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Integrating Positioning Algorithms for Transport Telematics Applications

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ABSTRACT

A range of transport telematics applications and services require continuous and accurate positioning information of the vehicles traveling on the road network. Examples are in-car navigation systems, dynamic route guidance, fleet management, incident management, public transport management and on-board emissions monitoring systems. Most of these services also need the vehicle to be displayed on a map in real time in an error-free fashion. Two types of information are essential for such telematics applications and services. These are the determination of the vehicle position and the determination of the physical location of the vehicle on the road network. Most common devices used for vehicle positioning are based on GPS, Dead-Reckoning (DR) sensors, Map Matching (MM) and microwave beacons. The use of these devices either in isolation or combination depend on the Required Navigation Performance (RNP) parameter specifications (accuracy, integrity, continuity and availability). Furthermore, the capability to identify the physical location of a vehicle is a key requirement in 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 could be used to enhance geometric positioning capability. MM 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. A key factor in the integration of different devices is the knowledge of the various failure modes (error sources).

This paper develops two integrated positioning algorithms for transport telematics applications and services. The first is an Extended Kalman Filter (EKF) algorithm for the integration of GPS and low cost DR sensors to provide continuous positioning in built-up areas. The second takes this further by integrating the GPS/DR output with map data in a novel a map-matching process to both identify the physical location of a vehicle on the road network and improve positioning capability. The proposed MM algorithm is validated using a higher accuracy reference (truth) of the vehicle trajectory as determined by high precision positioning achieved by the carrier phase observable from GPS

The results demonstrate a 90% coverage in a typical built-up environment over a 4-hour duration for a stand-alone GPS employing a single frequency high sensitivity receiver/antenna assembly. The integrated GPS/DR approach employing the EKF gives 100% coverage at an accuracy level better than 30m (2σ). The MM validation results show that about 100% link identification is achieved by the proposed MM algorithm. The vehicle positions determined from the MM results are within 6m of the truth positions. The results also demonstrated the importance of the quality of the digital map data to the map matching process.

INTRODUCTION

A range of transport telematics applications and services such as in-car navigation systems, dynamic route guidance systems, fleet management, collision avoidance systems, advanced traveler information and on-board emission monitoring require continuous accurate positioning information on motor vehicles traveling on the road network. Many services also require real-time display of the vehicle location on a map in an error-free fashion. Two essential components commonly used for such applications and services are, (1) sensors to determine the geometric position of the vehicles, and (2) Geographic Information Systems (GIS) based digital maps for the identification of the physical location of the vehicles. An interesting but challenging problem is to integrate positioning sensor data with digital map data to improve the accuracy with which the vehicle location on a road link is determined.

Common devices used for land vehicle navigation are Dead Reckoning (DR) sensors, ground-based (Terrestrial) radio frequency systems, satellite based radio navigation systems such as GPS, and integrated navigation systems such as GPS and DR. These state-of-the-art navigation systems usually rely on various types of sensors. Even with very good sensor calibration and sensor fusion technologies, inaccuracies are often inevitable. Moreover, there is also imprecision with GIS-based digital road maps due to plotting errors, map resolution and piece-wise linear links to approximate road curvature. As a result of such inaccuracies in the positioning system and the digital base map, actual geometric vehicle positions do not always map onto the spatial road map, when the vehicle is known to be on the road network. This phenomenon is known as *spatial mismatch*. The spatial mismatch is more severe at junctions, roundabouts, complicated fly-overs and built-up urban areas with complex route structures. These environments also decrease the level of performance achievable with GPS.

Therefore, Map Matching (MM) algorithms are usually used to reconcile the inaccurate locational data with inaccurate digital road network data. If both digital maps and vehicle location are perfectly accurate, the algorithm is simple and straightforward based on simply snapping the locational data to the nearest node or link in the network. However, in most cases it is not possible to use such simple algorithms. Therefore, more complex MM algorithms are a required component for vehicle location and navigation systems.

The complexity of the MM algorithms depends on the nature of the application and the availability of data inputs. Previous research by the authors developed a simple MM algorithm appropriate for motorways and relatively sparse road networks (Quddus et al. 2003). The algorithm was also designed for low accuracy digital base maps where the source map resolution was 1:10,000 or below. The research presented in this paper builds on this previous work to develop a MM algorithm for all types of digital base maps and road networks. The new algorithm takes into account the error sources associated with the positioning sensors, the historical trajectory of the vehicle, the topological information on the road network (e.g., connectivity and orientation of links), and the heading and speed information of the vehicle, for the precise identification of the correct link on which the vehicle is traveling. Furthermore, an optimal estimation of the vehicle position is established by taking into consideration error sources associated with both the navigation systems and the digital map database. No validation studies assessing the performance of MM algorithms have been reported in the literature. A MM algorithm can be validated using a higher accuracy reference (truth) of the vehicle trajectory. Therefore, this paper also presents a validation technique for MM algorithms using a reference trajectory determined from the high precision carrier phase observable from GPS.

