A FUZZY LOGIC BASED MAP MATCHING ALGORITHM FOR ROAD TRANSPORT

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ABSTRACT

Recent research effort on map matching algorithms for land vehicle navigation has been based on either a conventional topological analysis or a probabilistic approach. The input to these algorithms normally comes from the global positioning system and digital map data. Although the performance of some of these algorithms is good in relatively sparse road networks, they are not always reliable for complex roundabouts, merging or diverging sections of motorways and complex urban road networks. In high road density areas where the average distance between roads is less than 100m, there may be many road patterns matching the trajectory of the vehicle reported by the positioning system at any given moment. Consequently, it may be difficult to precisely identify the road on which the vehicle is travelling. To a certain extent, the map matching algorithm may suggest that the vehicle is "more likely" to be on certain roads, and "less likely" to be on others. Therefore, techniques for dealing with qualitative terms such as likeliness are essential for map matching algorithms to identify a correct link. Fuzzy logic is one technique that is an effective way to deal with qualitative terms, linguistic vagueness, and human intervention. This paper proposes a MM algorithm based on fuzzy logic theory. The inputs to the proposed algorithm come from global positioning system augmented with the deduced reckoning sensors data to provide continuous navigation. The basic characteristics of this map matching approach is to build various knowledge-based rules comprising the speed of the vehicle, the heading and the historical trajectory of the vehicle, the connectivity and the orientation of road links, and the contribution of satellite geometry to horizontal errors. The physical location of the vehicle on a link is then estimated using an optimal estimation technique which takes into account the error sources associated with the navigation sensors and the digital road map.

The algorithm is tested on different road networks of varying complexity. The validation of this algorithm is carried out using high precision positioning data obtained from GPS carrier phase observables. The performance of the proposed map matching algorithm is evaluated against the performance of several well-accepted existing map matching algorithms. The results show that the fuzzy logic-based map matching algorithm provides a significant improvement over existing map matching algorithms both in terms of identifying correct links and estimating the vehicle position on the links.

Keywords: GPS, digital road network, map matching, optimal estimation, and fuzzy logic

INTRODUCTION

In the last two decades, satellite navigation technology, especially the Global Positioning System (GPS), has been rapidly developed as a major positioning technology for road transport. This includes the use of radio-navigation for route guidance, dispatching roadside assistance vehicles, accident & 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 traveler information. Services such as Countdown in London provide information on bus arrival times at dispersed bus stop locations (TfL, 2004). Although service is currently based on microwave beacon technology, Transport for London (TfL) is considering a GPS-based upgrade to Countdown.

GPS provides 24-hour, all-weather 3D positioning and timing all over the world, with a predicted horizontal accuracy of 13 m (global average, signal-in-space) 95% of the time (US DoD, 2001). However, GPS suffers both systematic errors or biases and random noise. A real-world field test in London showed that the GPS positioning errors sometimes could be offset from the true position by more than 50 m (100%) (Zhao et al., 2003) while in Hong Kong it was found to be more than 80 m (Chen et al., 2003). A recent study to characterise the performance of GPS in a typical urban area showed 90% availability for a 4-hour trip in the Greater London area (Zhao et al., 2003). The implication of the outage involved here (i.e. 10%) was a potential loss of navigation capability during a crucial period. In order to achieve the required accuracy and availability in some areas, GPS data can be augmented with Deduced Reckoning (DR) sensor data with the use of an Extended Kalman Filter (EKF). Zhao et al. (2003) applied an EKF to combine GPS and DR data and achieved a 100% coverage with a 2D horizontal accuracy of 50m (3σ) relative to a high resolution (1:1,250) road centreline map for the same trip (Zhao et al., 2003). Integration of GPS and DR increases coverage but does not necessarily increase positioning accuracy (Zhao et al., 2003). Therefore, Map Matching (MM) algorithms are normally used to enhance the geometric positioning accuracy of land vehicle navigation.

The most commonly used MM algorithms are based on a simple search concept. In this approach, each position fix matches to the closest 'node' or 'shape point' in the network, which is known as point-to-point matching (Bernstein and Kornhauser, 1998). These methods are easy to implement, although they are very sensitive to outliers and to the way in which the network was digitized, hence leading to errors. Another MM approach is point-to-curve matching (e.g., Bernstein and Kornhauser, 1998; White et al., 2000; Taylor et al., 2001). In this approach, the position fix from the navigation system is matched with the closest curve in the network. Although this approach gives better results than point-to-point matching, it has several shortcomings that make it inappropriate in practice (in some cases), such as generating very unstable results in dense urban networks. Another geometric approach is to compare the vehicle's trajectory against known roads. This is also known as curve-to-curve matching (Bernstein and Kornhauser, 1998; White et al., 2000). This approach is quite sensitive to outliers and depends on point-to-point matching, sometimes giving unexpected results (Greenfeld 2002). Taylor et al. (2001) propose a novel method of map matching using GPS, height aiding from the digital terrain model (DTM) and virtual differential GPS (VDGPS) corrections, referred to as the *road reduction filter (RRF)* algorithm. In this approach, the final vehicle position is estimated without taking into account the error sources associated with the GPS position solution and the digital road network map data. The mean horizontal accuracy of the *RRF* algorithm was found to be 14 m. Since the study was carried out when the selective availability (S/A) was switched on, the performance of the RRF algorithm needs to be re-evaluated in the S/A free environment. Moreover, the RRF is not suitable for urban canyons as it requires at least three in-view satellites for a position solution and DTM data used in the RRF algorithm is not readily available with a desired level of accuracy needed for many transport telematics applications. Greenfeld (2002) reviews several approaches for solving the map matching problem and proposes a weighted topological algorithm. The algorithm is based on assessing the similarity between the characteristics of the street network and the positioning pattern of the user. The paper reports that the procedure computes correct matches virtually everywhere. Quddus et al. (2003) tested this algorithm for a relatively sparse road network and concluded that the algorithm identified 10% of the road segments incorrectly. Greenfeld (2002) also suggests that additional research is required to verify the performance of the algorithm.

The complexity of the MM algorithms depends on the nature of the application and the availability of data inputs. Previous research by the author and his colleagues resulted in the development of two MM algorithms. The first algorithm was based on a conventional topological analysis (Quddus et al., 2003) and the second was based on a probabilistic approach (Ochieng et al., 2004). Although the performance of these algorithms is quite good in relatively sparse road networks, they are not suitable for complex roundabouts, merging or diverging sections of a motorway and complex urban road networks. In high road density areas where the average distance between roads is less than 100m, there may be many road patterns matching the trajectory of the vehicle reported by the positioning system at any given moment. Consequently, it may be difficult to precisely identify the road on which the vehicle is travelling. To a certain extent, the MM algorithm may suggest that the vehicle is “more likely” to be on certain roads, and “less likely” to be on other roads. Therefore, techniques for dealing with qualitative terms such as likeliness are essential in the MM algorithm for the identification of a correct link.

Fuzzy logic is one technique that is an effective way to deal with qualitative terms, linguistic vagueness, and human intervention (Zhao, 1997). In fuzzy logic, linguistic terms with vague concepts can be expressed mathematically by making use of fuzzy sets. A set of rules representing expert knowledge and experience is used to draw inferences through an approximate reasoning process. In MM, identification of the correct link on which the vehicle is travelling is a qualitative decision-making process involving a degree of ambiguity. Fuzzy logic based MM algorithms have been developed by a number of researchers (e.g., Zhao, 1997; Kim et al., 1999, Syed and Cannon, 2004). The generic limitations of these algorithms include: (a) ignoring most of the available inputs to the fuzzy logic model (b) overlooking the connectivity among road links and the historical trajectory of the vehicle which can enhance the performance of MM algorithms (c) ignoring the error sources associated with the spatial road network and the navigation sensor, and (d) failing to validate the MM algorithms to assess their performance. Therefore, a robust fuzzy logic-based MM algorithm will be developed in this study to deal with these limitations.

