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The Effects of Navigation Sensors and Spatial Road Network Data Quality on the Performance of Map Matching Algorithms

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Abstract Map matching algorithms are utilised to support the navigation module of advanced transport telematics systems. The objective of this paper is to develop a framework to quantify the effects of spatial road network data and navigation sensor data on the performance of map matching algorithms. Three map matching algorithms are tested with different spatial road network data (map scale 1:1,250; 1:2,500 and 1:50,000) and navigation sensor data (global positioning system (GPS) and GPS augmented with deduced reckoning) in order to quantify their performance. The algorithms are applied to different road networks of varying complexity. The performance of the algorithms is then assessed for a suburban road network using high precision positioning data obtained from GPS carrier phase observables. The results show that there are considerable effects of spatial road network data on the performance of map matching algorithms. For an urban road network, the results suggest that both the quality of spatial road network data and the type of navigation system affect the link identification performance of map matching algorithms.

Keywords map matching · GPS · intelligent transport systems · road network data

1 Introduction

With the rapid progress in the development of radio-navigation technology, global positioning system (GPS)-based vehicle navigation systems are being widely used to

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provide location information in a range of transport telematics applications and services. This includes the use of radio-navigation for route guidance, dispatching roadside assistance vehicles, intersection collision avoidance, accident and emergency response, automated location tracking, and scheduling of commercial vehicles. Public transport systems also benefit from the same radio-navigation-based technologies by providing real-time traveller information. The positioning accuracy for such services is in the range of 1 to 40 m (95%).

The vehicle positioning data for such applications and services are also obtained from a range of navigation systems, such as inertial navigation systems (INS), deduced reckoning (DR) motion sensors, and systems that employ more than one sensor such as GPS and DR [22], [29]. The GPS Standard Positioning Service (SPS) is a positioning and timing service provided on the L1 signal for civilian use. Although GPS is widely used as a positioning sensor in land vehicle navigation, the SPS performance is affected in addition to geometry, by both systematic errors or biases and noise. Systematic errors include satellite dependent errors, receiver dependent errors and signal path dependent errors. Random errors comprise some forms of multipath and measurement noise. A detailed description of these error sources can be found in Kaplan [10], Hoffmann-Wellenhof et al. [8], Farrell and Barth [4], Hotchkiss [9], and US DoD [30]. With the removal of the effects of selective availability in May 2000, GPS positioning accuracy (two dimensional (2-D)) has improved from 100 m (95%) to 15–20 m (95%). Despite this improvement, a real-world field test conducted in London showed that GPS positioning errors in some cases could be offset from the true position by more than 50 m [29]. In a study in Hong Kong it was found to be off by more than 80 m [2]. Due to the errors associated with GPS, the Required Navigation Performance cannot be achieved in areas with urban canyons, streets with dense tree cover, and tunnels. DR, with the aid of an odometer and a gyroscope, is commonly used to bridge any gaps in GPS positioning, but the positioning error of stand-alone DR grows rapidly if not augmented by another sensor or system such as GPS.

Another essential element for land vehicle positioning and navigation is spatial road network data. Since the vehicle is essentially constrained to a finite network of roads, spatial road network data are used to provide a physical reference for the location of vehicles. However, spatial road network data also have errors [14]. For example, a road is represented as a single “centreline” and curvatures are represented as polylines. This generalization alters the features on the ground and potentially introduces significant bias [15]. Goodwin and Lau [5] emphasized the need for accurate electronic map data for vehicle navigation. Their study distinguished geometric and topological error as two types of errors associated with spatial road network data maps. Both errors could potentially confuse an en-route guidance system.

Bullock and Krakiwsky [1] analysed the use of spatial road network data in vehicle navigation. They found that most existing land vehicle navigation systems used data simply to display the vehicle’s position without taking into account errors associated with them. Kim et al. [12] described efficient use of spatial road network maps in various positioning and navigation systems for transport telematics applications. Their study concluded that accurate spatial road network data can effectively improve the positioning accuracy. Zhang et al. [27] studied the relationship among vehicle positioning performance, spatial data quality, and sensitivities and feasibilities of map matching algorithms. Their study investigated qualitatively how the representation of junctions and the representation of roadways by single or multiple centrelines affect the performance of map matching algorithms. Their study did not quantify the performance of different map matching algorithms in terms of link identifications or horizontal positioning accuracy. They concluded that an accurate spatial road network data and positioning sensor information are essential elements of a robust map matching algorithm.

Due to errors associated with location data and spatial road network data, as described above, there is always a level of uncertainty associated with map matching algorithms. Previous work by the authors resulted in the development of three map matching algorithms. The first was based on a conventional geometric approach [19]. The second was based on a probabilistic approach [16] and the third was based on a fuzzy logic concept [21]. However, the performance of the map matching algorithms largely depends on the nature of the application and the types of data inputs. The quality of spatial road network data and the types of navigation data may affect the performance of a map matching algorithm. The objective of this paper is to develop a framework to quantify the effects of road network map data and navigation data on the performance of map matching algorithms. Two types of navigation data (GPS and GPS integrated with DR) and three types of spatial road network data of different map scales (1:1,250, 1:2,500 and 1:50,000) are taken as inputs to the map matching algorithms in order to achieve this objective.

The framework proposed in this paper should benefit providers of transport telematics services as it facilitates the identification of the appropriate type of map matching algorithm, navigation sensor, and spatial road network data for a given service. Researchers should benefit from using the framework to develop further enhancements not only to the algorithms but practical implementations also. The paper offers a complete analysis for a suburban road network and a preliminary analysis for an urban road network. The preliminary nature of the latter is primarily due to the fact that it was not possible to obtain the reference (true) trajectory of the vehicle in the built-up areas due to frequent satellite loss-of-lock. Future research will explore the feasibility of using a high-grade GPS/INS for the determination of a reference trajectory in an urban area.

The paper is organized as follows. First a brief description of the features of positioning systems used in land vehicle navigation is provided. "Section 2" describes the quality of spatial road network data. This is followed by a brief description of three map matching algorithms previously developed by the authors. "Section 3.2" describes a consistency test at a junction which improves the performance of map matching algorithms, followed by a methodology to assess the algorithms. This is followed by the presentation of results and conclusions.

2 Spatial road network data quality

The creation of spatial road network data involves a series of decisions on how features of the earth will be represented in an electronic form. These are the map scale[1], digitization, level of generalization, map projection, datum, and coordinate system [15]. Each decision introduces a potential error in the creation of a map. Moreover, spatial road network data is usually based on a single-line-road-network representing the centreline of the road. Road attributes such as width, number of lanes, turn restrictions at junctions, and roadway

[1] Map scale is defined simply as the ratio of distance on a map over the corresponding distance on the ground, represented as 1:M where M is the scale denominator. Map scale is an issue because as scale becomes larger the amount of detail that can be presented in a map is also increased. The ability to measure the length of linear features on the ground (road centreline), the position of point features (junctions and roundabouts), and the areas of polygons with a high level of accuracy are also increased. Clearly there is a dependence between quality of systems/sensors used to create a map and map accuracy. Therefore, scale should reflect this.

classification (e.g., one-way or two-way road) normally do not exist in spatial data. Therefore, the accuracy and uncertainty of spatial road network data is a critical issue if the data is used for land vehicle navigation. One must be aware of the following concerns about the quality of road network data:

- The features (e.g., roundabouts, junctions, medians, curves) of the real-world which have been omitted or simplified in the road map. This is usually known as topological error.
- The missing segments or the existence of any old segment due to a lack of frequent updates.
- The correctness of the classification (e.g., junction or roundabout) of those features.
- Timeliness of the data such as how recently the data were created.
- The deviation between a map feature (e.g., road centreline, specific junction) and its actual location in the road. This is generally known as geometric error.