This paper is organized is as follows. First we provide a brief description of literature review on MM algorithms. This is followed by a short introduction of an algorithm for integrating GPS with DR employing with an extended Kalman filter (EKF). The next section describes a proposed MM algorithm. This is followed by a description of a validation strategy for MM algorithms. The next section describes the implementation of the algorithms using real-world data and a presentation of results. The paper ends by conclusions and recommendations for further avenues of study.

LITERATURE REVIEW

MM algorithms are often used to determine the accurate position of a vehicle on a road map. Most of the formulated algorithms utilize navigation data from GPS, DR, or integrated GPS/DR and the digital road network data. One of the common assumptions found in the literature for implementing MM is that the vehicle is essentially constrained to a finite network of roads. Most of the studies (e.g., Zhao, 1997) also reported that the digital map used for MM must be quite robust in order to generate the position outputs in an error-free fashion. Procedures for MM vary from those using simple search techniques (Kim et al., 1996), to those using more complex mathematical techniques such as Kalman Filters (KF) (Tanaka et al., 1990).

The most commonly used geometric MM approach is based on a simple search concept. In this approach, each positioning point matches to the closest ‘node’ or ‘shape point’ in the network. This is also known as point-to-

point matching (Bernstein and Kornhauser, 1996). A number of data structures and algorithms exist to identify the closest node (or shape point) from a given point in a network (e.g., Bentley and Maurer, 1980; Fuchs et al., 1980). These methods are easy to implement, although they are very sensitive to the way in which the network was digitized, hence leading to errors.

Another geometric MM approach is point-to-curve matching (e.g., Bernstein and Kornhauser, 1996; White et al., 2000; Taylor et al. 2001). In this approach, the positioning point from the navigation system is matched with the closest curve in the network. Each of the curves comprises line segments which are piece-wise linear. Distance is calculated from the positioning point to each of the line segments. The line segment which gives the smallest distance is selected as the one on which the vehicle is assumed to be traveling. Although this approach gives better results than point-to-point matching, it does have 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, 1996; White et al., 2000). In this approach, firstly the candidate node using point-to-point matching is identified. Then, given a candidate node, piecewise linear curves are constructed from the set of paths that originate from that node. Secondly, piece-wise linear curves are then constructed using the vehicle's trajectory. The distance between the curve along the vehicle trajectory and the curve corresponding to the road network is then determined. The road arc which is closest to the curve formed from the vehicle trajectory is taken as the one on which the vehicle is apparently traveling. 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 road map and virtual differential GPS (VDGPS) corrections, referred to as the *road reduction filter (RRF)* algorithm. Due to the use of height aiding, the paper reports that one less satellite is required for the computation of the vehicle positions (i.e., height aiding removes one of the unknown parameters) using GPS. The initial matching process of this algorithm is based on the geometric curve-to-curve matching proposed by White (1991) which is quite sensitive to outliers. The proposed algorithm does not consider link connectivity information which could improve the performance of the algorithm especially in the initial matching process. It is well known that the vehicle heading from GPS is not good if the vehicle speed is low. Although the proposed algorithm is based on the bearing of the vehicle, there was no indication how to deal with the situation when the vehicle was stopped on a road segment for a few seconds. Moreover, the orthogonal projected location of the GPS fixes on the arc is used to determine the vehicle positions. However, Greenfeld (2002) described that the orthogonal projection of the position fixes on the arc are different from the actual location of the vehicle on the arc.

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 sometimes the algorithm identifies incorrect road segments. Greenfeld (2002) also suggests that additional research is required to verify the accurate performance of the algorithm and to make an accurate position determination on a given road segment.

Xu et al. (2002) proposed a new MM method based on intersection information stored in a map database. The method identified whether the vehicle is near intersections or between intersections or whether a turn is detected using DR sensors. However, the study did not take into account speed information and error sources associated with DR sensors. The algorithm also failed to deal with parallel roads and possible U-turns at junctions. Moreover, it does not determine the vehicle location on the road segment. This is one of the key improvements made by the algorithm developed in this paper.

ALGORITHM 1: INTEGRATION OF GPS AND DR

In a variety of transport telematics applications and services, the vehicle position on the road network is usually determined by the positioning systems, e.g., DR, GPS and the integrated GPS/DR system. Each of these navigation systems has various sources of error that lead to the need to apply MM. The next section briefly describes these navigation systems and their error sources following by a brief description of integrated GPS/DR system.

Global Positioning System (GPS)

GPS is a satellite-based radio-navigation system owned and operated jointly by the US Department of Defense (DoD) and Department of Transportation (DoT). The system achieved full operational capability (FOC) in 1995 with a constellation of 24 active satellites (28 in March 2000). Theoretically, three or more GPS satellites are always visible from most points on the Earth Surface. The original objectives of GPS were the instantaneous

determination of position and velocity (i.e., navigation), and the precise coordination of time (i.e., time transfer). GPS provides 24-hour, all-weather 3D positioning and timing all over the world, with a predicted horizontal accuracy of 22m (95%) [US DoD, 2001]. However, GPS suffers both systematic errors or biases and random noise e.g., satellite related errors such as clock bias and orbital errors, propagation related errors such as ionospheric refraction and tropospheric refraction, and receiver related errors such as multipath and clock bias.

