for various types of MM matching methods to give the reader an outline of the measures used in geospatial matching techniques, which presents a critical review of the interventions used in almost 100 similar studies. Measures are arranged according to the proposed taxonomy in section 2 and the approaches are organized using the classification of features. Below we evaluate the numerous research questions identified in Section 1:

RQ1: What are the data pre-processing challenges that could increase the difficulty of map matching?
Assessment: The most prevalent problem in data pre-processing is incomplete trajectory data, which makes MM more challenging. Due to low satellite coverage, pure satellite-dependent localization systems may experience a prolonged shortage of data. Maps can include a complex combination of modelling, systematic, and random errors which would be tough for accounting. The initial issue in MM is coping with inaccuracies in positional data and maps. For MM, most studies favour the speed of the vehicle and heading degree variables. However, the elimination technique and neighbouring value filling are ineffective. One may see at the entire trajectory curve and fill in the unknown values.

Presently, the road network topology takes the shape of a point line, which will ultimately compromise the road's integrity. The loss of road integrity will raise the inaccuracy of matching in high-speed, three-dimensional, and other complicated roads. We can provide more space to a road network framework to hold full roadways. We may also cluster the large floating vehicle information to reconstruct the unknown road because of time lag for open road information.

RQ2: What are the various directions that need a lot of attention to be used in recent methods of MM?
Assessment: Taking into consideration the most basic property of a geospatial object, i.e., geometry, it can be found that nearly all recent research assesses these geometric properties. The Euclidean distance seems to be the most common among geometric measurements used in approximately half of the reports. The simplicity of the Hausdorff distance used with all matching levels is another discovery, while Frechet is only used at the function level. While maximum of the MM methods are relied on higher frequencies of sampling data, even though sampling data of low-frequency MM methods have become popular in recent years. We can concentrate on the recommendations given below while designing efficient MM techniques:

1. Because low-sampling frequency data is scarce, most research relies on hidden Markov probability or sophisticated models with just a few studies focusing on topological structures and geometric principles. By integrating additional features of low-frequency sample Floating car data (FCD) and road data, we may use algorithms based on topology and geometric principles.
2. Grid search seems to be more common when looking for candidate sections since it is faster. Most users opt to continue looking for eight neighbouring grids where candidate sections emerge in extreme places to prevent missing candidate sections, although this increases computing cost. To decrease the computation time, it is appropriate to build a circular zone

to pick the query results of nine grids using driving duration and vehicle speed product as the radius.

3. Massive data analysis and modelling issues may be efficiently supported by the increasingly developed distributed computing platform. We can increase the effectiveness of MM by utilizing cluster computational resources.

RQ3: How the performance of different map-matching should be measured?

Assessment: There is no agreement on the method to performance evaluation of map-matching. According to Bernstein and Kornhauser, the best suitable performance metrics or assessment scenario cannot be determined without practice. It is obvious that the algorithm works flawlessly when the mistakes are zero; however, it is unclear what implies in reality (Bernstein & Kornhauser, 1998). The study points out a problem that has prevented researchers from comparing their approaches until now. In an attempt to overcome this challenge, Kubika et al. (Kubicka et al., 2015) presented a 110 map-matched trajectories dataset. It is freely accessible on the internet. It may be used for learning algorithms and inference, and for comparison, validation, and experiment. The authors created a comprehensive collection of cases for the community to investigate MM using openly available traffic information. The authors frequently use private or confidential data to test their approaches. However, several exceptions appear in the literature. Newson and Krumm (Newson & Krumm, 2009) released their testing results as well as a detailed description of the validation technique they utilized.

RQ4: How the Integrity of map matching could be monitored for reporting the reliability of its output?

