

This item was submitted to Loughborough's Institutional Repository (<https://dspace.lboro.ac.uk/>) by the author and is made available under the following Creative Commons Licence conditions.



CC creative commons
COMMONS DEED

Attribution-NonCommercial-NoDerivs 2.5

You are free:

- to copy, distribute, display, and perform the work

Under the following conditions:

 **Attribution.** You must attribute the work in the manner specified by the author or licensor.

 **Noncommercial.** You may not use this work for commercial purposes.

 **No Derivative Works.** You may not alter, transform, or build upon this work.

- For any reuse or distribution, you must make clear to others the license terms of this work.
- Any of these conditions can be waived if you get permission from the copyright holder.

Your fair use and other rights are in no way affected by the above.

This is a human-readable summary of the [Legal Code \(the full license\)](#).

[Disclaimer](#) 

For the full text of this licence, please go to:
<http://creativecommons.org/licenses/by-nc-nd/2.5/>

Integrity of Map Matching Algorithms

Mohammed Quddus
Transport Research Group (TRG)
Department of Civil and Building Engineering
Loughborough University
Leicestershire LE11 3TU
UK

Tel: +44 (0) 15 0922 8545
Email: m.a.quddus@lboro.ac.uk

Washington Ochieng*, Robert Noland
Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London
LONDON SW7 2AZ

Tel: +44 (0) 2075946104
Email: w.ochieng@imperial.ac.uk

Abstract:

Map-Matching algorithms are used to integrate positioning data with digital road network data so that vehicles can be placed on a road map. However, due to error associated with both positioning and map data, there can be a high degree of uncertainty associated with the map-matched locations. A quality indicator representing the level of confidence (integrity) in map-matched locations is essential for some Intelligent Transport System applications and could provide a warning to the user and provide a means of fast recovery from a failure. The objective of this paper is to determine an empirical method to derive the integrity of a map matched location for three previously developed algorithms. This is achieved by formulating a metric based on various error sources associated with the positioning data and the map data. The metric ranges from 0 to 100 where 0 indicates a very high level of uncertainty in the map-matched location and 100 indicates a very low level of uncertainty. The integrity method is then tested for the three map matching algorithms in the cases when the positioning data is from either a stand-alone global positioning system (GPS) or GPS integrated with deduced reckoning (DR) and for map data from three different scales (1:1250, 1:2500, and 1:50000). The results suggest that the performance of the integrity method depends on the type of map matching algorithm and the quality of the digital map data. A valid integrity warning is achieved 98.2% of the time in the case of the fuzzy logic map matching algorithm with positioning data come from integrated GPS/DR and a digital map data with a scale of 1:2500.

Keywords: Global positioning system; digital road map; map matching; integrity, fuzzy logic

Integrity of Map Matching Algorithms

Mohammed Quddus
Transport Research Group (TRG)
Department of Civil and Building Engineering
Loughborough University
Leicestershire LE11 3TU
UK

Tel: +44 (0) 15 0922 8545
Email: m.a.quddus@lboro.ac.uk

Washington Ochieng*, Robert Noland
Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London
LONDON SW7 2AZ

Tel: +44 (0) 2075946104
Fax: +44 (0) 2075946102
Email: w.ochieng@imperial.ac.uk

1. INTRODUCTION

Navigation systems play a key role in almost all functional areas of Intelligent Transport Systems (ITS) (Drane and Rizos, 1998). While a positioning system is never considered as a stand-alone component of an ITS service, it is generally integrated into a larger system that is much more complex, involving many different subsystems with a man-machine interface, sensors, computers, and communication. In general, two essential components used in the navigation module of an ITS are: (1) a device to determine the geometric position of the vehicle, and (2) a Geographic Information System (GIS) based digital road map for determining the spatial (physical) reference for the vehicle location. The most common geometric positioning devices used for land vehicle navigation are Deduced Reckoning (DR) motion sensors, global navigation satellite systems such as the Global Positioning System (GPS), and integrated navigation systems such as the integration of GPS and DR.

GPS data may be augmented with DR sensor data with the use of an Extended Kalman Filter (EKF) to achieve the required availability in some areas (Zhao et al., 2003). This is known as an integrated navigation system (GPS/DR). DR readings are calibrated when GPS is available. If the GPS receiver suffers from signal masking or the quality of the position solution is not good, the calibrated DR readings are then used to determine the position of the vehicle.

The digital road network map is the other necessary component of a navigation module. Since land vehicles primarily travel on known road networks, the road map is used as a spatial reference for location. This assists drivers to relate their observed positions, obtained from the navigation system, with a physical location in the real-world and hence can guide them along a pre-calculated route. However, the digital road map also contains errors arising mainly from the processes of creation and digitization of maps. The errors can be estimated using either the scale of the map or field experiments.

System and sensor complementarity, such as the integration of GPS, DR and digital map data can be used to enhance the geometric positioning capability. A *map matching algorithm* can then be formulated to integrate the positioning data with the digital road network data. Map matching not only enables the physical location of the vehicle to be identified but also improves the positioning accuracy if a good digital map is available. If the vehicle position and the digital map are very accurate, the algorithm becomes very straightforward and simply snaps the positioning data to the nearest road. However, accurate positioning data and network data may not be available in the real world and hence map matching algorithms are essential.

The general purpose of a map matching algorithm is to identify the correct road segment on which the vehicle is travelling and to determine the vehicle location on that segment. The

parameters used to select a precise road segment are mainly based on the proximity between the position fix and the road, the degree of correlation between the vehicle trajectory derived from the position fixes and the road centreline, and the topology of the road network. Orthogonal projection of the position fix onto the selected road segment is normally used to calculate the vehicle location on the segment.

The complexity of the map matching algorithm necessarily depends on the nature of the application and the availability of data inputs. Therefore, various difficulty levels are associated with map matching algorithms. For example, map matching algorithms for a fixed bus-route are very simple because the bus is travelling on a known route. In this case, the purpose of the algorithm is to locate the bus on one of the road segments that builds up the bus route. In this way, the search domain to identify the correct road segment is significantly reduced. The most complex algorithm would be a general map matching algorithm that does not assume any prior knowledge or any other information regarding the expected location of the vehicle (Greenfeld, 2002).

The methodologies used in past research to develop map matching algorithms vary from a simple search technique (e.g., Kim et al., 1996; Bernstein and Kornhauser, 1996; White et al., 2000; Greenfeld, 2002) to a highly mathematical technique (e.g., Kim et al., 2000; Pyo et al., 2001; Najjar and Bonnifait, 2005; Yang et al., 2003, Syed and Cannon, 2004). Our previous work resulted in the development of three map matching algorithms. The first was based on a conventional topological approach (Quddus et al., 2003). The second was based on a probabilistic approach (Ochieng et al., 2004), and the third was based on a fuzzy logic concept (Quddus et al., 2005).

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

- The features (e.g., roundabouts, junctions, medians, curves) of the real-world that have been omitted or simplified in the road map. This is usually known as topological error.
- The accuracy of the classification (e.g., junction or roundabout) of those features
- Timeliness of the data such as how recently the map was created
- The displacement of a map feature (e.g., road centreline, specific junction) from its actual location in the road. This is generally known as geometric error.

Both geometric and topological errors in the map data may introduce significant horizontal errors in land vehicle positioning and navigation (Noronha and Goodchild, 2000; NRC, 2002; Goodwin and Lau, 1993; Quddus et al., 2003, Ochieng et al., 2004). Therefore, there is always a level of uncertainty associated with map matching algorithms. Moreover, it is essential to measure the quality (level of confidence) of map matching and detect anomalies in map-matched locations. This can be achieved by calculating the “*integrity*”, which represents the level of trust that can be placed in the information provided by the map matching algorithm for each position. Moreover, it is also necessary to evaluate the overall accuracy of map matching algorithms in order to estimate their performance. This can be attained by “*validity*” which is concerned with how well the map matching algorithms measure what they are intended to measure. “*Validity*” here refers to the overall performance characterisation of the algorithm; while “*integrity*” will clearly be required for each position fix in real-time. Quddus et al. (2004) describes a generic validation methodology for map matching algorithms.

Surprisingly very little research has been devoted to the “*integrity*” map matching. Therefore, the objective of this paper is to establish a generic methodology to determine empirically the integrity of a map matching algorithm. The methodology is then applied to the three map matching algorithms developed by the authors (Quddus et al., 2003; Ochieng et al., 2004; and Quddus et al., 2005). Moreover, the type of navigation system and the quality of the digital map influence the performance of the map matching algorithms (Quddus et al., 2005). In order to quantify such effects, the integrity of each map matching algorithm is investigated using a number of different digital maps (map scales 1:1250; 1:2500, and 1:50000) and a variety of navigation systems (GPS and GPS/DR). The results are validated using high precision GPS carrier phase observables.

This paper is organized as follows. First, a brief description on the selection of the map matching algorithms used to test the integrity method is presented. This is followed by a description of the integrity of a map matching algorithm including the definition, the influencing factors, and the derivation of a metric to quantify integrity. The next section describes the application of the metric to the map matching algorithms. The paper ends with conclusions and recommendations for further studies.