Dead Reckoning (DR)

The DR is based on the integration of an estimated or measured displacement vector. Usually, it is composed of two or more sensors that measure the heading and displacement of a vehicle. A gyroscope is the main device used to measure the rate of rotation in an inertial navigation system such as DR. The odometer uses the wheel rotation sensor to measure wheel revolutions. The wheel revolutions are then transformed into the distance traveled. Using time between two consecutive observations, the speed or velocity of the vehicle can also be determined. Errors associated with the rate gyroscope are gyro bias drift, gyro scale factor error, installation misalignment, temperature, and vibration and electro-mechanical properties of the operational environment. The most significant error is the bias drift that depends on the manufacturing process and the quality of the gyroscope. Factors affecting the odometer output accuracy are the scale factor error, status of the road and pulse truncation. The most significant error is the scale factor error that is caused by calibration error, tire wear and tear, tire pressure vibration and vehicle speed. The scale factor error is not significant over a short period of travel.

Integration of GPS and DR

In order to achieve the RNP in some areas e.g., urban canyons, streets with dense tree cover, and tunnels, GPS can be augmented with DR with the use of a Kalman Filter (KF) (Zhao et al., 2003). An understanding of the navigation errors involved is required to do this.

The KF is a set of mathematical equations that provides an efficient computational solution of the least-squares method. It is a linear minimum mean-square error (MMSE) filtering for combining noisy sensor outputs (i.e., GPS receivers, gyroscopes, odometers) to estimate the state of a system (i.e., position, velocity, heading, acceleration of a vehicle) with uncertain dynamics (i.e., unpredictable disturbances of the host vehicle, unpredictable changes in the sensor parameters). The nonlinear application of KF is known as the Extended Kalman Filter (EKF). An EKF algorithm can be used to estimate the optimal result of system states by integrating GPS and DR (Figure 1). A fuller description of this EKF algorithm can be found at Zhao et al (2003).

In this integrated navigation system, DR readings are calibrated when GPS is available using an EKF algorithm. If the GPS receiver suffers signal mask or the horizontal dilution of precision (HDOP) is greater than 10, which is an indication that navigation satellite geometry is not good enough to get a high accuracy position, the calibrated DR readings are used to measure the state of the vehicle as shown in Figure 1.

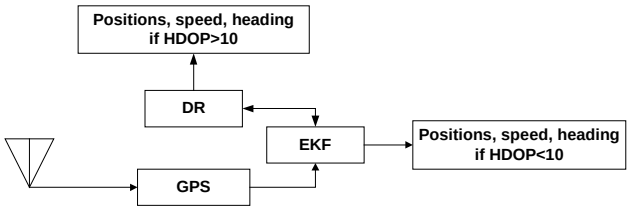


Figure 1: Integrated navigation system for the vehicle dynamic model

ALGORITHM 2: MAP MATCHING

Description of Algorithm Inputs

The inputs of the MM algorithm developed here are the locational data and topological information from the road network data. The locational data include position (e.g., easting and northing), speed, heading, and associated error variances. Locational data sources for this work included GPS, DR sensors (low cost gyro and odometer) and an integrated GPS/DR system employing an Extended Kalman Filter (EKF). A digital spatial road network database was the source of topological information. Error variances associated with the map resolution of the digital road network can also be taken as an input.

The algorithm makes use of the positioning data as well as the heading and speed information. Information on the historical trajectory of the vehicle is used to avoid sudden switching of the mapped locations between the unconnected road links. The topological aspects of the road network and the heading and speed information allow improvements in performance of the algorithm, especially at junctions. In addition, the physical location of the vehicle on the selected link is determined from an optimal estimation technique. Finally, the errors associated with the heading of the link (due to various error sources in the digital base map) and positioning sensors are applied to determine the physical location of the vehicle on the link. There are two main stages of the algorithm, namely the identification of the actual link, and the determination of the vehicle position on the selected link. These are explained below.

Identification of the Actual 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). Two distinct processes are defined for the identification of the correct link, namely (a) the *initial matching process* (IMP) and (b) the *subsequent matching process* (SMP). The function of the IMP is to identify an initial correct link for an initial position fix. Since the vehicle is expected to travel on this initial road segment for a few seconds, the subsequent position fixes are matched to this 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 given that specified criteria (as explained in SMP) are fulfilled. Otherwise, the algorithm goes back to the IMP for the identification of a new road segment for the last non-matched position fix. Both of these processes are explained below.

Initial Matching Process (IMP)

The IMP selects an initial road segment for the initial position fix. If an initial matching is incorrect then the subsequent matching will also be incorrect. Therefore, a sophisticated method is required for the IMP. 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 or GPS/DR. Road segments that are within the confidence region are taken as the pseudo candidate segments. If the confidence region does not contain any segments, then it is assumed that the vehicle is off the known road segments. In such a situation, the derived GPS or GPS/DR positions are used as the final locations of the vehicle. In a situation where the confidence region contains one or more pseudo candidate segments, a connectivity test or a filtering process is carried out based on the difference in heading between the pseudo candidate link and the derived vehicle heading to obtain the candidate road segments. If there is only one candidate segment, then the final selection process is very straightforward. However, in the case of more than one candidate segment, the link connectivity, vehicle heading relative to the candidate segments, closeness, and the historical information on vehicle location are used to select the most appropriate segment. In every application of the IMP, the algorithm selects a new road segment. The process is summarized in the flow chart in Figure 2.