The main objective of this paper is to develop an improved MM algorithm based on fuzzy logic theory. The algorithm will be validated using a higher accuracy reference (truth) of the vehicle trajectory as determined by GPS carrier phase observables. The algorithm will be tested on complex urban road networks and its performance will be evaluated against the performance of commonly used MM algorithms.

The paper is organized as follows. Firstly a brief overview of fuzzy logic theory is provided. This is followed by a detailed description of the proposed fuzzy logic-based MM algorithm. The next section briefly describes a validation strategy to assess the performance of the algorithm, followed by a description of the implementation of the algorithm using real-world data and a presentation of results. Conclusions and recommendations for further avenues of study are given at the end of the paper.

OVERVIEW OF FUZZY LOGIC THEORY

Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth i.e., truth values between "completely true" and "completely false". It was introduced in the 1960's by Zadeh (1965). Zadeh was working in the field of control engineering and his intention in introducing this fuzzy theory was to deal with problems involving knowledge expressed in vague, linguistic terms. To represent the shades of meaning of linguistic terms (e.g., the speed of the vehicle is *low*, the distance to the downstream junction is *long* etc), the concept of grades of membership or the concept of possibility values of membership was introduced in fuzzy logic. A comprehensive review of fuzzy logic theory can be found in Zadeh (1965, 1973, 1989), Mamdani and Assilian (1975), and Sugeno (1985). However, a brief overview is presented below.

Consider a simple knowledge-based fuzzy rule-"*If the speed of the vehicle is high and the travel time is low then the traffic congestion on the link is low*". The input variables of this rule are *the speed of the vehicle* and *the travel time* and the input fuzzy subsets are *high* and *low* respectively. The output variable is *the traffic congestion* and the output fuzzy subset is *low*. Since fuzzy subsets describe vague concepts, the truth of any proposition (i.e., the speed of the vehicle is *high*) in fuzzy logic becomes a matter of degree. This is achieved by the fuzzification of the input variable using a *membership function (MF)*. A *MF* is a curve that defines how each point in the input space (e.g., a speed range in the above example) is mapped to a membership value between 0 and 1.

One of the challenging issues in fuzzy logic is to define the shape of the *MF*. Different types of *MF*s are used. Examples are triangular, trapezoidal, Z-shaped, S-shaped, gaussian, generalised bell, and sigmoidal, etc. The shape of the *MFs* is usually determined empirically based on the linguistic statements associated with the inputs. After the fuzzification of all inputs, fuzzy knowledge-based IF-THEN rules are formulated. The output of each rule is also a fuzzy set which is achieved either a *min* (minimum) method (the mininum of all *degree of membership* values associated with inputs) or a *prod* (product) method (the product of all *degree of membership* values associated with inputs) (Mamdani and Assillian, 1975). The output fuzzy sets of each rule are then combined into a single fuzzy set using the *aggregation method*. Three methods are used for the aggregation method: (1) *max* (maximum), (2) *probor* (Probabilistic OR), (3) *sum* (Mamdani and Assillian, 1975). The last step is the defuzzification process. The input to this process is a fuzzy set obtained from the output of the aggregation method. The output of the defuzzification process is a single number (crisp). Several methods are available for the defuzzification process, e.g., centroid, the largest of maximum, the smallest of maximum, bisector, and weighted average, etc.

Figure 1 shows a fuzzy inference system (FIS) which is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping provides a basis from which a decision can be made. There are two main types of FIS: (1) Mamdani-type (Mamdani and Assillian, 1975) and (2) Sugeno-type (Sugeno, 1985).

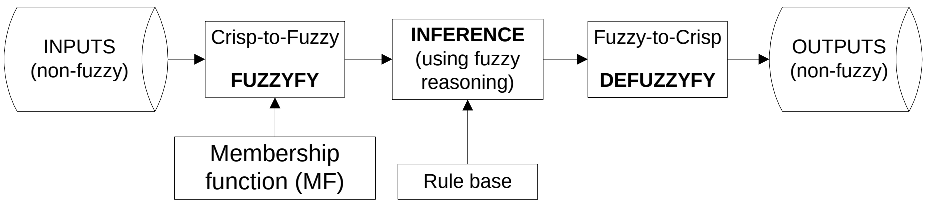


Figure 1: Fuzzy inference system (FIS)

Mamdani FIS

The FIS described in Figure 1 is a Mamdani FIS where the output inference is expected to also be a fuzzy set. The following six steps can be used to compute the system output from a set of given inputs.

1. Determine a set of state input variables and knowledge-based fuzzy rules

2. Fuzzify the inputs using the input membership functions

3. Combine the fuzzified inputs according to fuzzy rules to establish a rule strength

4. Determine the consequence of each rule by combining the rule strength and the output membership function

5. Combine the consequences to get an output distribution, and

6. Defuzzify the output distribution if a crisp output is needed.

Mamdani FIS can be illustrated with the following example. Consider a three-legged junction as shown in Figure 2. Assume that P represents a vehicle position obtained from an in-vehicle navigation sensor when the vehicle travels through the junction. The task is to identify a correct link among the candidate links (D-A, A-B or A-C) on which the vehicle is actually travelling. The direction of the vehicle at P obtained from the navigation sensor is θ.

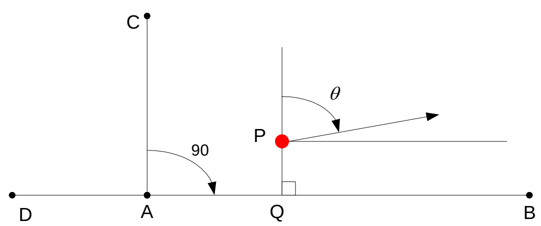


Figure 2: A three-legged junction with a vehicle position from a navigation sensor

PQ denotes a perpendicular distance from P to link A-B. The distance, PQ, and the angular difference, $|90^0 - \theta|$, are primarily the two determining factors as to whether P is matched onto the link A-B. The link A-B would be the actual link if PQ is short and the $|90^0 - \theta|$ is small. However, knowledge-based IF-THEN rules can be formed based on these two inputs, for example:

- If PQ is short and $|90^0 - \theta|$ is small then the possibility of matching P on the link A-B is high
- If PQ is short and $|90^0 - \theta|$ is high then the possibility of matching P on the link A-B is low

A Mamdani FIS for the above example is illustrated in

Figure **3**.