2. MAP MATCHING ALGORITHMS

The purpose of map matching algorithms is twofold: (1) to identify the correct link among the candidate links and (2) to determine the vehicle location on that link. Procedures for map matching vary from those using simple search techniques (Kim et al., 1996), to those using more advanced techniques such as fuzzy logic (Syed and Cannon, 2004, Quddus et al., 2005). Approaches for map matching algorithms found in the literature can be categorised into three groups: topological (White et al., 2000, Greenfeld et al., 2002, and Quddus et al., 2003) and ,

probabilistic (Zhao, 1997, Meng et al., 2003, and Ochieng et al., 2004), and advanced (Najjar and Bonnifait, 2005, Pyo et al., 2001, Yang et al., 2003, Quddus et al., 2005). The performance of any map matching algorithm varies widely depending on the types of inputs and the technique used in the algorithm. In order to test the integrity method (to be derived in the next section), the map matching algorithms need to be selected from each of the three groups. Therefore, three different map matching algorithms are used in this study. They are a conventional topological map matching algorithm, a probabilistic based map matching algorithm, and a fuzzy-logic based map matching algorithm. These algorithms were developed by the authors in earlier work and full details can be found in Quddus et al. (2003), Ochieng et al. (2004) and Quddus et al. (2005). However, a very brief overview of these algorithms is presented below.

A conventional topological approach was used to develop a relatively simple map matching algorithm in Quddus et al. (2003). In this algorithm, the map matching process is initiated with node-matching to identify a correct link (among all the links connected with the closest node to the position fix). Based on the various similarity criteria between the derived position fixes and the network topology, a weighting system is used to select the correct link. The criteria used in the algorithm are the similarity in orientation, proximity of the point to the link and the position of the fix relative to the link (see Quddus et al., 2003 for details).

A probabilistic map matching algorithm was then developed by the authors to overcome some of the limitations in the *topological map matching algorithm* (Ochieng et al., 2004). Instead of using the links connected to the closest node, the probabilistic map matching algorithm takes all links as candidate links that fall within an error ellipse around a position fix. An error ellipse is formed from the error variance-covariance matrix associated with the positioning system. The semi-major and semi-minor axes of the error ellipse are then increased to have a larger error ellipse that gives a higher level of confidence that the vehicle location is to be positioned on a link within the

boundary of the ellipse. This reduces the risk associated with residual outliers in the positioning data. Two distinct processes were developed for the identification of the correct link. These are (a) the *initial matching process* (IMP) and (b) the *subsequent matching process* (SMP). The function of the IMP is to identify a correct link for an initial position fix. Since the vehicle is expected to travel on this initial road segment for at least a few seconds, the subsequent position fixes are matched to that road segment. Therefore, after successfully identifying a correct link for an initial GPS or GPS/DR fix, the SMP starts matching the subsequent position fixes. In the SMP, the fixes are matched to the same road segment identified in the IMP if certain conditions are satisfied, such as if the distance travelled is short, the difference in heading between fixes is low, and the vehicle does not cross any junctions.

In urban areas, the vehicle trajectory derived from the positioning system is quite different from the actual route due to inherent problems associated with GPS in urban canyons as well as imperfections of the map database generated from digitization. Therefore, the error ellipse, derived from the quality of the position fix, is normally larger and contains a number of links. This may cause difficulty in the map matching process to distinguish precisely on which particular link the vehicle is travelling. In such a case, a map matching algorithm may suggest that the vehicle is more likely to be on a link and less likely to be on other links. This type of ambiguity needs to be resolved if relatively accurate location and navigation information is desired. Therefore, methods suitable for dealing with qualitative terms such as likeliness are necessary in map matching algorithms for the selection of a correct link among a number of candidate links. Therefore, a map matching process was developed based on fuzzy logic, which allows a qualitative decision making process to be modelled (Quddus et al., 2005). The inputs to the proposed algorithm come either from GPS or GPS augmented with the DR sensors to provide continuous navigation. The basic characteristic of this map matching approach is to build various knowledge-based IF-THEN rules comprising the speed of the vehicle, the heading and historical

trajectory of the vehicle, the connectivity and orientation of road links, and the contribution of satellite geometry to horizontal errors. Three distinct processes were developed for the identification of the correct link. They are (a) Initial map matching process, (b) Subsequent map matching process at a junction (SMP-junction), (c) Subsequent map matching process on a link (SMP-link). In all cases, a zero-order Sugeno Fuzzy Inference System (FIS) was used to identify the correct link.

In all three algorithms, the physical location of the vehicle on the link is 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 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

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

$$\hat{n} = \left(\frac{\sigma_{gps,n}^2}{\sigma_{map}^2 + \sigma_{gps,n}^2} \right) n_{map} + \left(\frac{\sigma_{map}^2}{\sigma_{map}^2 + \sigma_{gps,n}^2} \right) n_{gps} \quad (2)$$

where σ_{map}^2 is the error covariance associated with map data, $\sigma_{gps,e}^2$ and $\sigma_{gps,n}^2$ are the easting and northing components of the error covariance associated with the navigation sensor. These equations are only valid for errors with a Gaussian distribution and for which the easting and

northing components are not correlated. Quddus (2006) evaluates the same equations in the case of correlated error.

The error variance for the easting component is expressed as:

$$\frac{1}{\sigma_e^2} = \frac{1}{\sigma_{map,e}^2} + \frac{1}{\sigma_{gps,e}^2} \quad (3)$$

It is noticeable from equation (3) that the error variance, σ_e^2 , is less than either $\sigma_{map,e}^2$ or $\sigma_{gps,e}^2$ which is to say that the uncertainty in estimating the vehicle position is reduced by combining the two types of measurement methods. The error variance for the northing component (σ_n^2) can also be calculated from equation (3).

There are similarities and differences among these three algorithms. For the identification of the correct link, these algorithms use different techniques e.g., topological, probabilistic, and fuzzy logic techniques. For the determination of the location of the vehicle on the correct link, these algorithms use the same optimal estimation technique. However, the percentage of accurate identification of links affects the determination of the vehicle location. Our previous work found that the fuzzy-logic algorithm generally gives the best map-matched position fix (Quddus et al., 2005).

3. DERIVATION OF INTEGRITY MEASURE

To increase the level of confidence in the map-matched locations, the map matching algorithm should deliver a quality indicator for each position solution. A threshold for the quality indicator

can be established using a real input/output dataset. If the quality indicator exceeds a pre-defined threshold it can then be regarded as an incorrect position solution and the algorithm can then provide a warning to the driver not to depend on the information provided by the algorithm at that time. This concept is usually known as “*integrity*” in the navigation literature. The definition of “*integrity*”, the factors affecting it and the quantification of the “*integrity*” of a map matching algorithm are presented below.

3.1 Integrity in the context of navigation systems

Integrity is a measure of the trust that can be placed in the correctness of the information provided by the total system. Ochieng et al (2003) defined integrity in the context of aviation as “*the ability of the navigation system to provide timely and valid warnings to users when the system must not be used for the intended operation or phase of flight. Specifically, a navigation system is required to deliver a warning (an alert) of any malfunction (as a result of a set of alert limit being exceeded) to users within a given period of time (time-to-alarm) with a given probability (integrity risk)*”. Monitoring the integrity of a navigation system such as GPS is essential to ensure that the error in the navigation solution is within tolerable limits. Ideal integrity monitoring involves the detection, isolation and the removal of faulty measurement sources from the navigation solution. Various external and autonomous (receiver-based) integrity monitoring methods are available for GNSS. External monitoring of GNSS relies on a number of ground-based stations, positioned at known locations (Fernow and Loh, 1994). In this method, individual satellites are monitored by comparing the measured pseudoranges with those computed from the coordinates of the satellites and within the monitoring stations. A fault is indicated when a measurement error exceeds a predefined threshold, and then a warning is sent to the users within the time-to-alarm. The Receiver Autonomous Integrity Monitoring (RAIM) method, on the other hand, is applied within the user receiver to allow it to autonomously establish system integrity (Ochieng et al., 2003). RAIM addresses two basic concerns: (1) the existence of an unreliable “bad” measurement, and (2) the identification of the affected satellite.

The overall objective of measuring integrity is to protect a system against excessive positioning error. Therefore, the integrity of a map matching algorithm must detect an event when the horizontal error goes beyond a certain threshold, within a specified level of confidence. It should also detect whether the map matching algorithm selects an incorrect link. The integrity can then be used to deliver a warning to the driver (just as it does in the case of RAIM) that the map-matched location is not trustworthy for positioning or navigation. This is particularly important at a junction in dense areas where a number of candidate road segments fall within the error ellipse around the position fix.

The integrity of a map matching algorithm can be defined as its ability to correctly identify a link and to accurately determine the vehicle location on the link for a particular epoch. In the quantification of integrity, therefore, emphasis must be given to how correctly a map matching algorithm identifies a link and how closely the algorithm estimates the vehicle location compared to the actual location. A high integrity map matching algorithm means that its location estimation capability can be trusted or believed. Therefore, a specific criterion is needed to judge whether the new map matching algorithms can be trusted. This section introduces a simple empirical way to determine “*integrity*”.