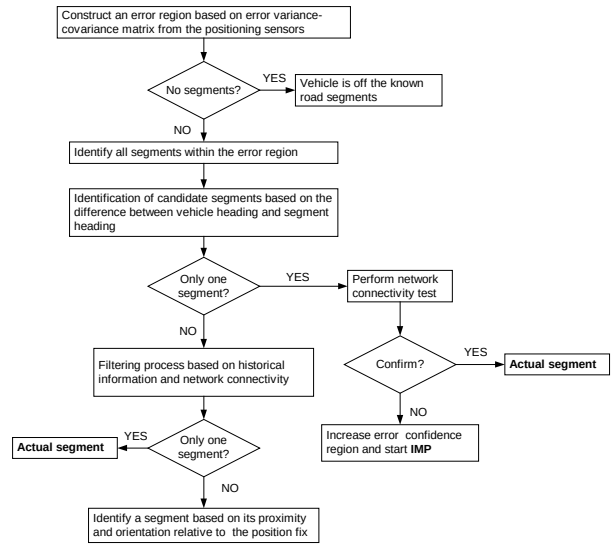


Figure 2: The identification of the actual segment in the initial matching process

Many methods are available for calculating the error region around a position fix. Variance-covariance information associated with GPS receiver outputs is often used to define an error ellipse. If an EKF algorithm is used for the integrated navigation system (GPS/DR), the variance-covariance information is available as a by-product of the filter computation. According to Zhao (1997), the error ellipse can be derived as

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

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

$$\phi = \pi/2 - 1/2 \arctan(\frac{2\sigma_{xy}}{\sigma_x^{\ 2} - \sigma_y^{\ 2}}) \quad (3)$$

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 (Figure 3a), 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).

In addition to the positioning sensor errors, there are also uncertainties associated with the digital road network data which could have errors due to plotting, errors in the original sources, measurement errors and processing mistakes. Hence, it is required to multiply the derived error region by another expansion factor to get a higher confidence level (Zhao, 1997). For simplicity, an error

rectangular can be used in place of the error ellipse as shown in Figure 3(b). In the case represented by Figure 3, the IMP selects 'link 3' for both cases, as the initial road segment for the position fix $P(x, y)$.

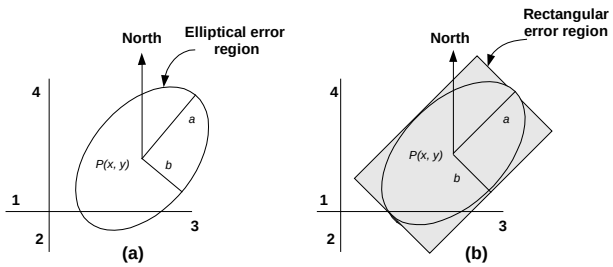


Figure 3: Error ellipse and rectangular around a position fix

Subsequent Matching Process (SMP)

The SMP is used to match the following position fixes on the previously selected road segment, which is identified using IMP. Several factors need to be considered for matching the subsequent position fixes to the link. These are the speed of the vehicle, whether there is a turning maneuver, or a maneuver through a junction. The speed of the vehicle needs to be taken into account since GPS or GPS/DR derived headings are not sufficiently accurate when the speed is low. On the other hand, the detection of a turning maneuver or a maneuver through a junction is a good indication that the vehicle no longer located on the original segment. If the vehicle speed is lower than the threshold for the minimum speed and there is no indication of any maneuvering through a junction by the vehicle, the SMP process continues. In such cases, the vehicle heading needs to be re-calculated to be equal to the heading of the road segment obtained from the map database. The new calculated vehicle heading is used to identify any turning maneuver for the next position fix. Field tests are necessary to determine a threshold for the minimum speed and this is explained in the next section.

In case of speeds higher than the threshold minimum speed, the SMP also continues if there is neither a turning maneuver nor junction crossing. The criterion to determine a turning maneuver is also explained in detail in the next section with some field test results. The decisive factor to determine whether the vehicle crosses any junction (in the case of maneuvers through a junction) can be determined from the relative position of the current GPS or GPS/DR fix compared to the previously selected road segment. The complete flow chart for the identification of the link on which a vehicle is traveling is presented in Figure 4.