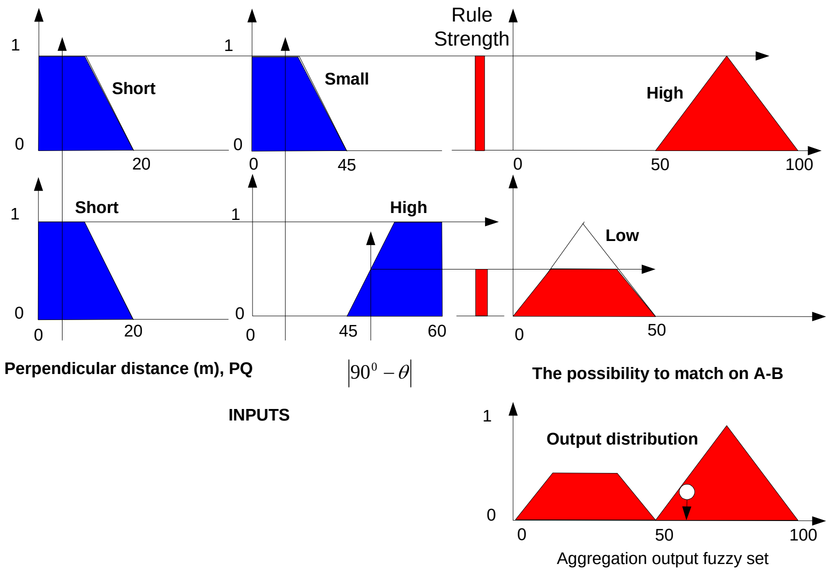


Figure 3: Mamdani's Fuzzy Inference System (FIS)

Sugeno FIS

Sugeno's FIS is quite similar to Mamdani's FIS. The basic difference is that the crisp output consequence is not computed by clipping an output membership function based on the rule strength as in Sugeno's FIS. In fact, there is no membership function for an output variable in Sugeno's FIS. Instead, the output is a crisp number called a singleton, computed by multiplying the output of each rule by a constant and then adding up the results. A generic rule for Sugeno's FIS is as follows:

If x is A and y is B then Z=$f(x,y)$

where $z=f(x,y)$ is either a first order polymonial (known as a '1st-order Sugeno fuzzy model') or a constant (known as a 'zero-order Sugeno fuzzy model'). Figure 4 illustrates a zero-order Sugeno's FIS with the same inputs and rules used in the previous example. Two constants are taken for the outputs (Z): high (Z_1) = 100 and low (Z_2) =25.

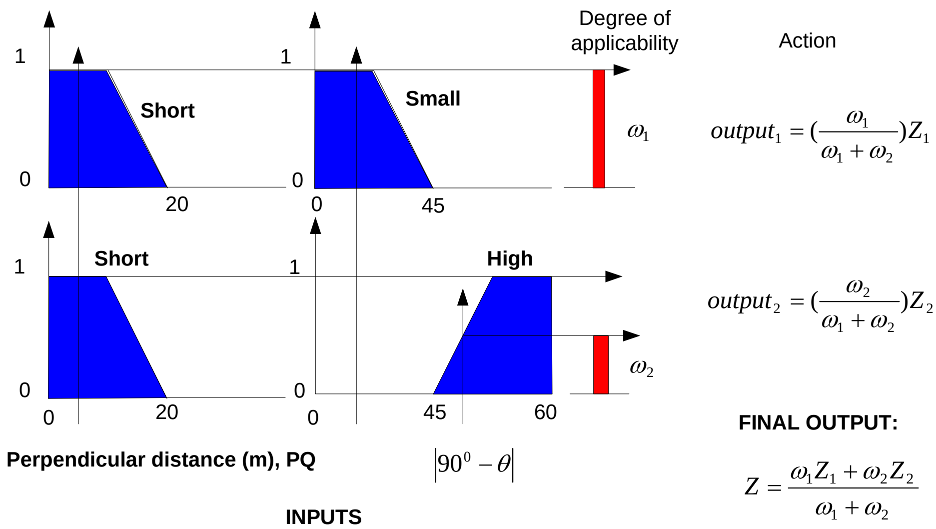


Figure 4: Sugeno's Fuzzy Inference System (FIS)

Rule strength in this FIS is referred to as the "degree of applicability" and the output is referred to as the "action" as shown in Figure 4. As can be seen, there is no output distribution, only a "resulting action" which is the weighted average of the rule strengths (degree of applicability) and the outputs (actions). This FIS usually needs a smaller number of rules as the output is already a linear function of the inputs rather than a fuzzy set (Abraham, 2001). Furthermore, the empirically chosen *f(x,y)* can be optimized by a set of input/output data using the fuzzy logic toolbox of Matlab. The Sugeno FIS is used further in the analysis in this paper.

MAP MATCHING (MM) ALGORITHM

The capability to identify the physical location of a vehicle on a link is a key requirement in any transport telematics applications. In order to achieve the RNP, system and sensor complementarity, such as in the case of the integration of GPS, DR, and digital map data (Figure 5) that could be used to enhance geometric positioning capability. This is achieved by a MM algorithm.

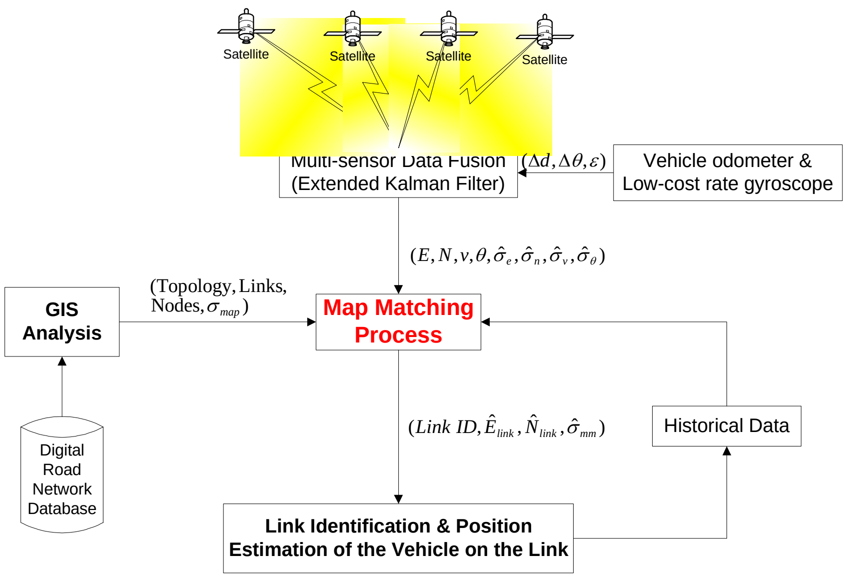


Figure 5: A schematic diagram of the GPS/DR/MM Process

The integration of GPS and DR is achieved via an Extended Kalman Filter (EKF) algorithm as described in Zhao et al. (2003). The EKF algorithm takes inputs from the GPS and DR (the gyro-rate reading ($\Delta\theta$), the odometer reading (Δd) and the errors associated with them (ε_θ and ε_d). The outputs of GPS/DR are Easting (E), Northing (N), vehicle speed (v), heading (θ), and the error variances associated with them (i.e., $\hat{\sigma}_e, \hat{\sigma}_n, \hat{\sigma}_v, \hat{\sigma}_h$ respectively). The MM algorithm takes inputs from the GPS/DR and the digital map data (e.g., topology, links, nodes, and the error variance of map data, σ_{map}). The outputs of the MM process are the correct link ID, the position solution (Easting, $\hat{E}_{link}$ and Northing, $\hat{N}_{link}$) on that link and the uncertainty associated with the position solution ($\hat{\sigma}_{mm}$). The MM process not only enables the physical location of the vehicle to be identified but also improves the positioning capability if a good digital map is available.

The MM algorithm developed in this paper has two stages: (1) the identification of the correct link and (2) the determination of the vehicle location on the selected link. These are explained below.