Both geometric and topological errors of spatial data may introduce significant horizontal error in land vehicle positioning and navigation. While the geometric error can be corrected with suitable hardware, software and algorithms, the topological error cannot be corrected easily [5]. If the accuracy (in terms of absolute error) of the spatial database is not supplied by the map vendors, the following existing methods can be applied.

The accuracy (2-D) of a spatial road network data (map) can be derived from the geometric error. Accuracy is defined as the closeness of measurements or estimates to true values. The true values of map attributes or labels can be obtained from an independent source of higher accuracy measurement such as GPS carrier phase observables, higher resolution satellite imagery, aerial photography, or a ground visit. If e^1, e^2, ..., e^n represent a series of differences between measurements on a map and their true values, the accuracy of this map is given by σ^2_{map}, where

$$\sigma^2_{\text{map}} = \frac{\sum_{i=1}^{n} (e^i - \mu)^2}{n-1} \tag{1}$$

in which $\mu = \frac{\sum_{i=1}^{n} e^i}{n}$ and n is the number of measurements.

There are also empirical methods available to estimate map accuracy. For instance, Chrismans [3] developed a method to compute map accuracy from knowledge of the errors introduced by different sources. This method calculates an estimate of overall accuracy by summing the squares of specified components of the map and taking the square root of the sum. For example, assuming 1:2,500, error due to the source document is 2.5 m (1 mm× 2,500), map registration is 1.25 m (0.5 mm×2,500) and digitizing is 0.5 m (0.2 mm× 2,500), the total error of a map of scale 1:2,500 is 2.84 m. For a map scale 1:25,000 the method gives an error of 28.39 m.

One of the UK Road network datasets used in this study was developed by Navigation Technology (NavTech) and supplied to us by Saturn Technology UK. This map dataset has a map scale of 1:2,500. Therefore, for this scale, the maximum horizontal error is 2.84 m (using Chrisman's method). Figure 1 shows a graphical comparison of this spatial road network data (road centreline) with UK Ordnance Survey (UKOS) network data (map scale 1:50,000). The true vehicle positions obtained from higher accuracy GPS carrier phase observables are denoted by the dot symbols. The NavTech map data and the data for true vehicle positions agree reasonably well and suggest that the road is a roundabout. However, the UKOS map data indicate that the relevant road section is a five-legged junction. Hence

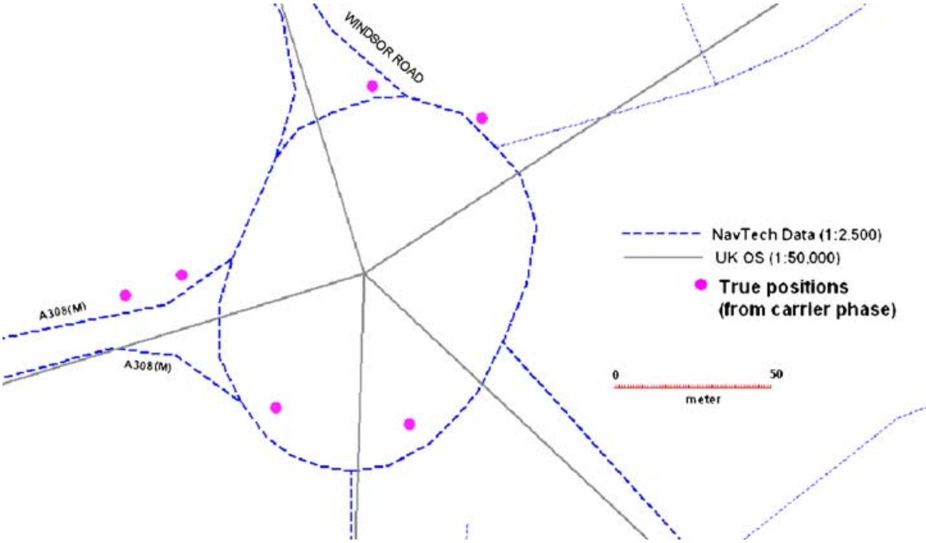


Fig. 1 A graphical comparison of spatial road network data from two different sources NavTech (map scale 1:2,500) and UK Ordnance Survey (map scale 1:50,000)

if UKOS road network data of this scale are used in vehicle navigation, the horizontal positioning error increases significantly.

It is apparent that most of the common devices used for vehicle navigation produce error and are not capable of placing the vehicle on the road due to various error sources associated with the devices. In addition, even though the positioning measurement data can be perfectly accurate, there are errors in the spatial road network database. As a result, there will still be spatial mismatch if these two datasets are combined in a single framework. Therefore, map matching algorithms are essential to reconcile the locational data with the spatial road network data.

3 Map matching algorithms

3.1 Description of algorithms

The capability to identify the physical location of a vehicle on a link is a key requirement in any transport telematics applications. This is achieved by map matching algorithms which integrate the navigation data with spatial road network data. Procedures for map matching vary from those using simple search techniques [11], to those using more advanced techniques such as the use of an Extended Kalman Filter and Belief Theory [13]. Approaches for map matching algorithms found in the literature can be categorised into three groups: topological ([2], [6], [19], [25]), probabilistic [16], [28], and other advanced techniques [13], [17], [21], [23], [26].

In order to examine the effects of various positioning systems and spatial road network data quality on the performance of map matching algorithms, three different algorithms are used in this paper. These are a conventional geometric map matching algorithm, a probabilistic map matching algorithm, and a fuzzy logic map matching algorithm. Due to the differences in methodologies, these algorithms are representative of map matching algorithms found in the literature. The full details of these three algorithms can be found in Quddus et al. [19], Ochieng et al. [16] and Quddus et al. [21]. The similarities and differences among these algorithms are shown in Table 1. According to Quddus [18], the probabilistic and fuzzy logic map matching algorithms used in this study outperform all existing algorithms in terms of correct link identification, horizontal accuracy, along-track, and cross-track errors. The fuzzy logic map matching algorithm gives the best results among all map matching algorithms evaluated for the test road networks in London.