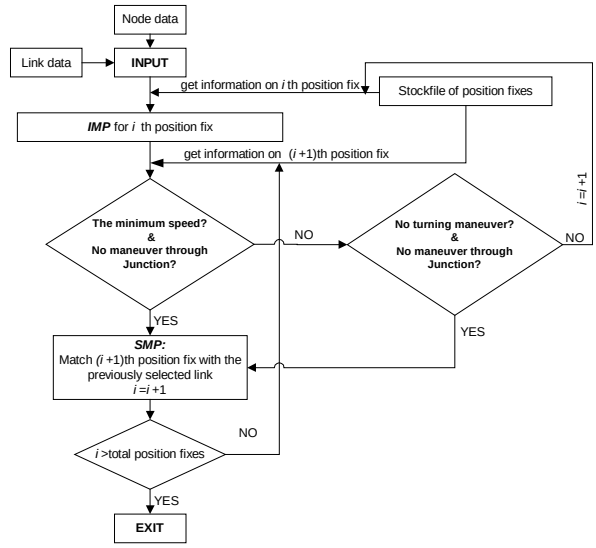


Figure 4: Flow chart for true road segment identification

Determination of a turning maneuver and the minimum speed

The MM algorithm makes use of the vehicle heading to identify whether there is a turning maneuver at a junction. A turning maneuver is an indication that the vehicle may have switched road segments. Therefore, the algorithm searches for a new road segment (using IMP) if a turning maneuver is confirmed. However, at low speed the error associated with vehicle heading is usually unacceptably low. Hence, it is essential to determine the minimum speed at which the MM algorithm should *not* rely on vehicle heading (either from GPS or integrated GPS/DR).

A field test was carried out to determine the minimum speed at which GPS or GPS/DR derived vehicle headings are not reliable. The test vehicle was driven on known road segments. Since the vehicle traveled on known road segments, the actual vehicle headings were calculated from the digital map database. The absolute deviation of vehicle heading was obtained from the difference between the calculated actual heading and the observed/estimated GPS or GPS/DR heading. The deviation of heading was then plotted against the corresponding vehicle speed (see Figure 5) for both GPS and GPS/DR system. For this case the difference in heading was always less than 30 degrees when the vehicle speed exceeded 3 m/sec (i.e., 10.8 km/hr) for both GPS and the GPS/DR systems i.e., the vehicle headings derived from the GPS and the road segment heading on which the vehicle is travelling is correlated when the vehicle speed is above 10.8 km/hr. Taylor et al. (2001) reports that the correlation is low when the vehicle is travelling at 8 km/hr or below. The satellite geometry was good since HDOP was always less than 2.0. Therefore, the algorithm can rely on the vehicle heading information, which is useful for determining a

turning maneuver, if the vehicle speed is greater than 3 m/sec. Hence the minimum speed threshold is set to 3m/sec (i.e., 10.8 km/hr). It is worthwhile to note that the threshold for the minimum speed may vary according to the types of GPS receivers and their error characteristics.

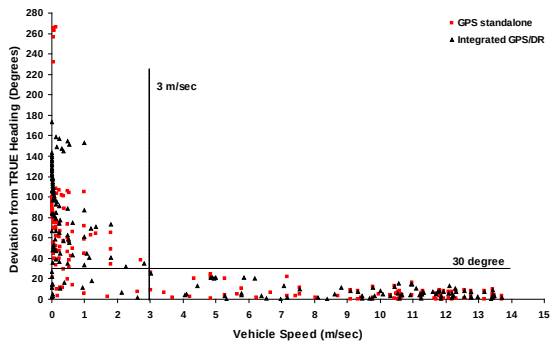


Figure 5: The absolute deviation of vehicle heading vs speed

In order to find out the threshold for the vehicle heading that could be used for detecting a turning maneuver, it is also necessary to know how the vehicle heading changes on a straight road segment. To determine this, another field test was carried out on a straight road segment. The vehicle was intentionally driven with a lot of overtaking maneuvers to examine the effects on heading changes. Figure 6 shows the change in vehicle headings on a typical straight road when the speed is greater than 3 m/sec. In all cases, HDOP was less than 2.0. The maximum difference between observed vehicle headings was 20 degrees for GPS and 15 for GPS/DR. The reason for such a large difference in heading on a straight road may be due to the overtaking maneuvers. However, neither an increasing nor decreasing trend was observed for the heading.

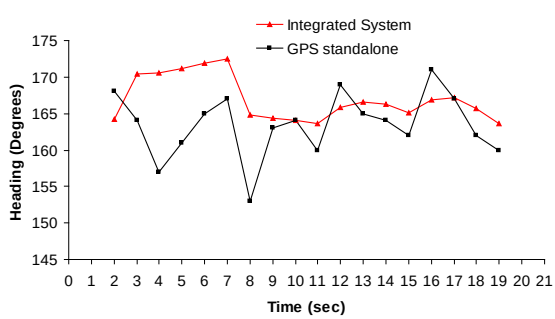


Figure 6: Characteristics of GPS/DR and GPS headings when the vehicle is traveling on a straight road.

Another field test was carried out to examine the change in vehicle headings during a turning maneuver at junction. This test was also useful for determining the time needed to complete a turning maneuver. Figure 7 shows the changes in observed vehicle heading during a right turning (British-style) i.e., left-turn elsewhere maneuver of a vehicle at a four-legged junction when the vehicle speed is above the minimum speed and HDOP less than 2.0. Clearly, there is a trend (in this case an increasing trend) of heading during the turning maneuver. Time to complete a right- or left-turning maneuver usually depends on speed and the size of the junction. In this case, the time to complete a right-turning maneuver was 4 sec.