Identification of the Correct Link

The most complex element of any MM algorithm is to identify the actual link among the candidate links (Greenfeld, 2002; Quddus et al. 2003, and Ochieng et al., 2004). Therefore, a novel approach consisting of two distinct processes was developed for the identification of the correct link. The processes are: (1) the *initial map-matching process* (IMP) and (2) the *subsequent map-matching process* (SMP). Both of these processes are described below.

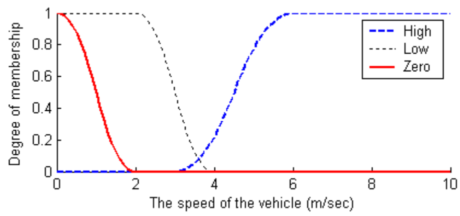
Initial map-matching process (IMP)

The selection of an initial link for the initial position fix is known as an initial map-matching process (IMP). If an initial matching is incorrect then the subsequent matching will also be incorrect. Therefore, a sophisticated method is employed for the IMP. The IMP approach used in this paper is a function of the GPS receiver's time-to-first-fix (TTFF), the search space based on the error ellipse derived from the error variances, the perpendicular distance from a position fix to the link, the bearing of the link, and the direction of the vehicle. A few first good position fixes on a link are used to identify the first link. This gives a level of confidence that the IMP is robust.

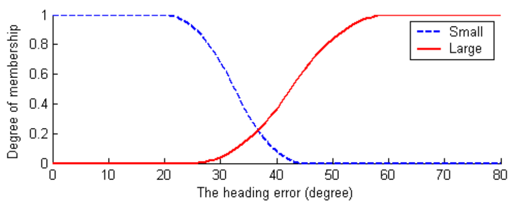
The IMP begins just after the initialization of the GPS receiver which may take a minute or two after switching it on depending on its surrounding environments. The basic characteristic of the IMP is the use of an elliptical or rectangular confidence region around a position fix based on error models associated with GPS/DR. Road links that are within the confidence region are taken as the candidate links. If the confidence region does not contain any link, then it is assumed that the vehicle is off the known road links. In such a situation, the derived GPS/DR position is used as the final location of the vehicle. In a situation where the confidence region contains only one segment, then the final selection process is very straightforward. In the case of more than one link, a fuzzy inference system (FIS) can be used to identify the correct link among the candidate links.

The most important variables available during IMP are the heading error (HE), which is defined as the absolute difference between the direction of the vehicle and the direction of the link, and the perpendicular distance (PD) from the position fix to the link. These two variables could be used as potential inputs for the FIS. However, the quality of the direction of vehicle data largely depends on the speed of the vehicle (Quddus et al., 2004, and Taylor et al., 1999). Therefore, the speed of the vehicle could be used as an additional input to the FIS. The satellite geometric contribution to the positioning error as determined by the horizontal dilution of precision (HDOP) could also be used as a quality indicator of the position fix.

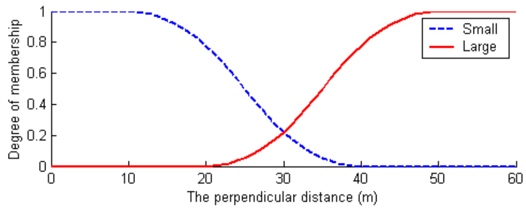
Therefore, the state input variables of this FIS are: (1) the speed of the vehicle, *v* (m/sec), (2) the heading error, HE (degree), (3) the perpendicular distance, PD (m), and (4) the HDOP. The speed of the vehicle can be obtained from GPS/DR and the fuzzy subsets associated with this variable are *zero*, *low* and *high*. The direction of the link is obtained from the spatial road network data and the direction of the vehicle is obtained from the GPS/DR. The fuzzy subsets related to the heading error are *small* and *large*. The PD is calculated as the minimum Euclidian distance between the position fix and the link. The fuzzy subsets associated with this variable are *low* and *high*. The HDOP could also be obtained from the GPS/DR and the fuzzy subsets are *good* and *bad*. The four system state input variables are fuzzified as shown in Figure 6. Z-shaped and S-shaped MFs are chosen in the fuzzification process. The single output of this FIS is the likelihood of matching the position fix to a link (denoted as *L1*). A zero-order Sugeno fuzzy model is considered which takes three constants for the output, *L1* e.g., *low (Z1)* = 10, *average(Z2)* = 50 and *high (Z3)* =100.



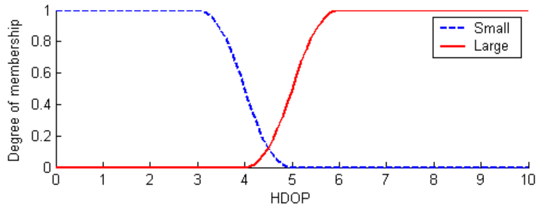
(a)



(b)



(c)



(d)

Figure 6: The fuzzification of the speed of the vehicle (a), the heading error (b), the perpendicular distance (c), and HDOP (d)

The next step is to formulate the fuzzy rules which are related to the number of system state variables. The following six rules comprising the fuzzy knowledge are applied to this FIS. The weight of each rule is shown within the brackets at the end of each rule. Quddus et al. (2003) and Greenfeld (2002) suggest that the heading error should be given more weight than the PD. Therefore, a higher weight is given to the rules associated with the heading error.

- *If (**v** is high) and (**HD** is small) then (**L1** is average) (3)*
- *If (**v** is high) and (**HD** is large) then (**L1** is low) (1)*
- *If (**HDOP** is good) and (**PD** is short) then (**L1** is average) (1)*
- *If (**HDOP** is good) and (**PD** is long) then (**L1** is low) (1)*
- *If (**HD** is small) and (**PD** is short) then (**L1** is high) (1)*
- *If (**HD** is large) and (**PD** is long) then (**L1** is low) (1)*

The *min* (*minimum*) method is used to derive the "degree of applicability" (ω_i) of each fuzzy rule. The weighted average method as shown in Figure 4 is used to obtain a crisp output. This crisp output is the likelihood associated with a link. The FIS is applied to all links within the confidence region. The link which gives the highest likelihood is taken as the correct link among the candidate links.

The above FIS is used to identify a link on which the vehicle is travelling. Since only a few inputs are available during IMP, the link identified by the FIS for the first position fix may not be the actual link. Therefore, the IMP is performed for a few first good position fixes. If the FIS identifies the same link for those position fixes, then the link is chosen as a first correct link as illustrated in Figure 7.

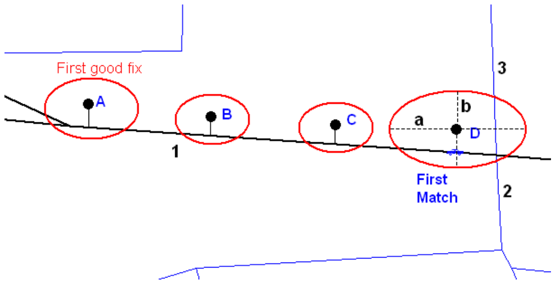


Figure 7: Example of initial map-matching process (IMP)

Assume that the first good position fix from the GPS/DR is denoted by the point A (Figure 7). The FIS identifies link 1 as a correct link for this position fix. The FIS then identifies link 1 as the correct link for the subsequent position fixes B, C, and D. Therefore, it can be said that the correct link for the position fix, D, is link 1.