Assessment: Because there is significant inconsistency between the trajectories and the map, or when the circumstance is unclear, accurate MM is not always feasible. In such a circumstance, the accuracy of MM is disputed. As a result, to remark on the output's trustworthiness, several MM techniques undertake monitoring of integrity. This is especially important in applications involving security and electronic fee collection systems. Integrity verification is a phrase derived from the navigation of aerial used to check the accuracy of GPS navigation-dependent location estimates. In the MM context, integrity verification can be expressed irrespective of the matching technique. It receives a map, MM output, and input trajectory, and outputs an integrity indication that represents MM reliability. The total accurate detection rate, which is calculated from the count of false alarms and failed detections, is often used to evaluate the effectiveness of integrity measurement. The results are sensitive to the alert levels used to compare integrity indicators. They are used to determine the sensitivities of the integrity verification system. They should be put up in such a way that both the false alarms and the missed detections could be avoided. Low sensitivity causes too many missed detections, whereas high sensitivity causes too many false alarms. So, there is always a trade-off between sensitivity and accurate detection rate. Because both positioning and map faults are not limited, there could still be unobservable missed detections in the framework of map-matching. It is theoretically possible to witness seemingly consistent circumstances in which the trajectory is lined with the incorrect routes. It indicates that no assurance can ever be given that the matching is accurate. Quddus' thesis (M. Quddus, 2006) was the first to mention MM integrity. Based on fuzzy logic, the author presented a technique that leverages uncertainty in location, direction error, and distance error to generate a heuristic integrity flag. He used three MM approaches to evaluate his integrity monitoring and claims a 91 percent overall rate of right detection, rate of missed detection less than 8.5 percent, and rate of false alarm of less than 10.1 percent.

RQ5: What approaches a researcher should take while selecting a MM method?

Assessment: Hidden Markov Models (HMM) (Mohamed et al., 2017)(C. Yang & Gidófalvi, 2017), fuzzy logic model (M. A. Quddus et al., 2006), Kalman filtering (Cho & Choi, 2014), etc. are used in several advanced MM methods to solve complex road markings. When dealing with noise and sparse location details, HMM (Mohamed et al., 2017)(C. Yang & Gidófalvi, 2017) is utilised to determine the best matching route. For different MM applications, numerous MM algorithms are appropriate. There is no uniform approach that will meet everyone's needs. We look at the trade-offs that must be considered when choosing a MM approach in this section. We consider tuning sensitivity, computational effort, MM performance, and the need for pre-processing and integrity monitoring. Online MM techniques with a high sample rate are required for navigating operations. Because the systems must respond in real-time, the computing effort must be kept minimal. When integrity verification is required, the Toledo-Moreo et al. approach (Toledo-Moreo et al., 2010) should be explored. This approach has demonstrated excellent lane-level matching precision while also offering constant matching result integrity verification. Fuzzy logic-based methods (M. A. Quddus et al., 2006), are said to offer great matching accuracy, although adjusting them requires specialist knowledge. Belief theory-based approaches (FENG & TIMMERMANS, 2013)(Nassreddine et al., 2009) are also tough to adjust, yet they are said to match properly. Multiple hypothesis techniques (Pyo et al., 2001)(Kubička et al., 2014) may provide an intriguing trade-off in matching accuracy and computational load. Geometric techniques and Hidden Markov model approaches are not well suited since they need a lot of computing power. To solve this problem, utilize the sliding window approach, in which just the last couple of observations are used to map-match the actual matching position. If there is not a high requirement for computing work, a robust approach against positioning errors such as Hummel's technique (Hummel, 2007) should be explored. The monitoring systems necessitate offline MM techniques with a low sample rate. Because the trajectory is processed after they have been collected, a computationally intensive effort may be allowed. In terms of matching quality, the route inference filter (Hunter et al., 2014) is said to be the advanced method. Its computational load, on the other hand, might be exorbitant. The approach proposed by Newson et al. (Newson & Krumm, 2009) provides better matching quality at a cheap computational cost. Another alternative is geometric technique proposed by Wei et al. (Wei et al., 2013), which is particularly useful when combined with Driemel et al. rapid Fréchet distance estimation technique (Driemel et al., 2010). If system need to handle many trajectories and precision is not important, Marchal et al. approach might be alternative way to go. Low-sampling based MM (Newson & Krumm, 2009)(Lou et al., 2009) may be useful if the application uses sparsely observed trajectories. Route inference filters are likely to perform better than these techniques, although they are generally easier to build. In the same way that tracking apps need offline techniques, mapping applications do as well. The trajectories, on the other hand, are intensively sampled. Because collected trajectories are utilised to estimate road form, the positioning system must be precise. When new roads are added to the map, it is used to introduce them. The precision of the match is crucial, but the computing effort is not. Geometric techniques (Alt et al., 2003)(Brakatsoulas et al., 2005) are well suited for this. Even when they are outliers sensitive, when a precise positioning system is employed, this is not a problem. Pink and Hummel's technique (O Pink & Hummel, 2008) also has intriguing features in terms of mapping. It employs a hidden Markov model and Kalman filter-based pre-processing that has demonstrated excellent matching accuracy while requiring fewer computing resources. The Kalman filter could be employed on its own or in conjunction with certain other MM techniques.