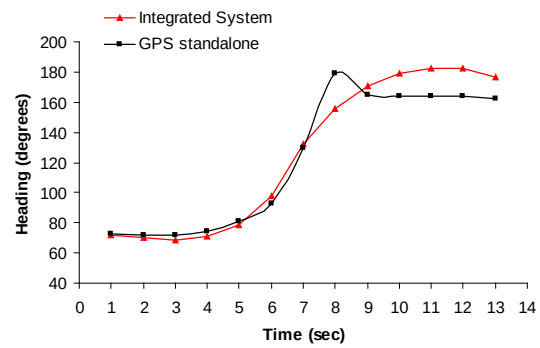


Figure 7: Characteristics of GPS and GPS/DR headings during a right turning maneuver of a vehicle at junction

Based on these above test results, the following conditions satisfy a turning maneuver (left, right or U-turn) of a vehicle at a junction.

- Increasing or decreasing trend in heading for about 2 to 5 sec
- Absolute difference in heading between the current and the last fix (assumed as α) is more then 30 degrees (for both GPS and GPS/DR)
- Absolute difference in heading between the current and the second last fix (assumed as β) is more then 35 degrees (for both GPS and GPS/DR)

Determination of 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 way is to use map data and vehicle speed from the positioning sensors and the other is to adopt the perpendicular projection of GPS or GPS/DR fix on to the link. Since both methods are associated with errors, an optimal estimation procedure is needed to determine the final location of the vehicle on the road segment.

The azimuth of the selected road segment and the vehicle speed (v) from the positioning unit can be used to calculate the vehicle position on a road segment. Suppose

P^t and P^{t+1} represent the vehicle position on a link at time t and $t+1$ respectively (Figure 8). The initial easting and northing of the vehicle at point P^t is known. From the bearing of the link (i.e., θ) and speed of the vehicle at P^{t+1}, the increment in easting and northing can be obtained as follows:

$$\left.\begin{aligned} \Delta E_i &= (v)\sin\theta \\ \Delta N_i &= (v)\cos\theta \end{aligned}\right\} \tag{4}$$

Therefore, the position of the vehicle at point P^{t+1} can be calculated as follows:

$$\left.\begin{aligned} E_{i+1} &= E_i + \Delta E_i \\ N_{i+1} &= N_i + \Delta N_i \end{aligned}\right\} \tag{5}$$

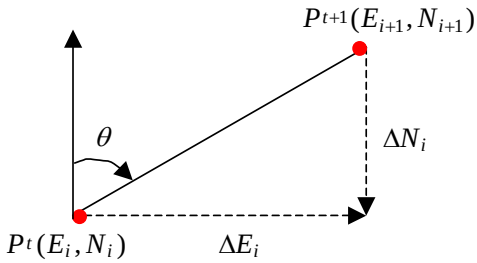


Figure 8: Determination of vehicle position using map data and vehicle speed

The other method for determining position is from the positioning sensor (Figure 9). Suppose the navigation unit locates the vehicle at point P^S with easting, e_S and northing, n_S. The projected easting (e_2) and northing (n_2) on the link can be obtained as follows:

$$\left.\begin{aligned} e_2 &= \frac{(x_2-x_1)[E_S(x_2-x_1)+N_S(y_2-y_1)]+(y_2-y_1)(x_1y_2-x_2y_1)}{(x_2-x_1)^2+(y_2-y_1)^2} \\ n_2 &= \frac{(y_2-y_1)[E_S(x_2-x_1)+N_S(y_2-y_1)]-(x_2-x_1)(x_1y_2-x_2y_1)}{(x_2-x_1)^2+(y_2-y_1)^2} \end{aligned}\right\}$$

(6)

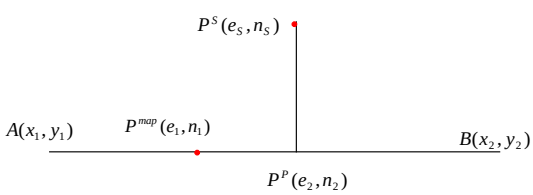


Figure 9: The vehicle location on a particular road segment from two methods

In Figure 9, the identified road segment for a position fix P^S is AB. The vehicle location P^{map} (e_1, n_1) on AB is measured from the digital base map and speed from the navigation system and P^P (e_2, n_2) is measured from the perpendicular projection of P^S on AB. Both techniques have random and unbiased measurement errors. Since both methods are associated with errors, an optimal estimation procedure 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

$$\hat{e} = \left(\frac{\sigma^2_{gps,e}}{\sigma^2_{map}+\sigma^2_{gps,e}}\right)e_{map} + \left(\frac{\sigma^2_{map}}{\sigma^2_{map}+\sigma^2_{gps,e}}\right)e_{gps} \tag{7}$$

$$\hat{n} = \left(\frac{\sigma^2_{gps,n}}{\sigma^2_{map}+\sigma^2_{gps,n}}\right)n_{map} + \left(\frac{\sigma^2_{map}}{\sigma^2_{map}+\sigma^2_{gps,n}}\right)n_{gps} \tag{8}$$