3.2 Factors Affecting the Integrity of a Map Matching Algorithm

The uncertainty (i.e., σ_e and σ_n) associated with a map-matched position as estimated by equation (3) can be used to derive the integrity of a map matching algorithm. A larger uncertainty usually indicates less confidence in the position solution and vice versa. Moreover, both the quality of the position fix obtained from the navigation sensors and the quality of the digital map may also

affect the integrity of a map matching algorithm. This involves the uncertainties associated with the raw GPS or GPS/DR measurements determined from the variance-covariance matrix, the bias introduced by the road centreline and the systematic error associated with the calculation of link heading due to errors in the map data. By taking into account these factors, a metric can be specified for measuring the quality (and level of confidence) of map matching and the detection of anomalies in map-matched locations.

3.2.1 Integrity based on the uncertainty associated with the position solution

Assume that P represents the vehicle position fix for a particular epoch and M denotes the corresponding map-matched location of the vehicle on the link AB (Figure 1). In this case link AB will have been selected as the correct link for the position fix P by a map matching algorithm. R refers to the true location of the vehicle for the same epoch.

“place Fig. 1 about here”

According to equation (3), the easting and northing components of uncertainties (i.e., σ_e and σ_n) associated with M can be given as

$$\sigma_e = \sqrt{\frac{\sigma_{map,e}^2 \sigma_{gps,e}^2}{\sigma_{map,e}^2 + \sigma_{gps,e}^2}} \quad (4)$$

$$\sigma_n = \sqrt{\frac{\sigma_{map,n}^2 \sigma_{gps,n}^2}{\sigma_{map,n}^2 + \sigma_{gps,n}^2}} \quad (5)$$

In which $\sigma_{map,e}$ and $\sigma_{map,n}$ are the standard deviation of the errors (easting and northing components respectively) associated with the map data and $\sigma_{gps,e}$ and $\sigma_{gps,n}$ are the standard deviation of the errors (easting and northing components respectively) associated with the navigation sensors. Assuming that there is no correlation between the easting and northing components of the position solution, the uncertainty associated with the horizontal position at M is

$$\sigma = r_o = \sqrt{\sigma_e^2 + \sigma_n^2} \quad (6)$$

Another common metric used to estimate the uncertainty associated with the horizontal position is the circular error probable (CEP) which is equivalent to $0.75*\sigma$. The real (true) position of the vehicle, R, may not fall inside the circle of radius r_o drawn at M as can be seen in Figure 1. Therefore, the value of σ may not always represent the uncertainty associated with the map-matched position. The probability that the true position, R, is within a circle of radius σ is about 63% (Kaplan, 1996). Moreover, a map matching algorithm essentially places the vehicle position fixes on the road centreline. This may introduce bias in the map-matched positions. Moreover, a map matching algorithm may identify a wrong link and hence the map-matched location may fail for the true position of the vehicle.

Consequently, the confidence level associated with a map-matched position should be $k\sigma$ where k is a growth factor and $k \geq 1$. An empirical study was conducted to derive the value of k . The basic idea is to increase the radius r_o so that the circle includes the real position, R. The minimum radius of a circle that includes R is denoted by r_f . Therefore, the value of k can be given by

$$k = \frac{r_f}{\sigma} \quad (7)$$

The value of r_f (i.e., $k\sigma$) can be used as the uncertainty or the level of confidence associated with the map-matched positions. A large value of $k\sigma$ may indicate a lower confidence level and vice versa.

To implement the above concept, a series of map-matched positions with their corresponding true positions is needed. Therefore, the dataset described below (section 3.4.1) can be employed to derive a relationship between k and σ . Figure 2 shows the observed relationship between them. The fuzzy logic map matching algorithm is applied to the navigation data from GPS/DR and the map data from the map of scale 1:2500 to obtain the map-matched positions. The corresponding true positions of the vehicle are obtained from the GPS carrier-phase observables using the fixed solutions only¹. This gives a total of 217 true positions of the vehicle.

“place Fig. 2 about here”

The growth factor can be as high as 16 as seen in Figure 2 meaning that the minimum radius of a circle which includes the real position of the vehicle is 16σ , implying that the map-matched position is far away from the true position and indicates the determination of an incorrect location or the wrong selection of a link. However, the higher values of k may not necessarily be due to the identification of wrong links by the map matching algorithm. The error introduced by the road centreline may also give a higher growth factor. Usually, a wider roadway (e.g., a motorway) produces a larger error and the results in Figure 2 indicate that the relationship between k and σ

¹ The details of the processing of GPS carrier phase data can be found in Quddus et al. (2004)

for a motorway is different from that of a non-motorway. Therefore, two types of relationships can be modelled: one for roadways with more than 2-lanes (in each direction) and the other for all other roadways.

Since the value of k is always non-negative, an additive model can be considered unsatisfactory as the model may predict negative values of k . Therefore, a log-linear relationship between k and σ is suggested:

$$\ln k_t = \theta D + \beta \sigma_t + \varepsilon_t \quad (8)$$

where $D=1$ if the vehicle travels on a motorway and $D=0$ otherwise, θ and β are the parameters to be estimated, and ε is an identically and independently distributed error term. The parameters are estimated using Ordinary Least Square (OLS) using 217 observations (see Table 1). The goodness-of-fit (adjusted R^2) is found to be 0.80.

“place Table 1 about here”

Therefore, the growth factor (k) can be calculated from the following equations.

For roadways with more than 2-lanes:

$$\hat{k} = \exp(1.3295 + 0.0706\sigma) \quad (9)$$

For all other roadways:

$$\hat{k} = \exp(0.0706\sigma) \quad (10)$$

Once σ is estimated by the map matching algorithm, the corresponding value of k can then be calculated using either equation (9) in the case of the vehicle travelling on a roadway with more

than 2-lanes (in each direction) or equation (10) in the case of all other roadways. Then the corrected uncertainty (i.e., $k\sigma$) associated with each map-matched position can easily be obtained. Figure 3 shows the estimated relationship between k and σ . The points surrounded by the ellipses are all incorrect map-matched positions associated with higher values of uncertainty. However, there are incorrect map-matched positions even when k is small. This suggests that other factors influencing the integrity of a map matching algorithm also need to be taken into account.

“place Fig. 3 about here”

3.2.2 Integrity based on the ability to identify the correct link

The vehicle direction, θ , (i.e., heading relative to the north) for a particular position fix can be obtained from the outputs of the navigation sensors (GPS or GPS/DR). The road network data can also be used to acquire vehicle direction. This is because a map matching algorithm identifies a link for a position fix and therefore, the direction of the link, β , should be the direction of the travelling vehicle. The absolute difference between these two directions, (i.e., $|\theta - \beta|$) can be used to derive an integrity measure for a map matching algorithm in terms of link identification. For example, if a map matching algorithm identifies the correct link for a position fix, then $|\theta - \beta|$ should be close to zero and the identification of the link may be trusted for the fix. However, the uncertainties associated with both direction measurements need to be considered before inferring any conclusion. If the vehicle heading is obtained by stand-alone GPS, then the heading is not accurate when the vehicle travels at a low speed (Quddus et al., 2003). Although heading information from GPS/DR is quite good, it may sometimes provide inaccurate results. The uncertainty in heading can be detected by the error variance for heading (σ_h^2) from the

variance-covariance matrix. In order to have a 99% confidence level, the true heading (θ_{true}) from the navigation system is:

$$\theta_{true} = \theta \pm 3\sigma_h \quad (11)$$

The error associated with the heading of a road link can be obtained from the quality of the map data. If the heading of a link AB of length L is denoted by β and the map scale is $1:m$ then the maximum error (3σ , a 99% confidence level) associated with β can be given by $\Delta\beta$ as shown in Figure 4. This is because the position of nodes A or B can be anywhere within a circle of radius m . In the worst-case scenario, the position of the node A may be at a , and the position of the node B may be at b .

“place Fig. 4 about here”

Therefore, the link ab has the largest heading error ($\Delta\beta$) relative to the original link AB. This can be derived as

$$\Delta\beta = \arctan\left(\frac{m}{L/2}\right) \quad (12)$$

Therefore, the true heading of the link AB is

$$\beta_{true} = \beta \pm \arctan\left(\frac{m}{L/2}\right) \quad (13)$$

The maximum error associated with θ is $3\sigma_h$, and β is $\Delta\beta$. Using an error propagation theorem, the combined heading error (HE) can be given by the following equation:

$$HE = \sqrt{(3\sigma_h)^2 + (\arctan(\frac{m}{L/2}))^2} \quad (14)$$

The identification of the link is said to be reliable if the difference between θ and β (i.e., the observed difference) is less than or equal to the combined heading error, HE . In other words, if the difference between $|\theta - \beta|$ and HE is less than or close to zero, then it can be said that the identification of the link by the map matching algorithm is more reliable. This difference can be termed as *the heading residual* (ΔH) and is given by:

$$\Delta H = |\theta - \beta| - HE \leq 0 \quad (15)$$

3.2.3 Integrity based on the ability to accurately estimate vehicle location

The proximity between the raw position fix and the corresponding map-matched location on a link can be used to derive the integrity of a map matching algorithm in terms of location determination. If a position fix and the map-matched location are close to each other then the map matching algorithm is normally assumed to be quite trustworthy given that the map matching algorithm takes into account both the road network connectivity and the recent history of the vehicle trajectory. However, the quality of the position fix and the error associated with the road width need to be taken into account.