The subsequent map-matching process (SMP)

After successfully implementing the IMP, the subsequent map-matching process (SMP) is used. The basic function of SMP is to match the following position fixes. Two types of SMPs are proposed: (1) SMP along a link (SMP-1) and (2) SMP at a junction (SMP-2). The purpose of SMP-1 is to match the subsequent position fixes with the link identified by IMP unless the vehicle is either about to cross or has already crossed a junction. The purpose of SMP-2 is to identify a new link among the candidate links at a junction for the last non-matched position fix. After identifying a new link by the SMP-2, the SMP-1 restarts to match the subsequent position fixes to the new link. Both of these processes are explained below.

SMP along a link (SMP-1)

The SMP-1 starts to match the following position fixes on the previously selected link, which is identified using IMP (or SMP-2). In SMP-1, a Sugeno FIS is used to see whether the following position fixes could be matched on the previously selected link. The SMP-1 is a function of the direction of the vehicle, the gyro-rate reading, the distance along the link from the last matched position fix to the downstream junction, and the speed of the vehicle.

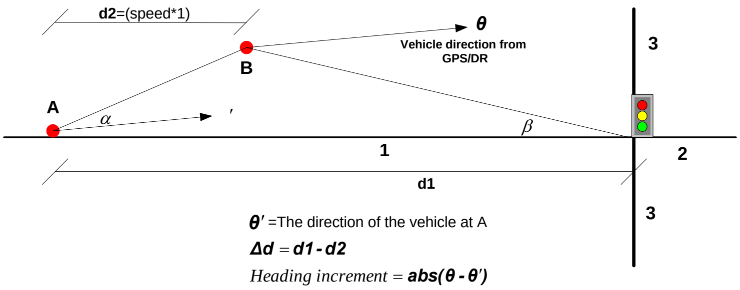
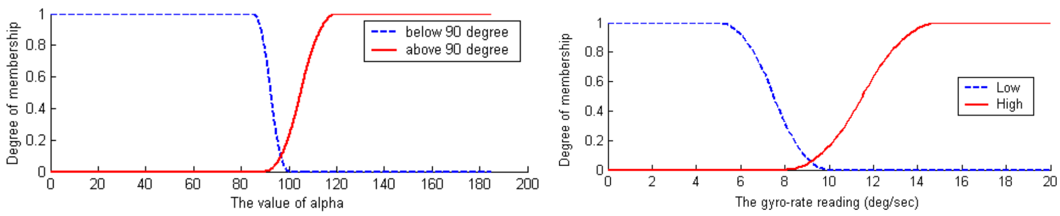


Figure 8: SMP along a link

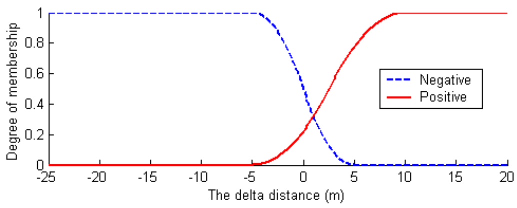
Figure 8 shows the state variables of the vehicle travelling on a link. Point A represents the last matched vehicle position on link 1 which was identified by IMP (or SMP-2). Therefore, the task of SMP-1 is to select the correct link for the subsequent position fix, B. The term *d1* refers to the distance from the last matched vehicle position to the downstream junction and *d2* refers to the distance travelled by the vehicle within the last second which can be calculated from vehicle speed at B. The difference between these two distances i.e., $\Delta d = (d1-d2)$ can be used to see whether the vehicle crosses a junction. For example, if the Δd is negative, then it is more likely that the vehicle has already crossed the junction. The α and β

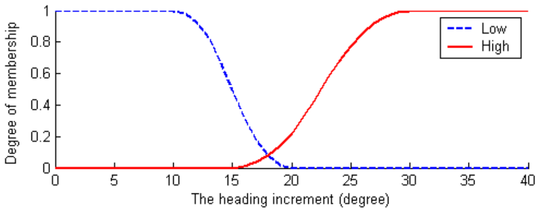
define the location of the position fix, B, relative to link 1. If both of these angles are less than 90^0, then it is more likely that the vehicle has not crossed the junction. The angles θ and θ' indicate the directions of the vehicle at B and A respectively. The absolute difference between these two angles i.e., $abs(\theta - \theta')$ gives a heading increment at B for the last epoch. The lower the heading increment the higher is the possibility that the vehicle is on the link 1. If the heading increment is close to zero, then it is more likely that there is no left or right turn. In addition, the gyro-rate reading at B, which is the rate of change of heading for the last epoch, can also be used to see whether there is a left or right turn.

Therefore, the fuzzy variables of this FIS are: (1) the speed of the vehicle, v (m/sec) (2) the heading increment (degree) (3) the gyro-rate reading, $\Delta\theta$ (deg/sec) (4) the Δd (m) (5) the value of α (degree) (6) the value of β (degree), and (7) the HDOP. The single output of this FIS is denoted as *L2* and is the possibility of matching the current point (in our case, B) on the previously identified link (in our case, link 1) denoted by *L2*. The fuzzification of the state input variables are shown in Figure 9. *Z*-shaped, *S*-shaped and *gauss* MFs (for the 180^0 heading increment) are used in the fuzzification process. A zero-order Sugeno fuzzy model is considered which takes three constants for the output *L2* e.g., *low(Z1)* = 10, *average(Z2)* = 50 and *high(Z3)* =100.



(a) (b)





(c) (d)

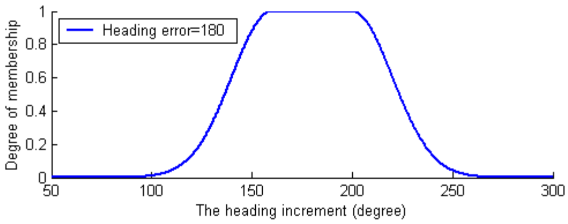


Figure 9: The *MF*s for the α or β (a), the gyro-rate reading (b) the Δd (c), the heading increment (d), and a 180 degree heading increment (e)

The following rules are applied to this FIS:

- *If ($\Delta\theta$ is small) and (α is below 90^0) and (β is below 90^0) then (* ***L2*** *is high) (1)*
- *If ($\Delta\theta$ is small) and (*Δ***d*** *is positive) and (α is above 90^0) then (* ***L2*** *is low) (1)*
- *If ($\Delta\theta$ is small) and (*Δ***d*** *is positive) and (β is above 90^0) then (* ***L2*** *is low) (1)*
- *If (***HD*** *is small) and (α is below 90^0) and (β is below 90^0) then (***L2*** *is high) (1)*
- *If (***HD*** *is small) and (*Δ***d*** *is positive) and (α is above 90^0) then (***L2*** *is low) (1)*
- *If (***HD*** *is small) and (*Δ***d*** *is positive) and (β is above 90^0) then (***L2*** *is low) (1)*
- *If ($\Delta\theta$ is high) and (α is below 90^0) and (β is below 90^0) then (***L2*** *is low) (1)*
- *If (***HD*** *is large) and (α is below 90^0) and (β is below 90^0) then (***L2*** *is low) (1)*
- *If (***HDOP*** *is good) and (***v*** *is zero) then (***L2*** *is high) (1)*
- *If (***HDOP*** *is good) and (*Δ***d*** *is negative) then (***L2*** *is average) (1)*

- *If (**HDOP** is good) and (**Δd** is positive) then (**L2** is low) (1)*

- *If (**v** is high) and (**HD** is small) then (**L2** is average) (1)*

- *If (**HDOP** is good) and (**v** is high) and (**HD** is 180^0) and ($\Delta\theta$ is high) then (**L2** is high) (1)*

A threshold output value can be used to determine whether the position fix should match with the previously selected link. The threshold value can empirically be derived by applying the FIS to a given (true) input/output dataset.