Table 1 Similarities and differences among the three map matching algorithms

Characteristics	Geometric map matching algorithm	Probabilistic map matching algorithm	Fuzzy Logic map matching algorithm
Methodology used in the algorithm	A topological approach based on a weighting scheme	A probabilistic approach based on an elliptical error region	Three Sugeno fuzzy inference systems (FIS)
Key features	Dependent on vehicle heading, proximity, and orientation	Dependent on vehicle heading	Rule-based system and hence each factor is important
Total number of distinct processes	*Two*: the first one is for matching at junctions and the second one is for matching on links	*Two*: the first one is for matching at junctions and the second one is for matching on links	*Three*: the first one is for the initial matching process, the second one is for matching at junctions, and the third one is for matching on links
Consideration of vehicle speed	Yes	Yes	Yes
Consideration of the quality of vehicle heading	No	Yes	Yes
Connectivity among the road segments	Yes	Yes	Yes
Consideration of historical information	Yes	Yes	Yes
Identification of the initial link	The link passes through the closest node from the first position fix	The link within an elliptical error drawn for the first fix	The link within an elliptical error drawn for the first fix
Initial matching process	Depends on the first position fix only	Depends on the first position fix only	Depends on the first few position fixes (4–6) and hence more robust
Estimation of vehicle position	Using an optimal estimation by taking into account errors in positioning sensors and spatial road network data	Using an optimal estimation by taking into account errors in positioning sensors and spatial road network data	Using an optimal estimation by taking into account errors in positioning sensors and spatial road network data
Suitability	Suburban road networks	Both suburban and urban road networks	Both suburban and urban networks

3.2 Consistency test to improve the performance of a map matching algorithm

The three algorithms discussed above represent incremental improvements in map matching algorithms. However, they still occasionally generate incorrect fixes. A further improvement to these algorithms is a consistency test which is derived here and used in the analysis that follows. Two basic functions of any map matching algorithm are to identify a correct link on which a travelling vehicle is more likely to be located and to determine the location of the vehicle on that link.

In some complex road networks, particularly at junctions, these map matching algorithms may fail to correctly identify a link. For example, in a motorway with a diverging section, as shown in Fig. 2, a good map matching algorithm may select the link BC as a correct link for the position fix P_4, as positioning data associated with this position solution (heading, distance etc.) gives this link a relatively higher weight and makes it a very good candidate link. Then the subsequent position fixes P_5, P_6, and P_7 are also matched on the link BC if certain conditions are satisfied. However, it can easily be judged from the vehicle trajectory that the correct link for these position fixes is the link BD. Therefore, in order to have a specified level of confidence in the identification of the correct links and hence the determination of the vehicle location, a simple test can be used.

The test, which can be termed as a consistency checking test, is to construct an elliptical error region around the position fix and examine whether the estimated vehicle location is within the error region. In a map matching algorithm (in addition to the application of error models built-in the sensor) GPS data are checked for reasonability using for example, the Horizontal Dilution of Precision (HDOP) factor and speed. Furthermore, DR and map data also undergo a reasonability check (e.g., similarity between headings obtained from GPS and DR) during the map matching process. Therefore, on the basis that gross errors and biases have been accounted for, it is reasonable to assume that the residual errors in the map-matched position follow a Gaussian distribution. The orientation of the ellipse largely depends on the correlation between x (easting) and y (northing) coordinates. If they are uncorrelated, then the semi-major and semi-minor axes of the ellipse will be parallel to x and y respectively. The error ellipse becomes a circle if the two coordinates (easting and northing) have equal precision. If the estimated vehicle position falls within the error ellipse, then it can be said that the consistency test is successful and the estimated position is correct as the error region is formed from the positioning error variance–covariance matrix. If the estimated vehicle fix on the link falls outside of the error region, then it can be said that the consistency test is unsuccessful and the estimated position is incorrect and the map matching process re-starts with the initialisation process. The process of consistency testing for Fig. 2 is shown in Fig. 3.

Fig. 2 Possible mismatch in map matching algorithms

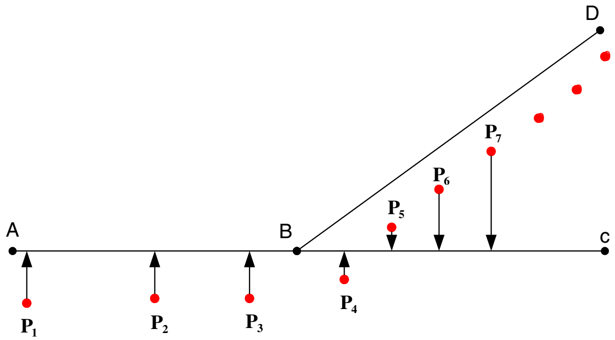
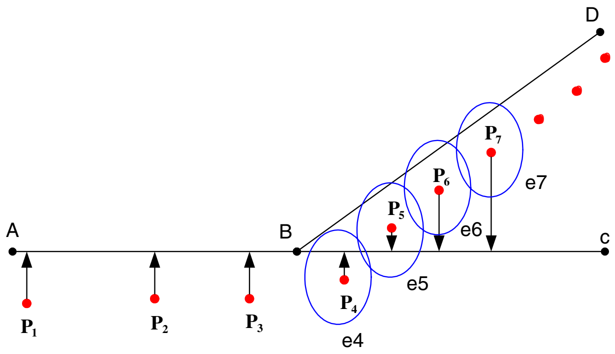


Fig. 3 The process of consistency testing for the scenario shown in Fig. 2



The error ellipses around the position fixes P_4, P_5, P_6, and P_7 are denoted by e_4, e_5, e_6, and e_7. It is obvious that the consistency test fails at position fix P_6 as the link BC falls outside the error ellipse e_6. The algorithm then goes back to the initialisation process at the position fix P_6 and can easily re-identify the correct link BD. In such a way, the performance of the algorithm improves notably.

In this example in Fig. 3, it is noticeable that the algorithm still fails to correctly identify a link for the position fixes P_4 and P_5. However, for services such as en-route guidance when the system knows the destination of the trip (for example, assume junction D on the map), this may not be a problem provided that the matching information on the link AB is correct. This is because when the vehicle is on the link AB, the driver is instructed to turn left at the next junction, B. Although the map matching algorithm places the vehicle on link BC for 2 s, the actual position of the vehicle during this period is on link BD. As a vehicle can only travel 62 m at 112 km/h along link BD (maximum speed on UK motorways) within these 2 s, it is very unlikely that it would reach another junction during this time period. This enables the initial matching process of a map matching algorithm to select a correct link before the vehicle reaches the next junction. Experiments show that the algorithm can only take 2 to 4 s using the consistency test discussed above to select a correct link in such an ambiguous situation where the two links are given almost the same weighting score. However, the map matching algorithm can easily correct these mismatches in a post-processing application. It should be noted that the addition of the consistency testing feature to the three algorithms compared in this paper results in appreciable improvement in performance compared to previous results.

4 Methodology to assess the performance of the algorithms

In order to assess the performance of map matching algorithms based on the quality of the spatial road network data and the navigation system error, a higher accuracy reference (truth) of the vehicle trajectory is essential. The reference of the vehicle trajectory is determined by the carrier phase observables from GPS [20]. From this reference trajectory, the actual (true) link on which the vehicle is travelling and the correct physical location (at the centimetre level) of the vehicle on that link are then determined. Our approach has three important elements:

1. The reference trajectory is also map-matched using our map matching algorithms in order to determine performance in terms of correct link identifications. It should be

noted that the reference trajectory was not map-matched in previous work reported in Quddus et al. [20].

2. The link determined in stage (1) is compared to that determined based on map-matched GPS/DR position fixes to identify the actual link.
3. Stage (2) above is verified using accuracy data based on reference trajectory points and the map-matched points.