Two-dimensional (2-D) horizontal positional accuracies are normally estimated and reported using distance root mean square (DRMS) radial error statistics (Kaplan, 1996). The DRMS error measures are approximations to the error ellipses that are computed for measured position fixes. The DRMS error statistic is related to the variance-covariance matrix associated with the outputs of the navigation sensors and can be defined as,

$$DRMS = \sqrt{\sigma_{gps,e}^2 + \sigma_{gps,n}^2} \quad (16)$$

where $\sigma_{gps,e}^2$ and $\sigma_{gps,n}^2$ are the error variances associated with the easting and northing components of a position fix.

DMRS statistics can have variable confidence levels. The probability that the measured position fix falls within the circle of radius of DRMS from the true position largely depends on the ratio between $\sigma_{gps,e}^2$ and $\sigma_{gps,n}^2$. If, for instance, the 2-D error distribution is close to being circular (i.e., $\sigma_{gps,e}^2 = \sigma_{gps,n}^2$), the probability of falling inside this circle is about 63%. If $\sigma_e^2 = 10 \sigma_n^2$, then the probability is about 68%. A circle twice this radius, i.e., 2DRMS represents 95% to 98% positional probability based on the ratio between σ_e^2 and σ_n^2 . The probability that the true position is within a circle of radius 3DRMS is more than 99% (Kaplan, 1996).

The 3DRMS error statistic can be used to deduce integrity for a map matching algorithm. A map-matched vehicle location is said to be trustworthy if this location is very close to its actual (true) location. Therefore, a good map-matched location for an epoch should be within a circle of radius 3DRMS drawn at the corresponding position fix. The distance between the raw position fix and the map-matched location is necessarily less than 3DRMS if a 99% or more confidence level is

desired. Since the road network data only contains road centreline data and a map matching algorithm takes the road centreline as the true reference for vehicle positioning, then an adjustment is essential for road width. This adjustment, which largely depends on the types of roadways (i.e., motorway, major road, minor road ,etc), can be regarded as the correction for the road centreline ($\Delta R_{centreline}$). The expanded radius of a circle can then be given by the following equation:

$$R_{3drms} = 3DRMS + \Delta R_{centreline} \quad (17)$$

Assuming that a vehicle equipped with a navigation sensor travels on a two-way road with 2-lanes in each direction as shown in Figure 5, P represents a position fix for an epoch t and T is the corresponding true location. AB is the road centreline which is a network representation of the two-way 2-lane road of width W . A map matching algorithm identifies link AB as the correct link for the position fix P. Q is the vehicle location on the link estimated by the algorithm. Although the true location of the vehicle (T) falls inside a circle of radius 3DRMS (i.e., r_{3drms}), the map-matched location falls outside. This is due to the fact that the map-matched location is always on the road centreline whereas the true location does not necessarily have to be on the centreline. However, the map-matched location, Q, is positioned within the confidence area of an expanded circle of radius R_{3drms} which includes the correction for road width..

“place Fig. 5 about here”

The correction for road centreline, $\Delta R_{centreline}$, is normally the deviation of the actual location of the vehicle relative to the centreline, i.e., the shortest distance from T to AB as can be seen in Figure 5. The deviation largely depends on the number of lanes associated with the roadway. For instance, the value of $\Delta R_{centreline}$ will normally be higher for a motorway than a minor road. With

navigation data from a low-cost GPS receiver, it is impossible to determine the particular lane on which the vehicle is travelling. Therefore, the maximum deviation can be considered as the correction for road centreline. Assuming a lane width of 3.5m, the maximum deviation of the actual vehicle location from the road centreline for roads with various numbers of lanes is shown in Table 2.

“place Table 2 about here”

For the UK, data on the number of lanes is not readily available in GIS format at this moment. However, UK Ordnance Survey is working towards the development of an integrated transport network (ITN) layer which will include road attributes such as road width and the number of lanes. For this study, a value of 3.5m for $\Delta R_{centreline}$ is assumed for all roads. Therefore, equation (17) becomes

$$R_{3drms} = 3\sqrt{\sigma_e^2 + \sigma_n^2} + 3.5 \quad (18)$$

The map-matched location is said to be good if the distance between the raw position fix (P) and the map-matched position (Q) is less than R_{3drms} . The difference between PQ and R_{3drms} can be termed as *the distance residual*, ΔD , which can be defined as

$$PQ - R_{3drms} = \Delta D \leq 0 \quad (19)$$

Therefore, the key variables required to derive a metric for measuring the quality of map matching are $k\sigma$, ΔD and ΔH . The integrity of a map matching algorithm can be regarded as high if:

- $k\sigma$ is small
- ΔD is less than or close to zero
- ΔH less than or close to zero

All the above conditions are linguistic statements. Therefore, the metric can best be derived using a qualitative decision-making process rather than a mathematical process. Hence, a fuzzy logic model is a good choice to deal with these linguistic terms. This is explained below.

3.3 The Derivation of an Integrity Metric using Fuzzy Logic

A Sugeno fuzzy inference system (FIS) developed by Sugeno (1985) is used to derive a metric (0 to 100) representing the integrity of the results of a map matching algorithm based on the parameters $k\sigma$, ΔD and ΔH .

The three state input variables of this FIS are: (1) the corrected uncertainty associated with the map-matched position, $k\sigma$ (m), (2) the distance residual, ΔD (m), and (3) the heading residual, ΔH (degree). The fuzzy subsets associated with the $k\sigma$ are *small*, *medium*, and *high*. The fuzzy subsets associated with the ΔD are *positive* and *negative*. The fuzzy subsets related to the ΔH are also *positive* and *negative*. All inputs are fuzzified and shown in Figure 6.

The single output of this FIS is the integrity of the map-matched position (denoted as LI). A zero-order Sugeno fuzzy model is considered which takes five constants for the output. These values are selected initially as e.g., *very low* ($Z1$) = 0, *low* ($Z2$) = 50, *average* ($Z3$) = 70, *high* ($Z4$) = 90, and *very high* ($Z5$) = 100. The next step is to formulate the fuzzy rules which are related to the

number of system state variables. Experience and engineering knowledge are used to formulate the fuzzy rules. For instance, if the corrected uncertainty ($k\sigma$) is close to zero and the distance residual is also close to zero then the integrity associated with the map-matched position should be high. Special attention is given to the overlap between the fuzzy subsets of a particular input. This can reduce the number of fuzzy rules as every input generates some response. Twelve rules comprising the fuzzy knowledge are applied to this FIS (see Table 3). The rules are established based on human knowledge and experience in interpreting the variables.

“place Table 3 about here”

“place Fig. 6 about here”

3.4 Statistical Performance of the Integrity Measure

The integrity measure derived above has to be transformed into quantifiable parameters in order to assess its performance. Three parameters are examined: (1) false alarm rates, (2) missed detection rates, and (3) overall correct detection rates. The procedures to determine these parameters are given below:

- Determine the integrity value (0 to 100) for each observation using the fuzzy logic method described in section 3.3.
- Determine a threshold for the integrity in order to represent a wrongly map-matched location (see section 3.4.1 below).
- Identify epochs where the integrity value falls below the threshold. These epochs (denoted as set A) can be regarded as the incorrect matches identified by the integrity method.

- Select epochs associated with the incorrect matches based on the reference (true) trajectory obtained from GPS carrier phase observables. These epochs (denoted as set B) are the true incorrect matches.
- Identify epochs which can be found in set A but cannot be found in set B. The total number of such epochs is termed as m . This means that the integrity method gives an incorrect warning for m epochs which can be regarded as total false alarms (FAR).
- Identify epochs which can be found in set B but cannot be found in set A. The total number of such epochs is termed as n . This indicates that the integrity method fails to give a warning for n epochs which can be regarded as total missed detections (MD).

If the total number of observations is denoted by r , then the false alarm rates (FAR) can be given as:

$$FAR = \frac{\text{total false alarms } (m)}{\text{total observations } (r)} \quad (20)$$

The missed detection rates (MDR) can be given as:

$$MDR = \frac{\text{total missed detections } (n)}{\text{total observations } (r)} \quad (21)$$

The overall correct detection rates, $OCDR$, which is the overall performance of the integrity method, can be given as:

$$OCDR = 1 - FAR - MDR \quad (22)$$

3.4.1 Derivation of the integrity threshold

In any integrity assessment it is necessary to define a threshold level below which the measurement should be discarded. In order to derive the threshold for the integrity measure previously described, the fuzzy logic-based integrity method was applied in combination with the fuzzy logic map matching algorithm. This analysis was done for the example case using navigation data obtained from GPS/DR and digital map data obtained from a map of scale 1:2500.

The positioning data was obtained from a comprehensive field test in London on the 5 July 2004. The test vehicle was equipped with a *GPSi-AVL*² navigation platform (115x113x45 mm) consisting of a 12-channel single frequency (L1) high sensitivity GPS receiver (for C/A code-ranging), a low-cost rate gyroscope and the interfaces required to connect to the vehicle speed sensor (odometer). The rate gyro and the vehicle odometer support the basic DR configuration. The positioning and speed accuracies of the GPS receiver are 25 m CEP (Circular Error Probable) and 0.1m/s respectively. The heading drift of the rate gyro is 3 deg/hr. An Extended Kalman Filter (EKF) developed by Zhao et al. (2003) is used to integrate GPS data with the DR data. In order to obtain the reference (truth) trajectory, the vehicle was also equipped with a 24-channel dual-frequency *Leica SR9500* 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 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 80km long and was chosen carefully to have good satellite visibility as GPS carrier-phase observables require observations from a large number of GPS satellites for reliable and correct ambiguity resolution. Therefore, it was also expected that the navigation data from stand-alone GPS would be quite good because of fewer effects of signal masking.