SMP at a junction (SMP-2)

The SMP-2 begins when the vehicle is either about to cross or has just crossed a junction. A new link is determined among the candidate links using the same FIS described in IMP. However, two more input variables are available at this moment. These are the link connectivity and the distance error as shown in Figure 10.

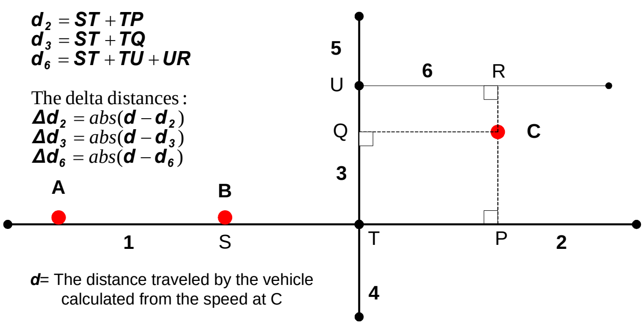
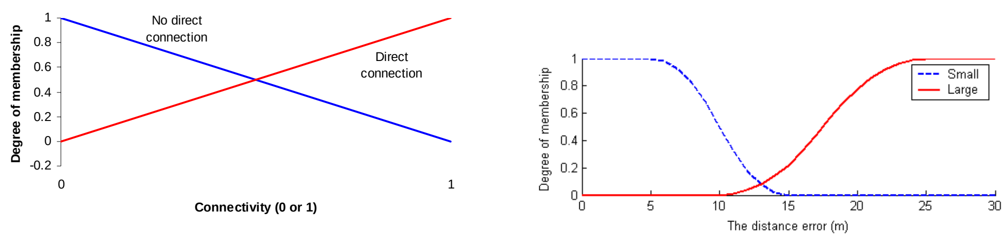


Figure 10: SMP at a junction

Assume that the vehicle is travelling on link 1. The last map-matched position on that link is S. The task of SMP-2 is to select a new link for the position fix, C, as the vehicle has already crossed the junction. The candidate links for this position fix are 2, 3 and 6. Since the location of the vehicle at the previous epoch is on link 1, the link connectivity helps to identify the correct link. For example, there is no direct connection between links 1 and 6. Therefore, it is unlikely that the vehicle is on link 6 for the position fix C. The term *d* refers to the distance travelled by the vehicle within the last second which can be calculated by the speed of the vehicle at C. The d_2, d_3, and d_6 represent the shortest paths travelled by the vehicle if the vehicle is on links 2, 3 and 6 respectively. The difference between *d* and d_2 (or d_3 or d_6) is the distance error associated with each of the link as shown in Figure 10. The distance error is an input to the FIS. For example, the link which gives the lowest distance error is a strong candidate for the correct link. The two additional state input variables are fuzzified as shown in Figure 11. The output variable of this FIS is the likelihood of matching to a link (*L3*). A zero-order Sugeno fuzzy model is considered which takes three constants for the output *L3*, e.g., *low (Z1)* = 10, *average (Z2)* = 50 and *high (Z3)* =100.



(a) (b)

Figure 11: The *MF*s for the link connectivity (a), and the delta distance (b)

Ten rules are used for this FIS. The first six rules are the same as presented in the FIS of IMP. The rest of the rules are given below.

- *If (The **connectivity with the previous link** is low) then (The **L3** is low) (1)*
- *If (The **connectivity with the previous link** is high) then (The **L3** is high) (1)*
- *If (The **distance error** is low) then (The **L3** is high) (1)*

- *If (The **distance error** is high) then (The **L3** is low) (1)*

The FIS is applied to all links within the error region and the link which gives the highest likelihood value is taken as the correct link.

Determination of the Vehicle Location on the Selected Link

Assuming that the correct link has been identified as per the IMP and/or SMP, the physical location of the vehicle on the link can be determined in two ways with the available data. One method is to use map data (i.e., link heading) and vehicle speed from the positioning sensors. If an initial position for the vehicle is known then the vehicle position (easting, e_{map} , northing, n_{map}) can be derived epoch-by-epoch from the link heading and speed information. The other method is to adopt the perpendicular projection of the GPS or the GPS/DR fix on to the link that results in the easting (e_{gps}) and northing (n_{gps}) coordinates. Since both methods are associated with errors, an optimal estimation procedure (combining the two methods) is used to determine the final location of the vehicle on the road segment. The optimal easting ($\hat{e}$) and northing ($\hat{n}$) for a particular epoch are expressed as

$$\hat{e} = \left(\frac{\sigma^2_{gps,e}}{\sigma^2_{map} + \sigma^2_{gps,e}}\right)e_{map} + \left(\frac{\sigma^2_{map}}{\sigma^2_{map} + \sigma^2_{gps,e}}\right)e_{gps} \tag{1}$$

$$\hat{n} = \left(\frac{\sigma^2_{gps,n}}{\sigma^2_{map} + \sigma^2_{gps,n}}\right)n_{map} + \left(\frac{\sigma^2_{map}}{\sigma^2_{map} + \sigma^2_{gps,n}}\right)n_{gps} \tag{2}$$

where σ^2_{map} is the error covariance associated with map data, $\sigma^2_{gps,e}$ and $\sigma^2_{gps,n}$ are the easting and northing components of the error covariance associated with the navigation sensor. The error variance associated with $\hat{e}$ can now be expressed as

$$\frac{1}{\sigma^2_{mm,e}} = \frac{1}{\sigma^2_{map}} + \frac{1}{\sigma^2_{gps,e}} \qquad (3)$$

where $\sigma^2_{mm,e}$ is the error variance associated with optimal estimation of $\hat{e}$. Note from equation (3) that $\sigma^2_{mm,e}$ is less than either σ^2_{map} or $\sigma^2_{gps,e}$. That is, the uncertainty in the estimation of the vehicle position using optimal estimation is decreased by combining two measurement methods. Similarly, the error variance associated with the optimal estimation of $\hat{n}$ can also be derived from equation (3).

Reliability of the MM Algorithm

The purpose of IMP is to select an initial correct link for an initial position fix whereas the purpose of SMP is to select correct links for subsequent position fixes obtained from the navigation sensor (GPS/DR). The optimal estimation is then used to determine the position of the vehicle on these links. In order to have a specified level of confidence in the identification of the correct links achieved by the SMP and hence the determination of the vehicle position, a simple test can be used. The test, which can be termed as a reliability test, is to construct an elliptical error region (i.e., confidence region) around the position fix and to find out whether the estimated vehicle position is within the error region. The error ellipse can be derived from the variance-covariance matrix associated with the positioning sensors output as

$$a = \hat{\sigma}_0 \sqrt{1/2(\sigma_x{}^2 + \sigma_y{}^2 + \sqrt{(\sigma_x{}^2 - \sigma_y{}^2)^2 + 4\sigma_{xy}{}^2})} \qquad (4)$$

$$b = \hat{\sigma}_0 \sqrt{1/2(\sigma_x{}^2 + \sigma_y{}^2 - \sqrt{(\sigma_x{}^2 - \sigma_y{}^2)^2 + 4\sigma_{xy}{}^2})} \qquad (5)$$

$$\phi = \pi/2 - 1/2 \arctan(\frac{2\sigma_{xy}}{\sigma_x{}^2 - \sigma_y{}^2}) \qquad (6)$$

where σ_x^2 and σ_y^2 are the positional error variances from the integrated GPS/DR, σ_{xy} is the covariance, *a* and *b* are the semi-major and semi-minor axis of the ellipse, ϕ is the orientation of the ellipse relative to the North, and $\hat{\sigma}_0$ (>1) is the expansion factor. The expansion factor is a term that compensates for the error associated with GPS due to orbital instability, atmospheric propagation, multipath, and receiver noise. To obtain a 99% confidence level, the value of the expansion factor should be taken as 3.03 (Zhao, 1997).