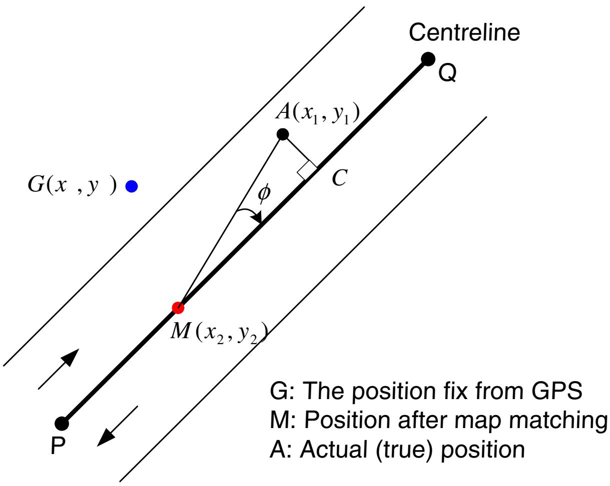
The task is then to compare the results (both the identification of the link and the physical location of the vehicle) obtained from the map matching algorithm and the reference trajectory. For a particular position fix, if a link determined by the reference of the vehicle trajectory (true link) is the same as the link determined by a map matching algorithm then it can be said that the map matching algorithm identifies the link correctly. Based on this criterion, a percentage of correct link identifications from all fixes can be calculated, which gives a good indication of the quality of a map matching algorithm.

Figure 4 shows a road segment in which the vehicle position from GPS (C/A code-ranging) is denoted by the point G (x, y), the corresponding position estimated from the map matching results (on the road centreline) is represented by the point M (x_2, y_2) and the actual (true) position of the vehicle from GPS (carrier phase measurements) is indicated by the point A (x_1, y_1) for a particular epoch t. Since the actual position of the vehicle at the same epoch t is at the point A, the map matching accuracy in the easting component is (x_2-x_1) and the accuracy in the northing component is (y_2-y_1). Therefore, the horizontal accuracy (2-D) at epoch t (MA), is given by,

$$MA = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{2}$$

A series of such horizontal accuracies can be derived from this equation for all epochs. The associated statistics derived from these accuracies (e.g., mean, standard deviation) can be used to determine the relative performance of a map matching algorithm. The along-track component of the horizontal accuracy MA is MC and the cross-track component is AC. The angle ϕ can easily be derived from the absolute heading differenced between the

Fig. 4 Determination of error in map matching



line AM and the link PQ. The along-track and the cross-track accuracy can then be calculated from

$$MC = MA \cos \phi \tag{3}$$

$$AC = MA \sin \phi \tag{4}$$

The percentage of the correct link identification, the horizontal accuracy (MA), the along-track accuracy (MC) and the cross-track accuracy (AC) are used in the analysis that follows to compare the performance of the map matching algorithms based on the spatial road network data quality and navigation sensor error.

5 Results and discussions

In order to collect the positioning data, a vehicle was equipped with a navigation platform consisting of a 12-channel single frequency (L1) high sensitivity GPS receiver (for C/A code-ranging), a low-cost gyroscope, and the interfaces required to connect to the vehicle speed sensor (odometer) and back-up indicator. The vehicle was also equipped with a dual-frequency geodetic receiver to obtain the reference (truth) trajectory using carrier phase measurements. High accuracy local measurement of 3-D offsets between the two antennae was undertaken in order that the position information was referenced to a single point. Positioning data was then collected from both suburban and urban road networks to quantify the effects of the navigation sensors and the spatial road network data quality on the performance of the map matching algorithms. If there is no road segment within the error ellipse of a GPS position fix, then it is assumed that the vehicle is off the road. Our data show that there were no off road situations. The results are described below.

5.1 Suburban road network

5.1.1 Preliminary discussion

The positioning data to assess the performance of the various map matching algorithms was obtained from a comprehensive field test in the west of London (a suburban area) on the 5th of July 2004. The test route had a good mixture of different roadway characteristics such as one-way, two-way, dual carriage-way, motorway, roundabout, merging and diverging sections. The route was a circular loop and about 80 km long and was chosen carefully to have good satellite visibility as the use of GPS carrier phase measurements requires observations from a large number of GPS satellites for reliable and correct ambiguity resolution. Therefore, it was expected that the navigation data from stand-alone GPS would be quite good because of the low potential for signal masking.

Positioning data (easting and northing), speed, and heading were collected at 1 s intervals for a period of 6,500 s from the high sensitivity GPS receiver (for C/A code-ranging). This GPS data was then augmented with DR sensor data in order to achieve continuous navigation, using an Extended Kalman Filter algorithm, as described in Zhao et al. [29]. This gave another set of the positioning (easting and northing), speed, and heading data for integrated GPS/DR. The reference of the vehicle trajectory was then obtained from the 24-channel dual-frequency geodetic receiver.

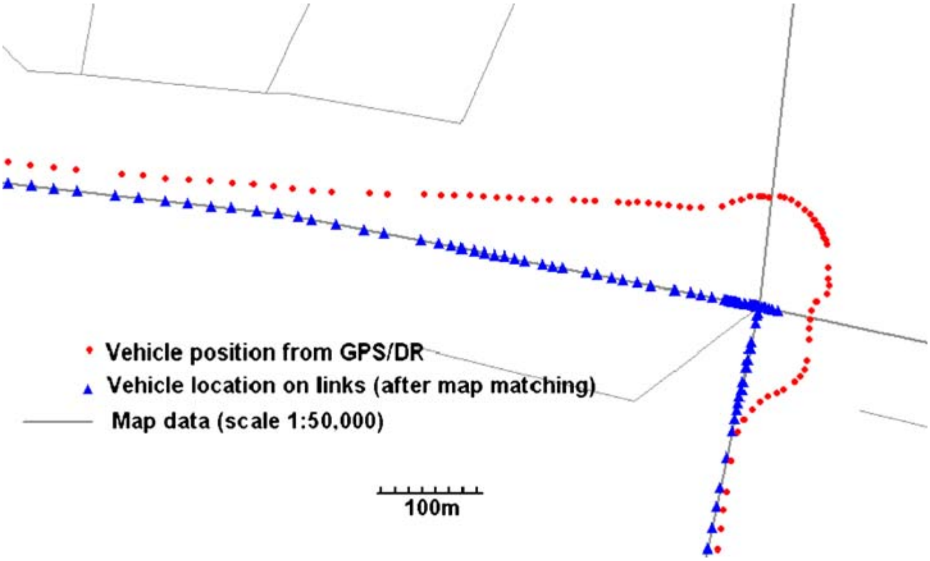


Fig. 5 Probabilistic map matching results for positioning data from GPS/DR and spatial road network data from map scale 1:50,000

In order to investigate the effects of spatial road network data quality on the performance of the map matching algorithms, three spatial road network datasets with different map scales were used. Two of them were obtained from the UKOS with map scales 1:1,250 and 1:50,000. The other was obtained from NavTech with a scale of 1:2,500. The spatial road data used in our analysis were obtained from different vendors with pre-specified map scales. Therefore, it is reasonable to assume that the data were generated largely through digitisation. The positioning data (easting, northing), speed, and heading were then available from two positioning systems, stand-alone GPS and GPS/DR. The spatial road network data were also available in three map scales. Therefore, the map matching algorithms were tested using the navigation data from both GPS and GPS/DR and the spatial road network data from each map scale. The map accuracy associated with the spatial road network data used in this study was not available from the vendors and therefore, it was estimated by the method developed by Chrismans [3].[2] A total of 18 analyses (two navigation systems, three spatial road network maps and three map matching algorithms) were carried out. For each case, the percentage of correct link identifications was calculated. 2-D horizontal, along-track and cross-track positioning accuracies were also estimated using Eqs. 2, 3 and 4.