² Manufactured by Neve Technologies, Home page: <http://www.neveits.com>

The positioning data (easting and northing), speed and heading were collected at one second intervals directly from both GPS receivers. The duration of data collection was about 2 hrs. For each of the map-matched locations obtained from the map matching algorithm, three input variables ($k\sigma$, ΔD and ΔH) to the Sugeno FIS were calculated. The corrected uncertainty ($k\sigma$) was calculated using either equations (9) or (10). The distance residual (ΔD) was estimated using equation (19) and the heading residual (ΔH) was obtained from equation (15). For each of the inputs, the corresponding crisp output from the Sugeno FIS was obtained and is the integrity measure for the map-matched location.

“place Fig. 7 about here”

Figure 7 shows the results of the metric representing the integrity of the map-matched locations. The value of the metric (level of confidence) varies from 0 to 100 where 0 means the map-matched location had no integrity and 100 means the map-matched location had a very high level of integrity. The level of confidence associated with each of the map-matched locations is then evaluated against the true location of the vehicle in order to test the capability of the integrity measure. Very good agreement was achieved, for example, in Figure 7, the fuzzy logic map matching algorithm selects a wrong link for one of the position fixes (indicated with a circle) and the corresponding integrity value is 20.

Figure 8 shows the relationship between the frequency for the correct and incorrect matches for the different bins of integrity values. It can be seen that larger values of the integrity measure are related to the correct map-matched locations. The frequency of the correct matches is close to zero when the integrity value is below 70 for the fuzzy logic map matching algorithms. The

topological and probabilistic map matching algorithms also give similar results. This suggests that the incorrect map-matched locations are usually associated with metric values of less than 70 which correspond to the middle *LI* output constant from the Sugeno FIS. This was chosen to represent an “average” level of integrity. For this example values below 70 can therefore be seen as having below average integrity and 70 can be taken as being an appropriate threshold value. In other words, if the value of the metric is below 70, then we are not confident that the map-matched location has integrity.

“place Fig. 8 about here”

3.5 Performance Evaluation of the Integrity Method

As discussed earlier, one of the applications of integrity monitoring is to deliver a warning to the driver that the map-matched location identified by the map matching algorithm is not reliable. Following the detection of the failure, the map matching algorithm aims to quickly recover from the failure. For our example in the previous section, it was found that an integrity value below 70 indicates a failure for all map matching algorithms.

This section describes the performance of the integrity method developed in section 3.4. This is accomplished using a new dataset of GPS carrier-phase observables which has not been used to determine the criteria for the integrity method. This new dataset was obtained from a field campaign using the same test vehicle described in section 3.4.1 in the West of London (near Reading) on the 18 August 2005. The nearest Ordnance Survey (OS) active station is *AMER* (located in Amersham). The raw data for this station is available at a 30 second sampling interval. This makes it difficult to use this data for the carrier-phase processing.

A reference station (R) was therefore created at Silwood Park near Reading (see Figure 9) in order to obtain continuous raw data at one second intervals. A *Leica SR9500* geodetic base station GPS receiver was used to record the data at the reference station. Another *Leica SR9500* geodetic receiver was used to collect GPS carrier phase data when the vehicle was travelling on the test route shown in Figure 9 for about an hour. The test route is within 15km of the reference station meaning that the length of the baseline is always less than 15km. All available datasets from the two receivers were then processed in a kinematic post-processing mode using the Leica SkiPro package. The satellite positions were computed using precise ephemerides. Both fixed and float solutions were obtained but only fixed solutions (840 epochs) were used in this analysis.

The navigation data from GPS/DR and the digital map data from a map of scale 1:2500 were used to implement the fuzzy logic map matching algorithm which was used to measure the performance of the integrity method.

For each of the map-matched locations obtained from the fuzzy logic map matching algorithm, the input variables $k\sigma$, ΔD and ΔH were calculated as inputs to the Sugeno FIS that derives the integrity measure. Although σ , ΔD and ΔH were obtained from the observed data, k was estimated from equations (9) or (10). In order to examine whether the coefficients in these equations were trustworthy, equation (8) was re-estimated using the new dataset described above. It was found that the newly estimated coefficients ($\beta=1.41$ and $\theta =0.052$) fell within the confidence limits shown in Table 1. Therefore, equations (9) and (10) were directly used to estimate k . The output of the FIS was also calculated when k was obtained from $\beta=1.41$ and $\theta =0.052$. The means of these two outputs were not found to be statistically different.

“place Fig. 9 about here”

In order to assess the performance of the integrity method for the fuzzy logic map matching algorithm, the step-by-step procedure presented in section 3.4 was implemented. The total number of valid observations was 840 (ambiguity fixed solutions only), the threshold to determine the parameters representing the statistical performance of integrity was taken as 70. Therefore, the total number of *false alarms* was found to be nine, and the total number of *missed detections* was found to be six. This gives a *FAR* of 0.011, a *MDR* of 0.007, and an *OCDR* of 0.982. Thus, the integrity method is capable of providing a valid warning to the driver 98.2% of the time when the fuzzy logic map matching algorithm is used. After detecting each failure mode (i.e., when the integrity value falls below 70), the map matching algorithm goes back to the MPJ (in the case of probabilistic map matching algorithm) or the SMP-junction (in the case of fuzzy logic map matching algorithm) to acquire a correct fix.

Although the integrity value for an average output of the FIS is 70, it is possible that selection of different thresholds could affect the performance of the integrity method. It is envisaged that higher number of *false alarms* is associated with higher thresholds and vice versa. On the other hand, higher *missed detections* is related to lower thresholds and vice versa. Figure 10 confirms the above assertion for the fuzzy logic map matching algorithm when the navigation data is obtained from GPS/DR and the digital map data is obtained from a map of scale 1:2500. The number of *false alarms* increases rapidly when the thresholds are higher than 70 and for these thresholds, the number of *missed detections* is small.

“place Fig. 10 about here”

Figure 11 shows how the selection of threshold affects the overall performance of the integrity method. *OCDR* (%) increases with an increase in threshold level. This is because the *missed detections* decrease. The *OCDR* is significantly reduced when the thresholds are above 70. This is

because the *false alarms* increase. The optimal performance of the integrity method is associated with the threshold value of 70, which is based on the average *L4* from the Sugeno FIS.

“place Fig. 11 about here”

3.6 Sensitivity Analysis

The performance of the integrity method for different map matching algorithms using inputs from various navigation sensors and digital maps is described in this section. Two types of navigation systems (GPS and GPS/DR) and three types of digital maps of different map scales (1:1250, 1:2500 and 1:50000) are taken as inputs to the map matching algorithms in order to assess the integrity measure derived in the previous section. A total of 18 analyses (2 navigation systems, 3 digital maps and 3 map matching algorithms) were carried out using the dataset described in the previous section. The results are shown in Table 4.

“place Table 4 about here”

If the integrity associated with a map-matched location falls below the threshold of 70, the algorithm gives a warning to the driver and the map matching algorithm re-identifies the vehicle location. The *MDR* ranges between 0.7% and 8.5%. Better map matching algorithms (probabilistic and fuzzy logic) increase *OCDR*. No major differences in *FAR*, *MDR*, and *OCDR* between the probabilistic and the fuzzy logic map matching algorithms is found. The highest *OCDR* is found to be 98.2% when the fuzzy logic map matching algorithm was employed using the navigation data from GPS/DR and the map data from the map of scale 1:2500. The lowest *OCDR* of 84.2% is achieved with the topological map matching algorithm when the navigation data is from GPS/DR and the map data is from a map of scale 1:50000.

Due to frequent satellite loss-of-lock in built up areas, an effort to obtain the true vehicle position using GPS carrier phase data was unsuccessful within dense urban areas. As a result, the determination of 2-D horizontal accuracy together with the cross-track and along-track errors

offered by the map matching algorithms could not be estimated due to the lack of true vehicle positioning information. Thus, it was also not possible to evaluate the performance of the integrity method in an urban area with a more complex road network. The higher accuracy GPS carrier phase observations coupled with a high-grade inertial navigation system (INS) will potentially facilitate the measurement of reference (true) positioning data in urban areas.

4. CONCLUSIONS

A generic method for the assessment of integrity (level of confidence) of a map matching algorithm has been developed in this study. This is achieved by formulating a metric between 0 to 100 where '0' means the map-matched location has no integrity and '100' means the location has a high level of integrity. The metric which represents the integrity of the map-matched locations is determined based on various error sources associated with the position fixes and map data using a fuzzy logic technique. A threshold level is derived, which is essential to determine the statistical performance of the integrity measure and to provide a warning to the driver regarding any erroneous location estimation. The information on incorrect map-matched locations can be presented to the driver by an audible announcement within a specified Time to Alarm (TTA). TTA can depend on safety requirements, network geometry, and speed, among other factors. During this period, the driver may depend on other sources of location information (i.e., pre-trip guidance). The integrity method developed in this study is generic and transferable and hence is applicable to any map matching algorithms. The method has been tested in this study using three different map matching algorithms of varying complexity. The results have been validated using high precision GPS carrier phase observables.