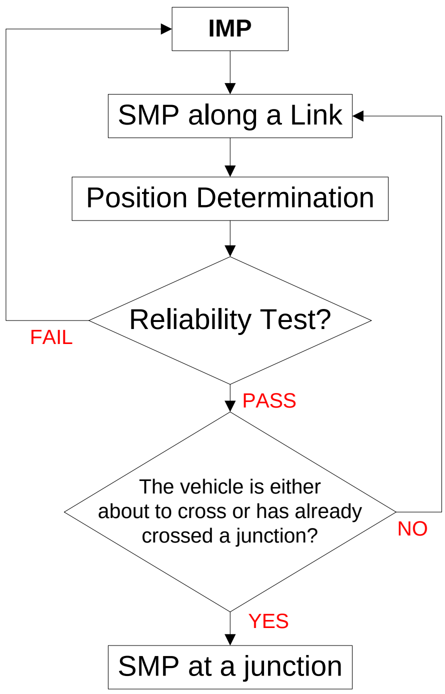


Figure 12: A schematic diagram of the proposed MM algorithm

If the estimated vehicle position falls within the error ellipse, then it can be said that the reliability 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 position falls outside of the error region, then it can be said that the reliability test is unsuccessful and the estimated position is incorrect and the map matching process re-starts with IMP. The whole process is shown in Figure 12.

VALIDATION STRATEGY

The Federal Radionavigation Plan (FRP) (2001) reports RNP for land transport telematics applications and services as shown in

Table 1. As can be seen, many applications of GPS based technologies are likely to require a high level of accuracy. One example is identifying the location of accidents via automatic accident notification (AAN) methods (many vehicles have GPS and communications technology that summons emergency services upon deployment of an airbag). Existing map-matching algorithms are not always capable of identifying the correct road link especially in dense urban areas, and hence could place the vehicle imprecisely, resulting in life-threatening delays in the arrival of emergency services. Technologies for automatic speed control may require precise mapping of speed zones at specific locations on road links (e.g. near school zones).

Table 1 RNP for some transport telematics applications

Applications & services	Accuracy (m, 2σ)	Availability (%)	Integrity (sec)
Navigation and route guidance	5-20	99.7	1-15
Automatic vehicle identification	30	99.7	1-15
Public safety	10	99.7	1-15
Accident and emergency response	30	99.7	1-15
Collision avoidance	1	99.7	1-15
Rail position location	10-30	99.9	5

Automatic bus stop annunciation	5	99.7	1-15
Transit vehicle control and command	30-50	99.7	1-15

In order to determine whether a MM algorithm is capable of achieving the required horizontal accuracy for various applications as given in Table 1, the MM algorithm needs to be validated.

In order to validate the results of a MM algorithm, 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 (Quddus et al., 2004). From this reference trajectory, the actual (truth) 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.

The next step is to compare the results (both the identification of the link and the physical location of the vehicle) obtained from the MM algorithm and the reference trajectory. Since the location data used in the MM algorithms and the reference trajectory is obtained from two different receivers, time synchronization is a crucial issue. This can be resolved if both sensors are based on the same time reference, such as, GPS time or Coordinated Universal Time (UTC). It should be noted that GPS time is 13 seconds ahead of UTC time in 2004. Once time synchronization is achieved between the receivers, the comparison can be performed.

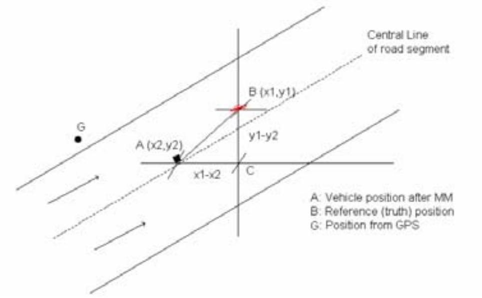


Figure 13: Determination of Error in MM

Figure 13 shows a road segment in which the vehicle position from GPS (C/A code-ranging) is denoted by the point G, the corresponding position estimated from the MM results (on the road centreline) is represented by the point A (x2, y2) and the truth position of the vehicle from GPS (carrier-phase observable) is indicated by the point B (x1, y1) for a particular epoch t. Since the actual position of the vehicle at epoch t is at the point B, the error in the easting coordinate is AC and the error in the northing component is BC. The horizontal error at epoch t (HE_t), therefore, is given by,

$$HE_t = \sqrt{(x1 - x2)^2 + (y1 - y2)^2} \qquad (7)$$

A series of such horizontal errors can be derived using equation (7) for all epochs. The associated statistics derived from these errors (e.g., mean, standard deviation and RMS of the along-track and cross-track component of the error) can be used to determine the relative performance of the MM algorithm.

RESULTS

A comprehensive field test was carried out to collect positioning data from various road environments including motorway merging/diverging scenarios, complex roundabouts, and complex urban roads. This is necessary because the performance of MM algorithms largely depends on road network characteristics. The test route was chosen carefully to have a good mix of important spatial urban characteristics including open spaces, urban canyons, tall buildings, tunnels, bridges, and potential sources of electromagnetic interference. The duration of data collection was about 4 hrs. In order to validate the proposed positioning algorithms, the carrier phase observables from GPS are used. For this purpose, the route was selected carefully to have good satellite visibility as GPS carrier phase observables require observations from a large number of GPS satellites (Ochieng et al., 2004). The duration of GPS carrier phase data collection was about 2 hrs.

A vehicle was equipped with a navigation platform consisting of a 12-channel single frequency high sensitivity GPS receiver, a low-cost rate gyroscope and the interfaces required to connect to the vehicle speed sensor (odometer) and back-up indicator. In order to obtain the reference (truth) trajectory by GPS carrier phase observables, the vehicle was also equipped with a 24-channel dual-frequency geodetic receiver. 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.

The positioning data (easting and northing), speed, heading and associated error variances were collected at one-second intervals directly from the integrated navigation system (GPS/DR sensors) employing an Extended Kalman Filter (EKF) algorithm. The fuzzy logic-based MM algorithm was tested for various scenarios with different network characteristics and with different traffic manoeuvres. Only a complex roundabout with a motorway diverging (Figure 14) and a complex urban road network (Figure 15) are shown here as an example. Each of the blue round dots in the Figures (14 and 15) represents the vehicle position before MM. The arrow symbols in the figures show the path followed by the vehicle on the network. Each of the triangular symbols on the road segments represents the vehicle position after MM.