5.1.2 Graphical presentation of the results

Details of the probabilistic map matching process are presented to show the variation in how the vehicle position fixes (before and after map matching) was plotted on different maps. The results for a part of the test route are shown in Fig. 5 for the map scale 1:50,000, Fig. 6 for the map scale 1:2,500, and Fig. 7 for the map scale 1:1,250. In all cases, the navigation data was obtained from GPS/DR. Each of the round dots represents the vehicle

[2] Vendor supplied accuracy data would give a further improvement, but was unavailable.

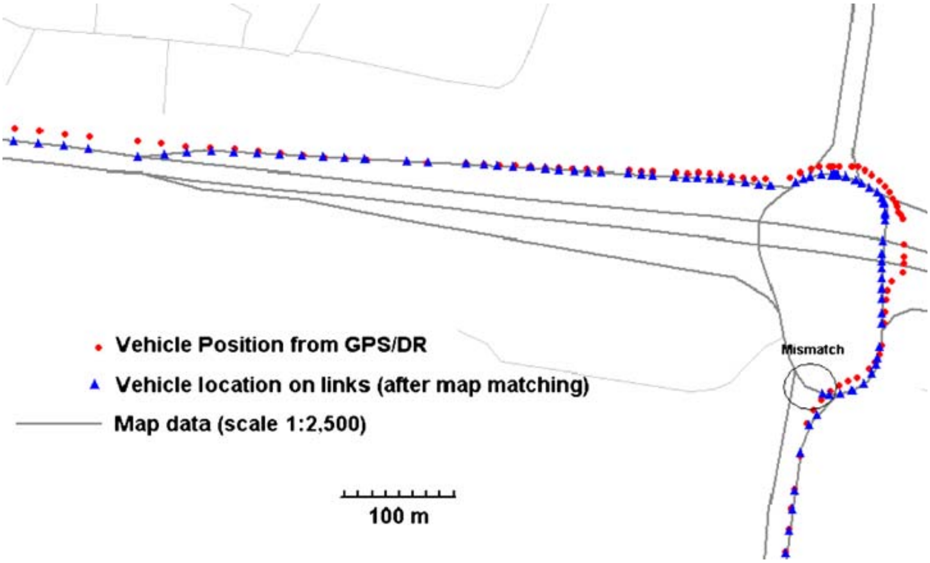


Fig. 6 Probabilistic map matching results for positioning data from GPS/DR and spatial road network data from map scale 1:2,500

position before map matching. The arrow symbols show the direction of travel direction of the vehicle. Each of the triangular symbols represents the vehicle location on the links estimated by the map matching algorithm.

From the layout of the spatial road network data presented in Figs. 5, 6 and 7, it is apparent that the map data in Fig. 5 has the highest topological and geometric errors, since

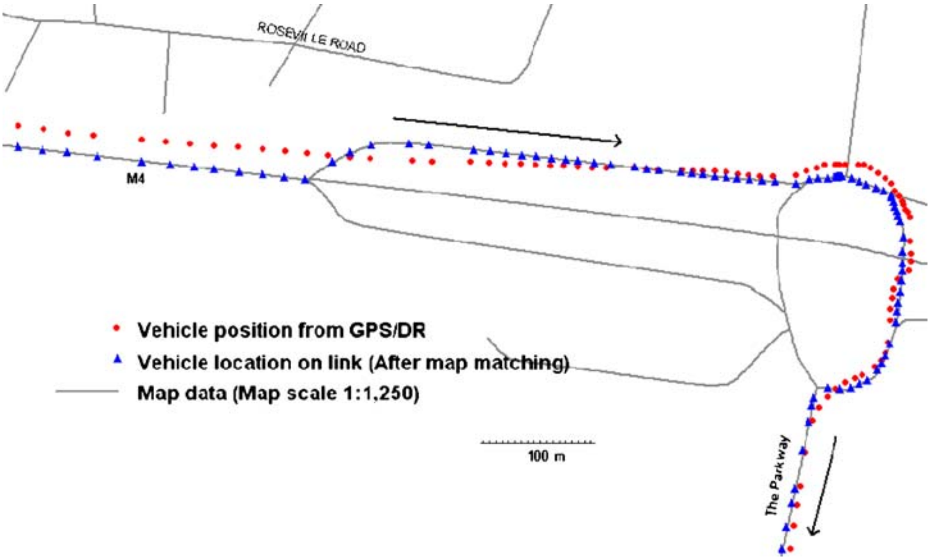


Fig. 7 Probabilistic map matching results for positioning data from GPS/DR and spatial road network data from map scale 1:1,250

many links are omitted compared to the other maps (Figs. 6 and 7) and the vehicle trajectory derived from the positioning system deviates more from the road centreline. Therefore, one would expect that this map data (map scale 1:50,000) could result in higher map matching errors compared with the others. The spatial road network data in Fig. 7 has the highest map scale (1:1,250) but the data in Fig. 6 (1:2,500) has more topological information. For example, the motorway (M4) and dual carriage-way are represented as two centrelines in Fig. 6—one for each way whereas they are represented as one centreline in Fig. 7. This should, at least, reduce map matching errors in terms of location estimation in Fig. 6. It is, however, noticeable that the map matching algorithm selects a wrong link for two of the position fixes as shown in Fig. 6 and indicated with a circle. The consistency test described in "Section 3.2" helps the algorithm to select correct links immediately following these two incorrect position fixes.

5.1.3 Numerical presentation of the results

Since all three map matching algorithms were tested using navigation data from both positioning systems and map data from three spatial road network data sets for the whole test road network, each map matching algorithm provides six sets (3×2) of different results. The results are shown in Table 2. The fourth column represents the percentage of correctly matched links. If a link ID estimated by a map matching algorithm for a particular position fix is the same as the link ID estimated by the higher accuracy GPS carrier phase for the same fix, then it is said that the algorithm identifies the link correctly. The fifth, sixth and seventh columns of Table 2 show horizontal accuracy (2σ), along-track accuracy (2σ) and cross-track accuracy (2σ) respectively. Horizontal accuracy was estimated using Eq. 2 and along-track and cross-track accuracies were computed from Eqs. 3 and 4.