There is always a certain level of integrity risk associated with a threshold. The risk can be seen as representing the acceptable trade-off between the probabilities of *missed detections* and *false alarms*. Some ITS services, such as emergency services, route guidance, bus priority at signalised junctions require a low level of integrity risk and hence the threshold should be increased (e.g., >70). Integrity risk may not be less critical for some services. In these cases the threshold for the integrity measure could perhaps be decreased (i.e., <70).

The developed integrity method was validated using real-world field data collected from a suburban area in London. Due to inherent problems associated with GPS signal masking and multipath error in dense urban areas, it was not possible to obtain the true vehicle positions from the GPS carrier phase observations in central London. Therefore, the performance offered by the developed integrity method could not be estimated under dense urban conditions. However, a *tightly coupled* integrated navigation system employing GPS and a high-grade Inertial Navigation System (INS) may be used to obtain true vehicle trajectories in urban areas at the centimetre level.

Not surprisingly, it has been found that the performance of the integrity method developed in this study largely depends on the type of map matching algorithm. The results suggest that while the OCDR value is quite high for all the map matching algorithms tested, the fuzzy logic map matching algorithm has the highest potential to provide valid warnings to the driver.

It has also been found that the performance of the integrity method also varies based on the type of input data used for implementing the map matching algorithm. The results indicate that the OCDR of a specific map matching algorithm largely depends on the type of digital road network map used in implementing the algorithm. However, the type of navigation system has very little effect on the integrity. This is because the test data used were collected from a suburban area

where the performance of a stand-alone GPS is quite similar to that of a GPS/DR. These results are not surprising, as the analysis in Quddus et al. (2005) found that the fuzzy-logic algorithm performed best with the same 1:2500 scale map that provided the best integrity performance in this analysis and that the sensor type made little difference.

This paper describes a simple empirical method to derive the *integrity* of a map matching algorithm. Although the performance of the integrity method developed in this study is quite robust for the test route used, it is essential to investigate further the performance of the integrity method with other test routes, especially in urban areas. An alternative to the empirical approach would be to consider more rigorous statistical approaches similar to that used in autonomous integrity monitoring systems such as Receiver Autonomous Integrity Monitoring (RAIM) which would be based on consistency checking and redundancy measurements (outlier detection capability) within a sensors/data integration architecture, but would need to consider the quality of the digital road network data.

REFERENCES

- Bernstein, D., Kornhauser, A., 1996. An introduction to map matching for personal navigation assistants. Working paper, New Jersey TIDE Centre, New Jersey Institute of Technology..
- Drane, C.R., Rizos, R., 1998. Positioning systems in intelligent transportation systems, Norwood MA: Artech House.
- Fernow, J. and Loh, R., 1994. Integrity Monitoring in a GPS Wide-Area Augmentation System (WAAS). In: Proceedings of DSNS 94, London, UK, pp. 1-8.
- Goodwin, C., Lau, J. 1993. Vehicle Navigation and Map Quality. In: Proceedings of the IEEE-IEE Vehicle Navigation & Information Systems Conference, Ottawa, pp. 17-20.
- Greenfeld, J.S., 2002. Matching GPS observations to locations on a digital map. In: Proceedings of the 81st Annual Meeting of the Transportation Research Board, January, Washington D.C, Paper No. 00692.
- Kaplan E.D., 1996. Understanding GPS: Principles and Applications, Artech House,

London.

Kim, J.S., Lee, J.H., Kang, T.H., Lee, W.Y., Kim, Y.G., 1996. Node based map matching algorithm for car navigation system. In: Proceeding of the 29th ISATA Symposium, Florence, pp. 121-126.

Kim, W., Jee, G, Lee, J., 2000. Efficient use of digital road map in various positioning for ITS. In: Proceedings of the IEEE Symposium on Position Location and Navigation, San Deigo, CA, 13-16 March, pp.170-176.

El Najjar, M.E., Bonnifait, P., 2005, A road-matching method for precise vehicle localization using Belief theory and Kalman filtering. *Autonomous Robots*, 19(2), pp. 173-191.

Noronha, V., Goodchild, M.F., 2000. Map accuracy and location expression in transportation reality and prospects. *Transportation Research C*, 8, 53-69.

NRC, National Research Council, 2002. Collecting, processing and integrating GPS data with GIS. NCHRP Synthesis 301. National Academy Press; Washington D.C.

Ochieng, W.Y., Sauer, K., Walsh, D., Brodin, G., Griffin, S., Denney, M., 2003. GPS integrity and potential impact on aviation safety, *The Journal of Navigation*, 56 (1), 51-65.

Ochieng, W.Y., 2004. The Global Positioning System (GPS): an overview and data processing models. MSc. (Transport) Lecture Notes, Centre for Transport Studies, Imperial College London.

Ochieng, W.Y., Quddus, M.A., Noland, R.B., 2004. Integrated positioning algorithms for transport telematics applications. In: proceedings of the Institute of Navigation (ION) annual conference, 20-24 September, California, USA, pp. 692-705.

Pyo, J., Shin, D., Sung, T., 2001. Development of a map matching method using the multiple hypothesis technique. In: IEEE Proceedings on Intelligent Transportation Systems, 23-27, 25-29 August, pp. 23-27.

Quddus, M.A., 2006, High integrity map matching algorithms for advanced transport telematics applications, PhD Thesis, Centre for Transport Studies, Department of Civil and Environmental Engineering, Imperial College London.

Quddus, M.A., Ochieng, W.Y., Zhao, L., Noland, R.B., 2003. A general map matching algorithm for transport telematics applications. *GPS Solutions*, 7 (3), 157-167.

Quddus, M.A., Noland, R.B., and Ochieng, W.Y., 2004. Validation of map matching algorithm using high precision positioning with GPS. *Journal of Navigation*, 58 (2), 257-271

Quddus, M.A., Noland R.B., Ochieng, W.Y., 2005. A high accuracy fuzzy logic based map matching algorithm for road transport. *The Intelligent Transport Systems (ITS) Journal*, 10 (3), 103-115.

Sugeno, M., 1985. Industrial applications of fuzzy control. Elsevier Science.

Syed, S., Cannon, M.E., 2004. Fuzzy logic-based map matching algorithm for vehicle navigation system in urban canyons. In: proceedings of the Institute of Navigation (ION) national technical meeting, 26-28 January, California, USA, pp. 982-993.

White, C.E., Bernstein, D., Kornhauser, A.L., 2000. Some map matching algorithms for personal navigation assistants. *Transportation Research Part C*, 8, 91-108.

Yang, D., Cai, B., Yuan, Y., 2003. An improved map-matching algorithm used in vehicle navigation system. In: *IEEE Proceedings on Intelligent Transportation Systems*, 2, pp. 1246-1250.

Zhao, Y., 1997, *Vehicle Location and Navigation System*. Artech House.

Zhao, L., Ochieng, W.Y., Quddus, M.A, Noland, R.B., 2003. An Extended Kalman Filter algorithm for Integrating GPS and low-cost Dead reckoning system data for vehicle performance and emissions monitoring. *The Journal of Navigation*, 56 (2), 257-275.

LIST OF FIGURES

Figure 1: Derivation of the expansion factor

Figure 2: Observed relationship between k and σ

Figure 3: Estimated relationship between k and σ

Figure 4: Error associated with the heading of a link

Figure 5: Correction for road width

Figure 6 : Membership functions for the corrected uncertainty (a), the distance residual (b), and the heading residual (c)

Figure 7: The level of confidence for the map-matched locations

Figure 8: Frequencies of the matches vs integrity values (bins)

Figure 9: The test site used to validate the integrity method

Figure 10: The variation of FA and MD with thresholds

Figure 11: The variation of OCDR with thresholds

LIST OF TABLES

Table 1: The parameter estimation results

Table 2: Correction for road centreline

Table 3: Fuzzy rules used in the fuzzy inference system

Table 4: The performance of the integrity measure for map matching algorithms using various positioning systems and digital map data