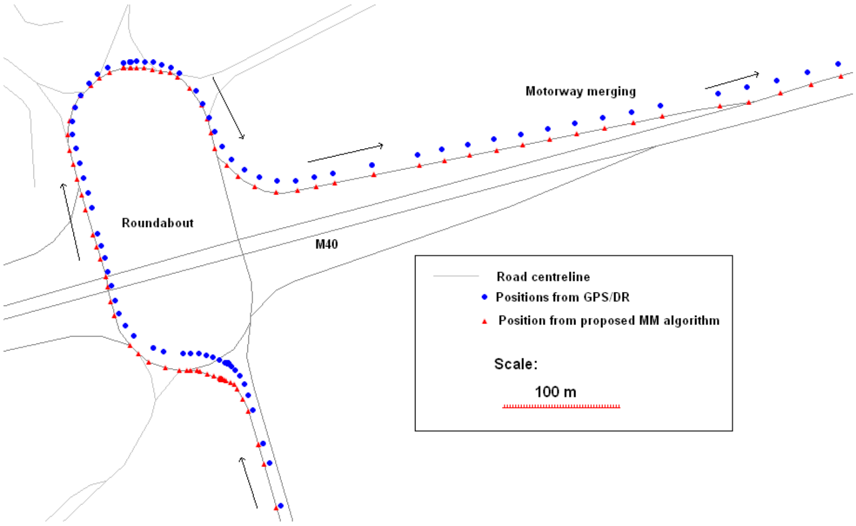


Figure 14: Map matching results for a part of test network which includes a roundabout and a motorway merging

A threshold value of 60 for the likelihood (L2) (the output of FIS in SMP-1) was found to be adequate to identify whether the vehicle position should match with the previously selected road segment. This threshold value was empirically determined from a true input/output dataset. The *MF*s of all input variables was also trained and modified with the same input/output dataset using the fuzzy logic toolbox of Matlab (MathWorks, 2000). The position of the vehicle on a selected road segment was estimated using two positioning methods (estimation using map data with the vehicle speed information from the positioning unit and the other is from the orthogonal projection of the GPS/DR fix on the road segment as shown in equations (1) and (2). The reliability test was performed after matching each position fix to the centreline of road network map.

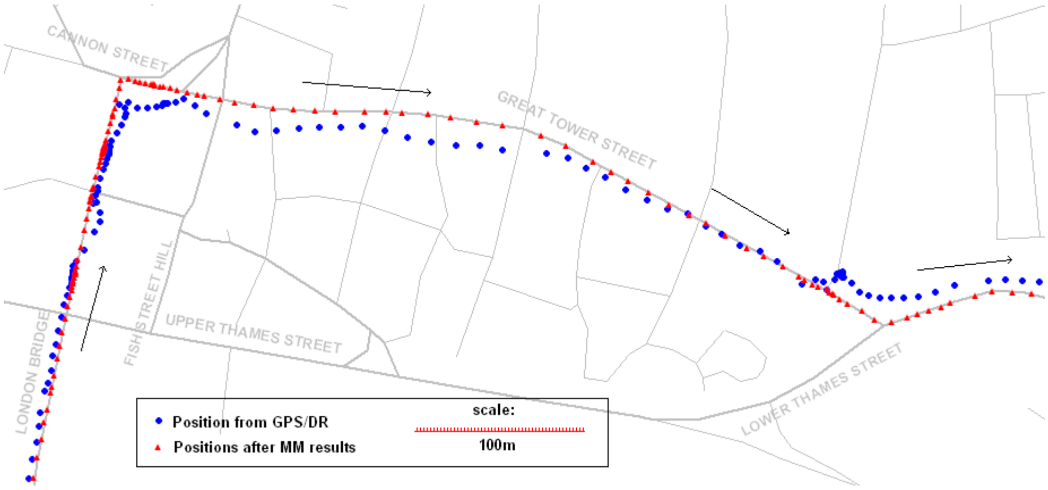


Figure 15: Map matching results for a part of test route in dense urban streets

The MM algorithm was validated using the validation strategy explained in the previous section. The GPS carrier phase measurements were used as the reference (truth) of the vehicle positions. A set of correct links on which the vehicle was travelling was identified based on the true vehicle trajectory. Another set of links was identified for the corresponding epochs from the developed MM algorithm. The results showed that the fuzzy logic-based MM algorithm identified a 99.2% of the links correctly (4570 correct links out of 4605 total links).

In terms of physical location of the vehicle, different categories of horizontal positioning errors were derived. The errors associated with the positions from the GPS augmented with DR were within 34m relative to the truth positions. The errors were calculated by equation (7). The horizontal accuracy was 10.3m (2σ) and the standard deviation was 6.2m. The next step was to compute the horizontal errors associated with the positions estimated from the developed MM algorithm. It was found that all MM positions on the road centreline were within 11m (maximum error) of the truth positions of the vehicle. The horizontal accuracy was 5.5m (2σ) and the standard deviation of the errors was 2.3m. The RMS of the along-track component of the error was 5.3m and the cross-track component of the error was 6.2m.

The performance of the fuzzy logic-based MM algorithm was evaluated against the performance of other existing MM algorithms for a test network of 204 sq km from London. The most utilised existing MM algorithms in the literature are point-to-point matching (Bernstein and Kornhauser, 1998), point-to-curve matching (White et al., 2000), weighted topological analysis (Greenfeld, 2002), advanced weighted topological analysis (Quddus et al., 2003) and probabilistic method (Ochieng et al., 2004). The outputs of these algorithms along with the fuzzy logic-based algorithm proposed in this study were also validated with the high accuracy GPS carrier phase observations. The results are shown in Table 2.

Table 2: Performance of MM algorithms

MM algorithms	Correct identification of road segments (%)	Horizontal errors (m)	Along-track errors (RMSE) , m	Cross-track errors (RMSE), m
Point-to-point matching	70.5	46	28	10.3
Point-to-curve matching	76.8	32	26.5	10.1
Weighted topological	90.3	16.3	18.6	8.6
Advanced weighted topological	95.4	9.4	8.5	7.5
Probabilistic method	98.1	5.9	5.7	6.4
Proposed fuzzy logic-based method	99.2	5.5	5.3	6.2

To evaluate the performance of the algorithms, the percentage of correct link matches on the given network was calculated as shown in the second column of Table 1. The third, fourth and the fifth columns show horizontal errors (2σ), along-track errors (RMS) and cross-track errors (RMS) respectively. It is evident that the fuzzy logic-based MM algorithm outperforms the other existing MM algorithms both in terms of identifying the correct links and estimating the horizontal positions.

CONCLUSIONS

A fuzzy logic-based MM algorithm was developed for land vehicle navigation. In this algorithm, the factors considered to build various knowledge-based IF-THEN rules were the speed, heading and historical trajectory of the vehicle, the connectivity and the orientation of the links and the satellite geometric contribution to the positioning error (HDOP). A Sugeno-type fuzzy inference system was used to develop the algorithm and the membership functions were trained and modified using a given input/output dataset obtained from GPS carrier phase observations. The inputs to the MM algorithm were taken from an integrated navigation system (GPS/DR) in order to attain vehicle location data continuously. The developed MM algorithm was tested in different road networks with varying complexity. These included complex roundabouts, merging or diverging sections of a motorway and complex road networks. A digital road centreline map of scale 1:2,500 was used to match the vehicle position on roads. The accuracy of the proposed MM algorithm was validated against the high accuracy GPS carrier phase observables on a network of 204 sq km in London. It was found that the algorithm identified 99.2% of the road segments correctly with a horizontal accuracy of 5.5m (2σ).

The performance of the proposed MM algorithm was also evaluated against the performance of existing MM algorithms. For this reason, several well-accepted existing MM algorithms were also tested and validated. It was found that the developed MM algorithm performed better than the existing MM algorithms in terms of identifying correct links and estimating the vehicle position on the links.

Future research will consider the integrity of map matching. This will include the specification of a metric for measuring the quality (and level of confidence of map matching) and the detection of anomalies (in raw and positional data).

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