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

$$\frac{1}{\sigma^2_{mm,e}} = \frac{1}{\sigma^2_{map}} + \frac{1}{\sigma^2_{gps,e}} \tag{9}$$

where $\sigma^2_{mm,e}$ is the error variance associated with optimal estimation of $\hat{e}$. Note from equation (9) that $\sigma^2_{mm,e}$ is less than either σ^2_{map} or $\sigma^2_{gps,e}$. That is, the uncertainty in estimation of the vehicle position using optimal estimation is decreased by combining two measurement methods. The error variance associated with the optimal estimation of $\hat{n}$ can also be derived from the equation (9).

VALIDATION STRATEGY FOR MM ALGORITHMS

The input to MM algorithms are usually obtained from GPS SPS based on single frequency (L1) C/A code-ranging. The main reason is that the SPS is designed for civilian use. Furthermore, the receivers that support SPS are also relatively cheap. However, the positioning data from GPS C/A code measurements need to be augmented

with a Dead Reckoning (DR) sensor in order to achieve continuous vehicle location data in some areas, especially urban areas with urban canyons, streets with dense tree cover, and tunnels (Ochieng et al., 2003). Although the integration of GPS and DR improves the level of coverage (ability to obtain a position fix), it does not improve accuracy (position fixing with a desired level of accuracy) (Zhao et al., 2003).

The output of a MM algorithm is the link on which the vehicle is traveling and the physical location of the vehicle on that link. 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 with a high degree of precision. From this reference trajectory, the actual (truth) link on which the vehicle is traveling and the correct physical location (at the centimeter 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 e.g., 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.

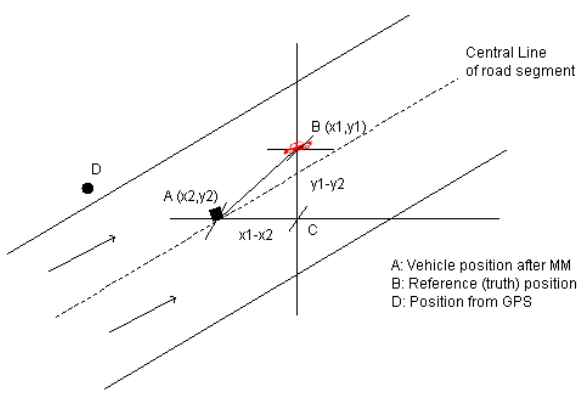


Figure 10: Determination of Error in MM

Figure 10 shows a road segment in which the vehicle position from GPS (C/A code-ranging) is denoted by the point D, the corresponding position estimated from the MM results (on the road centerline) 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,

$$HE_t = \sqrt{(x1 - x2)^2 + (y1 - y2)^2} \qquad (10)$$

A series of such horizontal errors can be derived using equation (10) for all epochs. The associated statistics derived from these errors (e.g., mean, standard deviation and RMS of the easting and northing component of the error) can be used to determine the relative performance of the MM algorithm.

Most of the road network map data contains only road centerline information. In this case MM algorithms take the centerline of the road segment as a reference and subsequently match the vehicle location data to it. Since the vehicle's actual position is not always constrained to be on the road centerline, a correction is required to the position of the vehicle matched onto the centerline.

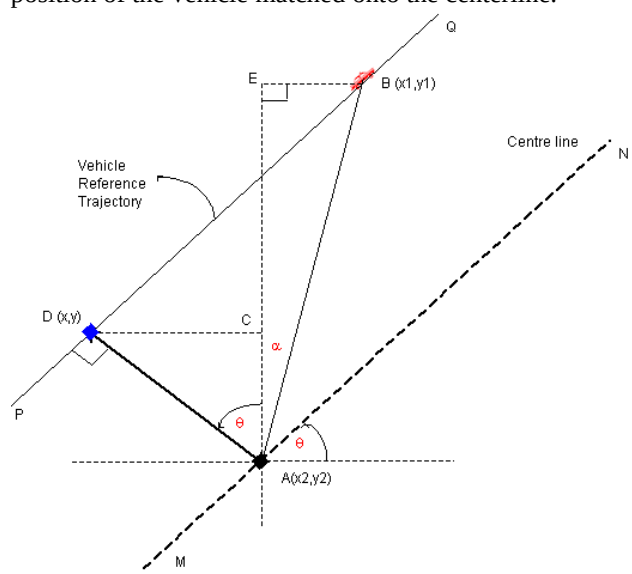


Figure 11: Corrections for Road Centerline

In Figure 11, the line MN represents a road centerline on which the MM process matches a vehicle position at point A(x2, y2) at a particular epoch t. The corresponding truth position of the vehicle at the same epoch is at point B(x1, y1). Line PQ (parallel to line MN) is drawn through point B. Point A is then orthogonally projected onto line PQ. Therefore, the final location of the vehicle position is at D (x, y) on the line PQ. Now the task is to determine the new easting, x, and northing, y, coordinate of the point D. The new easting coordinate is given by

$$x = x2 - CD = x2 - AB\cos(\theta + \alpha)\sin\theta \qquad (11)$$

The new northing coordinate is given by

$$y = y2 + AC = y2 + AB\cos(\theta + \alpha)\cos\theta \qquad (12)$$

where θ can be derived from the heading of the road segment MN and can be obtained from the map data. The line AB is the known distance between A and B, α can be derived from ΔAEB. The equations (11) and (12) are derived for a particular orientation of A and B (i..e, the truth position and the position estimated from the MM results). For other orientations of A and B, these equations can easily be derived.