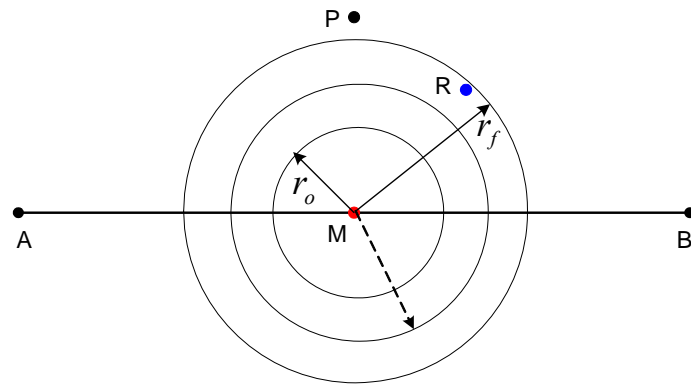


Figure 1

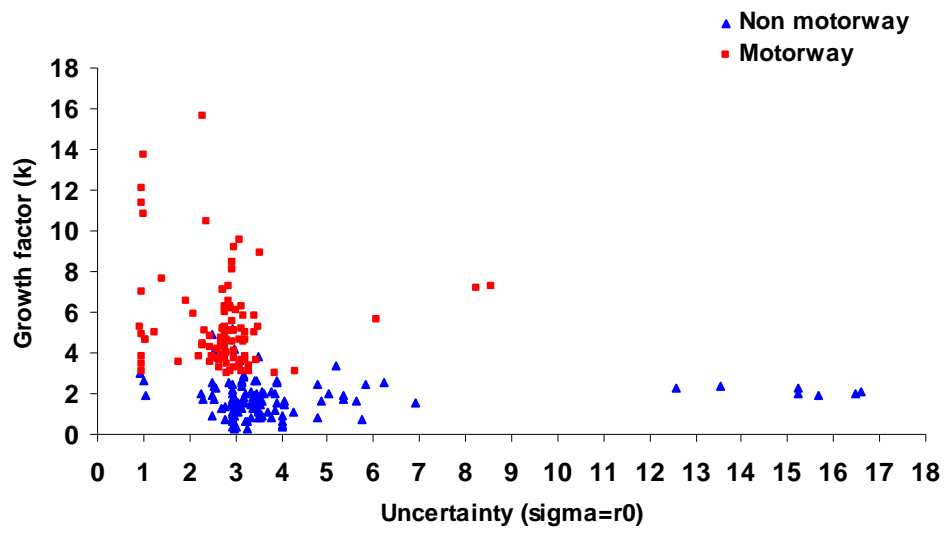


Figure 2

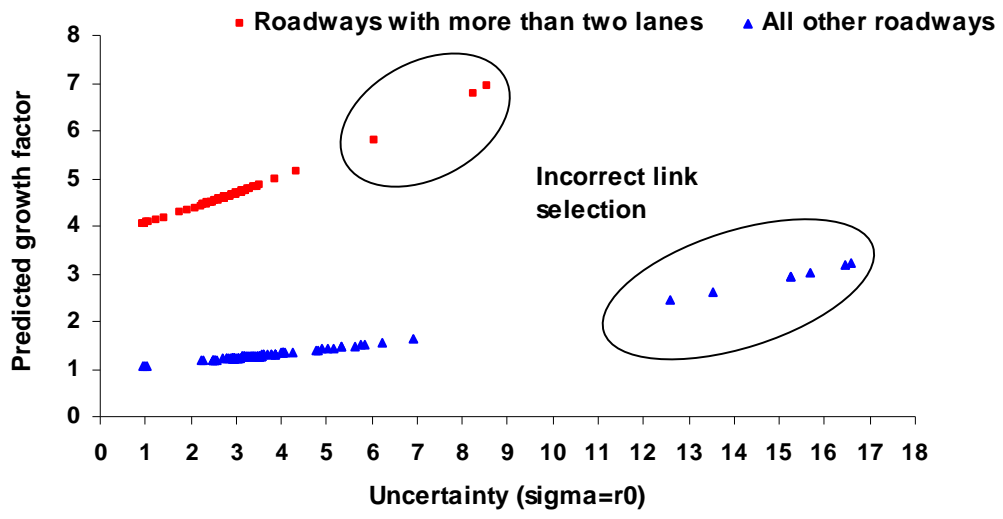


Figure 3

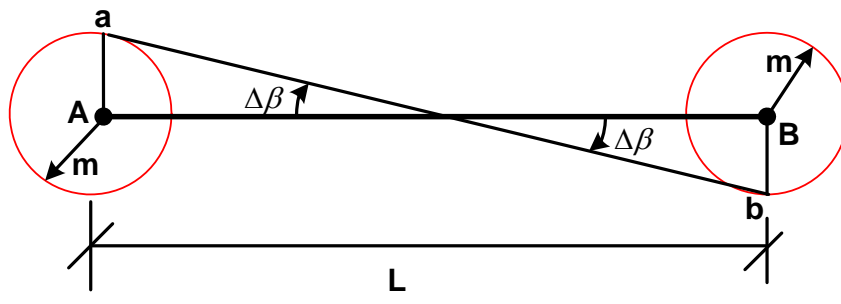


Figure 4

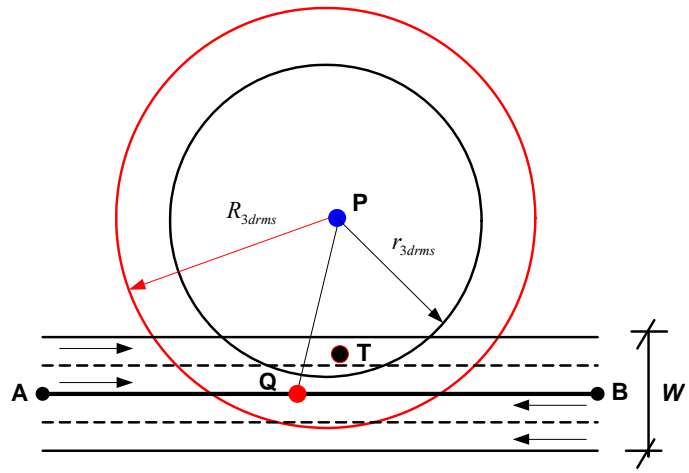
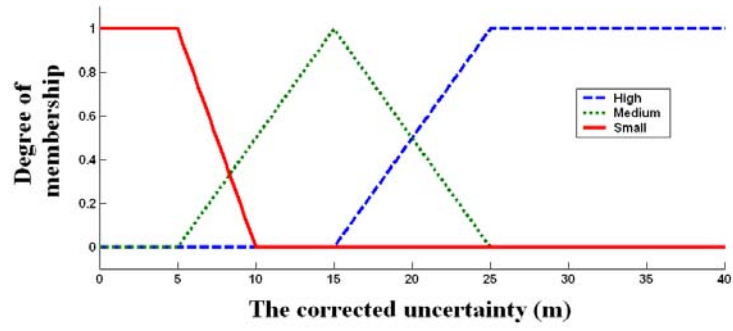
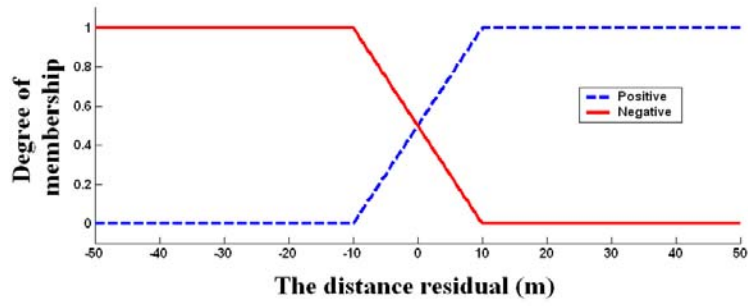


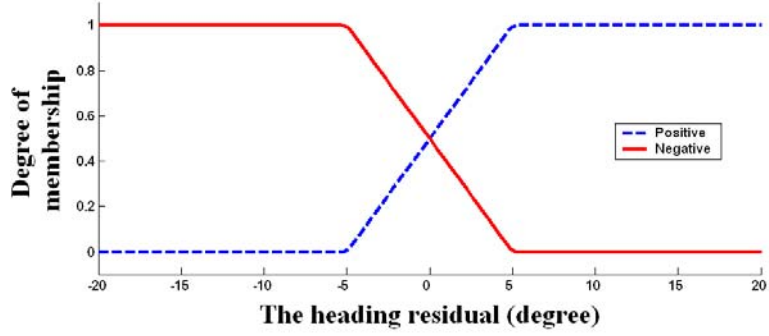
Figure 5



(a)



(b)



(c)