Table 2 The performance of map matching algorithms for various positioning systems and spatial road network data for the test road network

Map matching algorithms	Positioning systems	Map scale of spatial road network data	Correct identification of links (%)	Horizontal accuracy (2σ, m)	Along-track accuracy (2σ, m)	Cross-track accuracy (2σ, m)
Conventional geometric approach	GPS	1:1,250	88.7	20.3	19.5	4.7
		1:2,500	87.5	20	19.1	4.8
		1:50,000	75.5	42.8	41.8	9.8
	GPS/DR	1:1,250	88.9	18.9	18.1	4.3
		1:2,500	88.6	18.5	17.6	4.8
		1:50,000	76.2	40.1	39.2	9.2
Probabilistic approach	GPS	1:1,250	97.6	10.5	9.8	4.1
		1:2,500	97.8	9.2	8.1	4.5
		1:50,000	83.2	30.2	28.9	8.1
	GPS/DR	1:1,250	98	9.5	8.6	4.2
		1:2,500	98.1	9	8.2	4.0
		1:50,000	84.1	29.5	28.5	7.8
Fuzzy logic approach	GPS	1:1,250	98.3	7.1	6.0	3.6
		1:2,500	99	6.5	5.6	3.4
		1:50,000	83.5	25.9	24.6	7.7
	GPS/DR	1:1,250	99.1	5.5	4.3	3.5
		1:2,500	99.2	5.5	4.2	3.2
		1:50,000	84.1	24	22.8	7.7

Table 2 shows that both positioning systems and the spatial road network data quality affects the performance of the map matching algorithms. In particular, the effects of the quality of spatial road network data sets are quite apparent. The conventional geometric map matching algorithm identifies about 88% of the links correctly if the spatial road network data of map scale 1:1,250 or 1:2,500 are used. The identification of the correct links decreases to 76% for the map with scale 1:50,000. The horizontal accuracy (2σ) is about 20 m for map scale 1:1,250 or 1:2,500. However, this accuracy falls to 43 m for the map data with scale 1:50,000. Along-track and cross-track accuracies also exhibit similar results. The condition improves in all cases when the navigation data is derived from GPS/DR. However, the effects of the spatial road network data remain considerable in the performance of the geometric map matching algorithm. The results are also similar for the probabilistic and fuzzy logic map matching algorithms (see Table 2).

Interestingly, the effects of positioning systems (GPS and GPS/DR) on the performance of the map matching algorithm for a particular spatial road network data set is found to be minor both in terms of link identification and location estimation. The probabilistic map matching algorithm, for instance, identifies 97.6% of the links correctly when the navigation data comes from stand-alone GPS and the spatial road network data comes from map scale 1:1,250. This is only increased to 98% for the same spatial road network data set when the navigation data comes from GPS/DR. This is perhaps due to the fact that the test road network is within a suburban area (non built-up with wide roads) which is predominately open and clear where the effect of multipath error is relatively low. The GPS/DR gives 100% coverage whereas GPS gives 98% coverage for the whole test road network and the maximum GPS outage is found to be only 5 s. Therefore, the position solutions from GPS and GPS/DR do not vary markedly. The situation might be different in built-up urban areas where GPS signal masking is a common phenomenon. "Section 5.1.4" presents results from a preliminary assessment of the urban road network in London. Taylor et al. [24] found a substantial improvement in the horizontal accuracy of bus position when they utilized positioning data from GPS integrated with vehicle odometers in Central London. For a particular bus route, they showed that the integrated system provided a mean error of 8.8 m compared with 53.7 m for raw GPS without an odometer.

There is also no major difference in the performance of the map matching algorithms when the spatial road network data come from either scale 1:1,250 or scale 1:2,500 (Table 2). This is surprising as one would expect that a larger scale spatial road network data set (e.g., 1:1,250) would give better map matching results. However, a larger scale map does not necessarily imply fewer geometric and topological errors, as shown in Figs. 6 and 7. The map data of scale 1:2,500 sometimes gives better results in terms of both correct link selection and location determination. The fuzzy logic map matching algorithm, for instance, identifies 99% of the link correctly with a horizontal accuracy of 6.5 m (2σ) if the navigation data come from stand-alone GPS and map data come from the map with scale 1:2,500. This is reduced to 98.3% with a horizontal accuracy of 7.1 m (2σ) if the map data comes from the map with scale 1:1,250.

Along-track accuracies (between 4 m and 42 m, 2σ) are larger than cross-track accuracies (between 3 and 10 m, 2σ) in all 18 cases presented in Table 2. This is an expected result as cross-track accuracy is significantly reduced by the projection of the position fix on the road, if the map matching algorithms can select the link correctly. The results are also consistent with the result described in Kim et al. [12].

The techniques used in the map matching algorithm also play an important role in the identification of the correct link and the determination of vehicle location. The geometric map matching algorithm identifies about 76% of the links correctly with an accuracy of 40 m (2σ) when the worst spatial road network data set (map scale 1:50,000) is used. This increases to 84% with an accuracy of 30 m (2σ) when the probabilistic map matching is applied.

For the test road network and for a particular positioning system and spatial road network data set, the fuzzy logic map matching algorithm is found to perform better compared to the geometric and the probabilistic map matching algorithms. The fuzzy logic algorithm gives the best results when the positioning data is from GPS/DR and the map data is from a spatial road network data set of scale 1:2,500. In this case, the map matching algorithm identifies 99.2% of the links correctly with a horizontal accuracy of 5.5 m (2σ), along-track accuracy 4.2 m (2σ) and cross-track accuracy 3.2 m (2σ).

5.1.4 Comparative assessment

To further investigate the results presented in Table 2, an analysis of variance (ANOVA) test was conducted to determine whether the horizontal accuracies obtained from different combinations of inputs (e.g., the road network data and the positioning systems) are the same. Table 3 shows the results for the fuzzy logic map matching algorithm. For a particular positioning system (e.g., GPS), the results suggest that the horizontal accuracy obtained from the spatial road network data of map scale 1:50,000 is statistically and significantly different from that of map scale 1:1,250 or 1:2,500. However, there are no significant differences between the results obtained from the maps of scales 1:1,250 and 1:2,500. Similar results are obtained for the other map matching algorithms.

The ANOVA test is also applied to examine the variations in horizontal accuracies obtained from the three map matching algorithms using different types of navigation sensors and spatial road network data. The results are shown in Table 4 when the positioning data are obtained from the GPS/DR. The results suggest that the horizontal accuracy offered by the geometric map matching algorithm is statistically and significantly different from that of the probabilistic or the fuzzy logic map matching algorithms for all map data. Results from the probabilistic and the fuzzy logic map matching algorithms are not statistically different if the map data come from either the map of scale 1:1,250 or 1:2,500.

To gain a full picture of the assessment, it is also essential to investigate how the quality of the navigation data affects the performance of the map matching algorithms. For this

Table 3 Analysis of variance (ANOVA) test on horizontal accuracy in the case of the fuzzy logic map matching algorithm

ANOVA test for horizontal accuracy		GPS			GPS/DR		
		1:1,250	1:2,500	1:50,000	1:1,250	1:2,500	1:50,000
GPS	1:1,250	–					
	1:2,500	×	–				
	1:50,000	√	√	–			
GPS/DR	1:1,250	×	×	√	–		
	1:2,500	×	×	√	×	–	
	1:50,000	√	√	√	√	√	–

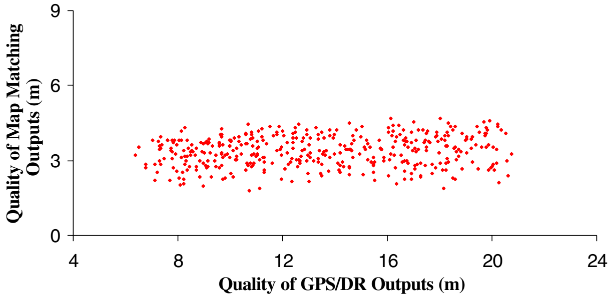
× Means the result is not statistically different (95% confidence level), √ means the result is statistically and significantly different (95% confidence level), – means the inputs are the same