6. RESEARCH CHALLENGES & OPEN ISSUES

Assessments of state-of-the-art real-time MM approaches show certain questions that require further study:

1. The MM methods reviewed in the literature show a mandatory requirement that the vehicle are required to turn only on valid sections of road. But this constraint may not attain if the driver unintentionally moved to the wrong part of the road. This dilemma must be solved by potential algorithms.
2. Most of the developed MM approaches focused on trust value ignoring the difficulty and density of routes through GPS points.

3. The most prevalent problem in data pre-processing is incomplete trajectory data, which makes MM more challenging. The initial issue in MM is coping with inaccuracies in positional data and maps. We may train a model with past data and use it to forecast the missing values if the volume of data is significant enough. The trajectory information with more properties such as altitude, vehicle slope, and other parameters can further be investigated and incorporated to MM techniques to increase map matching precision.
4. It is theoretically possible to witness seemingly consistent circumstances in which the trajectory is lined with the incorrect routes. Therefore, a MM integrity monitoring method for different sampling rates should be devised for reporting the reliability of its output.
5. Massive data analysis and modelling issues need to be resolved for distributed computing platform. The effectiveness of MM could be maximized by cluster computational resources.
6. The bulk of studies have concentrated on two-dimensional road networks with little emphasis paid to MM of three-dimensional road networks such as overpasses, and no comprehensive research on lane-level real-time MM has been done. As a result, developing an effective MM approach for three-dimensional road networks is still a work in progress.

7. CONCLUSION

This study encompassed more than 30 years of geospatial matching analysis by introducing and discussing the recent methodologies. On the basis of different functions and metrics, different taxonomies are identified for map matching methods. The notable difficulties in map matching methods include the first-location selection of candidate segments, next-place selection of candidate segments, identification of crossing intersections, determination of the best section of initial GPS point and locating a given part from the GPS site. More data convergence and thus faster and more reliable map matching methods would undoubtedly today's need in the geospatial domain. In this sense, one can quote the Carpenter and Snell article (CB, 2012), where the authors described the use of sensor data (Internet of Things) and social media data superimposed on top of GIS data as potential patterns.

On the basis of Map matching literature, one can also say that the simple map approximation cannot be adequate for modern applications. In many cases, it is necessary to integrate different methods that can locate the corresponding objects. We have tried to draw some guidelines based on the researched studies for map matching of the vector datasets:

1. The precision/recall process of telling outcomes can be used in modern map matching methods.
2. New techniques should focus on time complexity aspect in the entire process and also their comparison with other existing approaches.
3. Benchmark test data should be provided by the map matching testing group to facilitate as many instances as possible in the real world. This benchmark data will be a helpful tool for testing map matching strategies because many techniques are usable with decent outcomes at their test sites; however, they may change drastically when the circumstances are modified.
4. In geospatial map matching, several questions and research opportunities are remained open which can be seen as future scope for further investigation.

At last, we can say that it provides a critical study of measurements and methods applied to matching geospatial data to map available in recently published approaches.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author (Gupta, A. K.) on reasonable request.

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