Figure 6

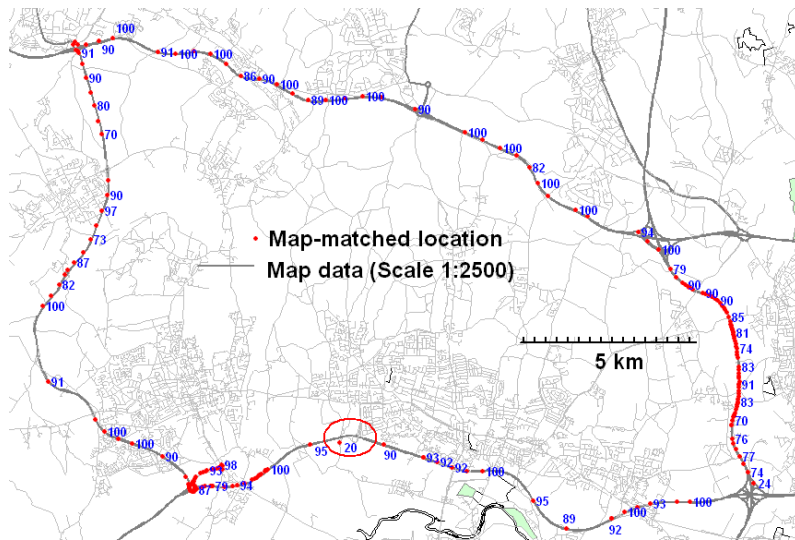


Figure 7

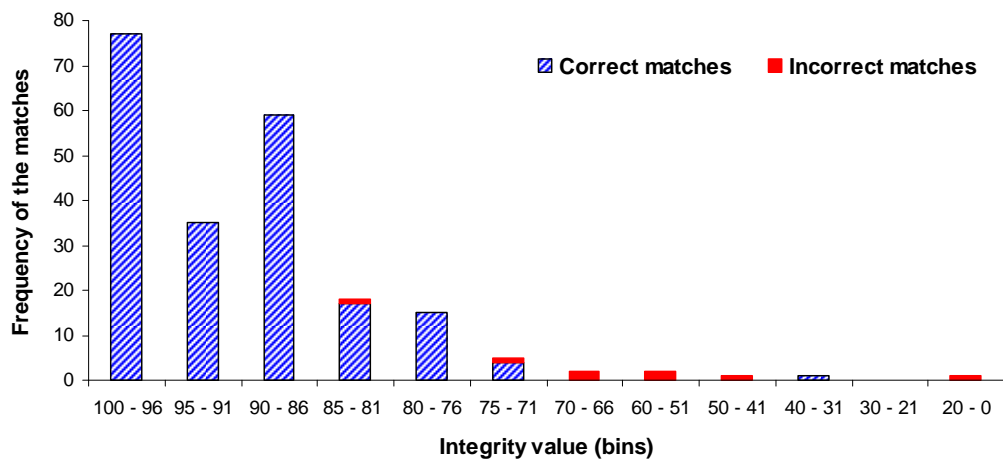


Figure 8

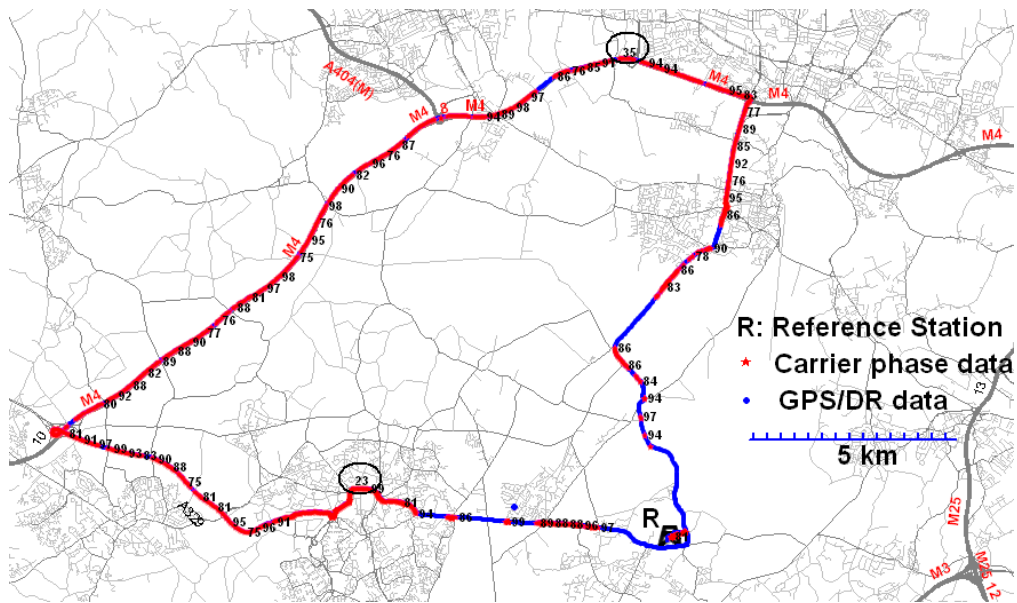


Figure 9

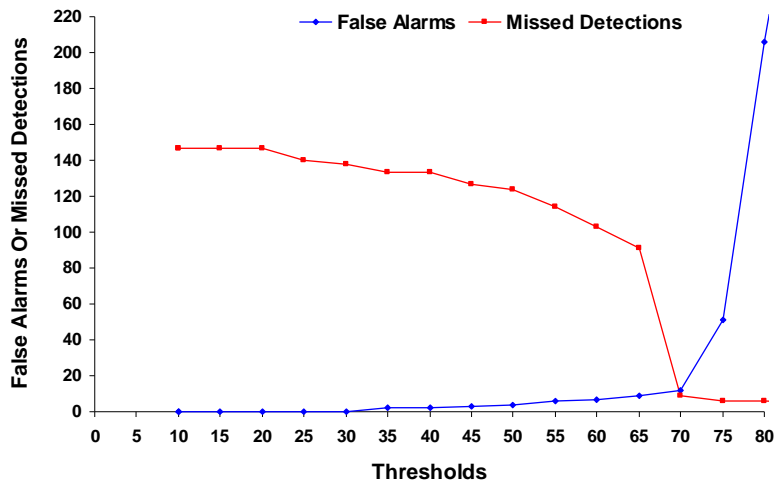


Figure 10

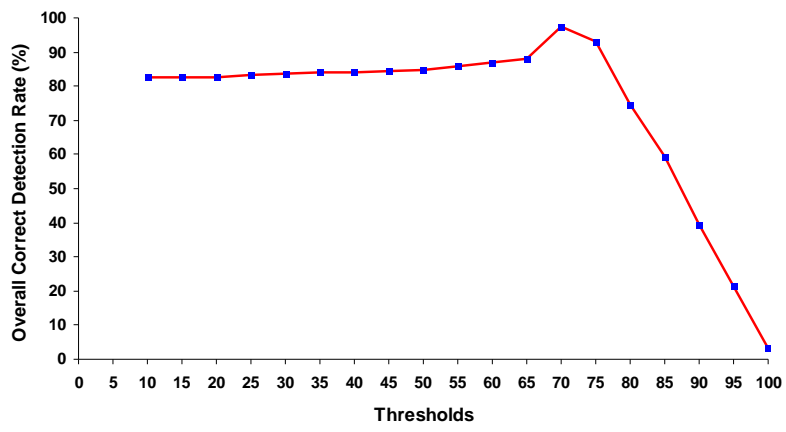


Figure 11

Table 1

Parameters	Coefficients	<i>t</i> -statistics	<i>p</i> -value	<i>95% confidence intervals</i>	
				<i>Lower limit</i>	<i>Upper limit</i>
Error sigma (β)	1.3295	21.14	0.00	1.205	1.454
Dummy variable (θ)	0.0706	6.20	0.00	0.048	0.093

Table 2

The number of lanes	The maximum deviation ($\Delta R_{\text{centreline}}$), m
5	7
4	5.25
3	3.5
2	1.75
1	0

Table 3

R1: if $k\sigma$ is *high* and ΔD is *positive* and ΔH is *positive* then the integrity associated with map-matched location ($L1$) is *very low* ($Z1$)

R2: if $k\sigma$ is *high* and ΔD is *positive* and ΔH is *negative* then the $L1$ is *low* ($Z2$)

R3: if $k\sigma$ is *high* and ΔD is *negative* and ΔH is *positive* then the $L1$ is *low* ($Z2$)

R4: if $k\sigma$ is *high* and ΔD is *negative* and ΔH is *negative* then the $L1$ is *average* ($Z3$)

R5: if $k\sigma$ is *medium* and ΔD is *positive* and ΔH is *positive* then the $L1$ is *low* ($Z2$)

R6: if $k\sigma$ is *medium* and ΔD is *positive* and ΔH is *negative* then the $L1$ is *average* ($Z3$)

R7: if $k\sigma$ is *medium* and ΔD is *negative* and ΔH is *positive* then the $L1$ is *average* ($Z3$)

R8: if $k\sigma$ is *medium* and ΔD is *negative* and ΔH is *negative* then the $L1$ is *high* ($Z4$)

R9: if $k\sigma$ is *small* and ΔD is *positive* and ΔH is *positive* then the $L1$ is *average* ($Z3$)

R10: if $k\sigma$ is *small* and ΔD is *positive* and ΔH is *negative* then the $L1$ is *high* ($Z4$)

R11: if $k\sigma$ is *small* and ΔD is *negative* and ΔH is *positive* then the $L1$ is *high* ($Z3$)

R12: if $k\sigma$ is *small* and ΔD is *negative* and ΔH is *negative* then the $L1$ is *very high* ($Z5$)

Table 4

Map Matching Algorithms	Positioning Systems	Map Scale	<i>FAR</i> (%)	<i>MDR</i> (%)	<i>OCDR</i> (%)
Topological	GPS	1:1250	5.6	3.5	91.0
		1:2500	5.8	3.0	91.2
		1:50000	9.8	7.9	82.4
	GPS/DR	1:1250	5.7	3.6	90.7
		1:2500	6.0	3.0	91.1
		1:50000	10.2	8.5	81.3
Probabilistic	GPS	1:1250	1.5	1.0	97.5
		1:2500	1.3	1.2	97.5
		1:50000	3.1	4.3	92.6
	GPS/DR	1:1250	1.4	1.0	97.6
		1:2500	1.4	1.1	97.5
		1:50000	3.5	3.6	93.0
Fuzzy Logic	GPS	1:1250	1.3	1.0	97.7
		1:2500	1.3	0.7	98.0
		1:50000	2.5	3.0	94.5
	GPS/DR	1:1250	1.2	0.7	98.1
		1:2500	1.1	0.7	98.2
		1:50000	3.0	2.6	94.4