Table 4 Analysis of variance (ANOVA) test on horizontal accuracy for all algorithms

ANOVA test for horizontal accuracy			Geometric			Probabilistic			Fuzzy logic		
			GPS/DR			GPS/DR			GPS/DR		
			1:1,250	1:2,500	1:50,000	1:1,250	1:2,500	1:50,000	1:1,250	1:2,500	1:50,000
Geometric	GPS/DR	1:1,250	–								
		1:2,500	×	–							
		1:50,000	√	√	–						
Probabilistic	GPS/DR	1:1,250	√	√	√	–					
		1:2,500	√	√	√	×	–				
		1:50,000	√	√	√	√	√	–			
Fuzzy logic	GPS/DR	1:1,250	√	√	√	×	×	√	–		
		1:2,500	√	√	√	×	×	√	×	–	
		1:50,000	√	√	√	√	√	√	√	√	–

× Means the result is not statistically different (95% confidence level), √ means the result is statistically and significantly different (95% confidence level), – means the inputs are the same

Fig. 8 The sensitivities of GPS/DR on the performance of the probabilistic map matching algorithm



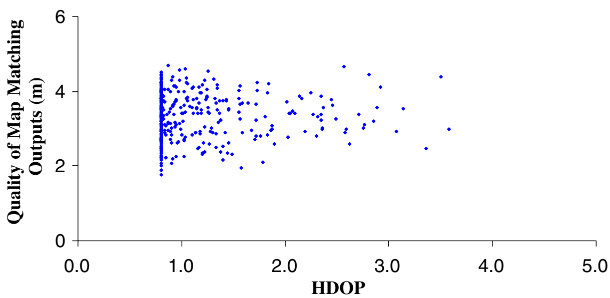
purpose, the epoch-by-epoch standard deviation (variance) of the errors associated with the map matching algorithm (calculated using Eq. 2) and the navigation sensors (obtained from the variance–covariance (vcv) matrix) are examined.

Figure 8 shows how the quality of the navigation sensors (GPS/DR) varies with the quality of the probabilistic map matching algorithm for the 1:2,500 spatial road network dataset. The uncertainties involved with GPS/DR are between 5 and 22 m. Given that the experiment is conducted in a suburban area with open spaces, this is an expected result. It is noticeable that the quality of the map matching algorithm is quite stable (3±1 m) for such reasonable uncertainties in the navigation system.

5.1.5 Role of satellite geometry

The geometrical position of the user's receiver with respect to the satellites being tracked plays a considerable role in the position error [28]. This geometry can be expressed in terms of various Dilution of Precision parameters to characterise its contribution to the positioning error. The HDOP is a measurement of the accuracy in 2-D horizontal position for a constant User Equivalent Range Error. Figure 9 shows the relationship between the quality of the probabilistic map matching algorithm and HDOP when the positioning data come from the GPS/DR and the road map data come from a map of scale 1:2,500. It is noticeable that the HDOP values are in an acceptable range and therefore, the driver of the stochastic relationship is the error in the navigation sensors and the map matching process. The results are relatively similar for other map matching algorithms. However, it is envisaged that the circumstances may be different in built-up areas where the effects of multipath and signal masking error usually result in larger uncertainties associated with the GPS or GPS/DR data.

Fig. 9 The relationship between the quality of probabilistic map matching outputs and GPS HDOP



5.2 Urban road networks

To assess the performance of the map matching algorithms in an urban area, a large amount of navigation data (about 60,000 s) was obtained from several field trials in London conducted between 2002 and 2005 (Fig. 10). In order to investigate the level of coverage offered by GPS and integrated GPS/DR, the position fixing data was overlaid onto a London spatial road network base map of scale 1:2,500. The coverage in this study was defined as the percentage of time when the minimum number of satellites was at least four and the HDOP was less than six.

The results showed that GPS coverage (with the high sensitivity receiver) was available over 95.5% of the total period, while the availability of the integrated system was 100%. The topological, probabilistic, and fuzzy logic map matching algorithms were applied to three types of spatial road network data of different map scales (1:1,250, 1:2,500 and 1:50,000) together with two types of navigation systems (GPS and GPS/DR).

The statistics generated from the results are shown in Table 5. The fourth column represents the percentage of unfixed positions. The vehicle position is considered as unfixed when the stand-alone GPS does not provide a position fix and the map matching algorithm is unable to fix the vehicle position during this period. The fifth column gives the percentage of correctly matched links. The determination of 2-D horizontal accuracy together with the cross-track and along-track accuracies offered by the map matching algorithms could not be estimated due to the lack of true vehicle positioning data. As a result, it was also not possible to investigate directly the sensitivities of the navigation sensors on the performance of the map matching algorithms. Because of frequent satellite loss-of-lock in the built-up areas, an effort to obtain the true vehicle positions using GPS carrier phase data was unsuccessful. This can be addressed in the future using GPS integrated with a high-grade INS. However, the performance of the map matching algorithms in terms of correct link identification could still be evaluated as the test vehicle travelled on a known route.

Table 5 shows that both positioning systems and spatial road network data affect the performance of the map matching algorithms in urban road networks in terms of the

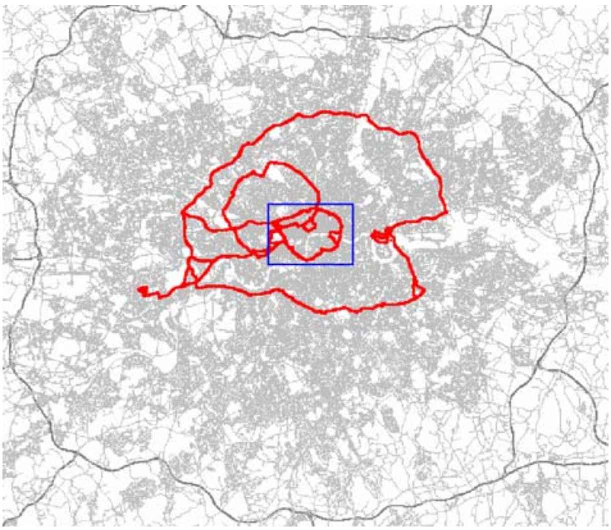


Fig. 10 The urban test route in Inner London

Table 5 The performance of map matching algorithms in urban road networks

Map matching algorithms	Positioning systems	Map scale of spatial road network maps	Unfixed (%)	Correct identification of links (%)
Geometric	GPS	1:1,250	4.5	74.8
		1:2,500	4.5	75.6
		1:50,000	4.5	68.9
	GPS/DR	1:1,250	0	79.1
		1:2,500	0	80.1
		1:50,000	0	76.5
Probabilistic	GPS	1:1,250	4.5	91.1
		1:2,500	4.5	90.2
		1:50,000	4.5	77.1
	GPS/DR	1:1,250	0	96.8
		1:2,500	0	97.1
		1:50,000	0	83.2
Fuzzy Logic	GPS	1:1,250	4.5	92.2
		1:2,500	4.5	93.1
		1:50,000	4.5	78.9
	GPS/DR	1:1,250	0	97.8
		1:2,500	0	98.5
		1:50,000	0	83.3

identification of the correct links. The percentage of correct link identifications is higher for the suburban road network (Table 2) compared to the urban road network in all 18 cases. The effects of the quality of spatial road network data are quite similar to the effects obtained for the suburban road networks. However, the effects of navigation sensors (GPS and GPS/DR) in urban areas are found to be quite significant. The probabilistic map matching algorithm, for instance, identifies 90.2% of the links correctly when the navigation data comes from stand-alone GPS and the spatial road network data come from a map of scale 1:1,250. This is increased to about 97% when the navigation data is obtained from GPS/DR using the same spatial road network data. Due to inherent problems associated with satellite signal masking along the test route, the stand-alone GPS is unable to provide position fixes during 4.5% of the total period. The positioning data from GPS is considered not to be fixed during the implementation of the map matching algorithm if the number of satellites is less than four, or the HDOP is greater than six.

Similar to the suburban road networks, as shown in Table 2, the fuzzy logic algorithm also gives the best results in the urban road network when the navigation data is obtained from GPS/DR and the map data is obtained from a spatial road network data of scale 1:2,500.

Although the performance of the map matching algorithms tested in this analysis is very good, an investigation was also carried out to see where and when a map matching algorithm identifies a wrong road segment in which case the positioning error is normally high. This is done for both the suburban and urban datasets. The results suggest that most of the incorrect identifications of road segments occur near junctions (specifically three-legged junctions and roundabouts) where the angle between two segments is quite small. As illustrated in Fig. 11, given that a map matching algorithm identifies the correct link, AB, for the position fixes P_1 and P_2, the identification of the correct link for the fix P_3 may be incorrect if the perpendicular distance from P_3 to link BC and BD is *equal*, and the heading of the vehicle from the navigation sensor is 90°. However, it might be possible to identify

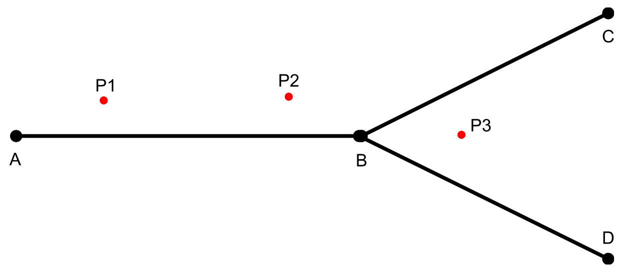


Fig. 11 A three-legged junction where a map matching may identify a segment incorrectly

the correct road segment in this situation if the positioning data can be obtained from GPS integrated with a high performance INS and the spatial road network data can be obtained from a high-quality spatial road network database. In addition to this, a more advanced map matching algorithm is also essential.

The map matching algorithms studied in this paper are highly flexible and are able to take into account other road attributes such as turn restrictions at junctions, road classifications (one-way or two-way), and lane number. For example, data on turn restrictions at junctions may improve the performance of a map matching algorithm at junction. Height data from a navigation sensor could also be included. This height data together with the data from a 3-D spatial road network can effectively identify the correct road segment at a section of roadway with flyovers. However, this will largely depend on the accuracy of height data and the availability of a high-quality 3-D road map.

Future research will investigate how to assess the effects of the navigation sensors on the performance of map matching algorithms in built-up areas in more detail. Higher accuracy GPS carrier phase observations coupled with a high-grade INS will potentially enable the determination of the reference (true) trajectory of vehicles in urban areas. Experiments carried out at the centre of the city of Nottingham (a medium rise city similar to London) showed that high-grade INS with calibration is capable of decimetre accuracy over a period of minutes [7]. As London's built environment is to a large extent similar to that of Nottingham, the findings from the latter can be assumed to be transferable to the former where a typical maximum period of continuous GPS outage of the order of 65 s is typical. This suggests that an integrated system (carrier phase GPS/high-grade INS) is a viable choice to measure the performance of map matching algorithms within urban areas. This will then allow us to quantify the effects of the navigation sensors and the spatial road network data quality in terms of horizontal accuracy.

6 Conclusions

The effects of navigation sensors and spatial road network data quality on the performance of three different map matching algorithms were investigated in this paper. The navigation sensors used for this purpose are stand-alone GPS and GPS integrated with DR. Three spatial road network data sets of different map scales (1:1,250; 1:2,500; and 1:50,000) were used. The map matching algorithms were then tested in different road networks with varying complexity both in suburban and urban road networks. In the case of the suburban road networks, the accuracy of the map matching algorithms is validated against the high accuracy GPS carrier phase observables both in terms of the correct link identification and the horizontal positioning accuracy. In the case of the urban road networks, the accuracy of the map matching algorithms was validated only in terms of the correct link identification. This is because of the inability to obtain the high accuracy GPS carrier phase measurements in urban areas due to frequent satellite loss-of-lock.

It was found that the percentage of correct link identification and the estimation of vehicle location (horizontal accuracy) by a map matching algorithm largely depends on the map scale of the spatial road network data in the case of suburban road networks. The geometric map matching algorithm, for instance, identifies about 76% of the links correctly with a horizontal accuracy of 43 m (2σ) when the spatial road network data of map scale 1:50,000 are used. The correct link identification increases to about 88% with a horizontal accuracy of 20 m (2σ) when the spatial road network data of map scale 1:1,250 or 1:2,500 are used. Similar results are obtained by the other map matching algorithms. However, the difference in the performance of a map matching algorithm is small when the spatial road network data are taken from a large scale map (1:1,250 or 2,500). The spatial road network data of map scale 1:2,500 gave better results in most cases. This is because this spatial road network map has more topological features than the spatial road map of scale 1:1,250. Therefore, one should not only rely on the map scale of the spatial road network map if a precise vehicle location is desired. More accurate road geometry as well as more detailed and accurate attributes (i.e., error related to topology) are also equally important. Interestingly, the types of navigation data have very little effect on the performance of the map matching algorithm in the case of the suburban road network. This may be due to the fact that the test route is from a suburban area which is predominately open and clear where the effect of multipath error is relatively low.

In the case of urban road networks, both the navigation system and the spatial road network map quality affect the performance of a map matching algorithm. The probabilistic map matching algorithm, for example, identifies about 91% of the links correctly when the navigation data were obtained from GPS. This increases to about 97% when the navigation data were from GPS/DR. The differences in the performance are largely due to the unavailability of GPS signals in the urban area in which the test was done. Of the three map matching algorithms tested, the fuzzy logic map matching process outperforms other map matching algorithms in urban areas.

Among other factors, the performance of a map matching algorithm is largely found to be dependent on the methodology used in the algorithm. However, there is no assurance that all fuzzy logic map matching algorithms, for instance, could provide identical performance for a particular set of inputs. This is due to the distinct processes used in the algorithm and the formulation of knowledge-based rules in the fuzzy inference system.

It should be noted that there are a variety of sensitivity-type analyses that could be carried out. An example is to investigate the effects of the spatial road network data quality on the performance of map matching algorithms employing the spatial road network data sets with the same topological data but with varying map scales (for example, various datasets from a particular vendor with scales 1:1,250; 1:2,500; 1:5,000; 1:10,000; and 1:50,000).

In summary, this paper proposes and executes a methodology to analyse the impact of data quality on map matching algorithms. Although, the results produced by applying the methodology are largely specific to the associated data sets, the methodology itself is flexible and transferable to different operational environments.

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