The horizontal error after adjusting for the road centerline at epoch *t* (HE_{at}) is therefore given by

$$HE_{at} = \sqrt{(x - x1)^2 + (y - y1)^2} \tag{13}$$

The difference between equations (10) and (13) can be viewed as the bias introduced by the MM algorithms for matching the location data on the road centerline.

APPLICATIONS AND RESULTS

The testing of the two positioning algorithms (i.e., EKF algorithm for the integration of GPS/DR and the MM algorithm) is essential to evaluate its performance in real-world applications. A comprehensive field test is required to collect the positioning data from various road environments. This is necessary because the performance of MM algorithms depend on road network characteristics. The route in London 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 essential. For this purpose, the route 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. The duration of GPS carrier phase data collection is about 2 hrs.

A vehicle was equipped with a navigation platform consisting of a 12-channel single frequency (L1) high sensitivity GPS receiver (for C/A code-ranging), a low-cost 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 consisting of L1 and L2 with C/A code and P code-ranging.

The positioning data (easting and northing), speed, and heading were collected at a one second interval directly from the GPS receiver. Corresponding data together with the associated error variances were also obtained from the integrated navigation system (GPS/DR) employing an EKF algorithm.

In order to see the level of coverage and the accuracy offered by GPS and the integrated system, the position fixing data was overlaid onto a high-resolution digital road network base map. The statistics generated from the field data show that GPS coverage was obtained for 90% of the mission duration, while that of the integrated system was 100%. The longest period of GPS outage was found to be 100s.

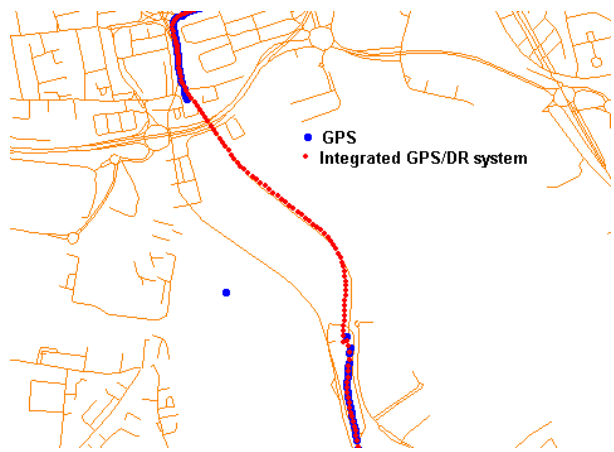


Figure 12: Travelling inside Blackwall Tunnel

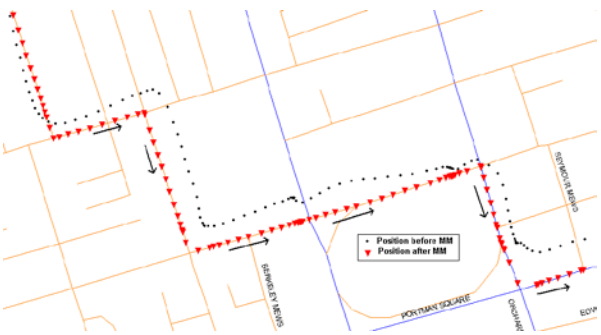
Figure 12 shows the vehicle travelling inside the Blackwall tunnel where there was a GPS outage for a period of 100*s*. It was found that 49% of the fixes were within 10*m* of the centreline of the road and 100% of the fixes were within 30*m*. This is a measure of the performance of the dead reckoning unit working on its own but using calibration factors derived when GPS position fixing capability was available.

The MM algorithm can be used with locational data from either GPS or the integrated GPS/DR system and any large-scale digital spatial road network data (source scale 1:1 to 1: 24,000). Maps for ITS (i.e., Transport telematics) applications may be at scales between 1:5,000 to 1:10,000 in cities and at smaller scales along the major roads outside metropolitan areas (Zhao, 1997). In order to see the performance of the algorithm, various scenarios were tested. Since the locational data from the integrated GPS/DR system are more reliable than GPS (Zhao et al. 2003), the performance of the algorithm has been tested using the navigation data from the integrated GPS/DR system. A large-scale digital spatial road network data (source scale 1:2500) supplied by *Saturn Technologies UK* is used to test the performance of the algorithm.

The algorithm was tested for various scenarios with different network characteristics and with different traffic maneuvers. These were a complex urban road network where the distance between roads was very small (Figure 13), and traveling through a roundabout (Figure 14).

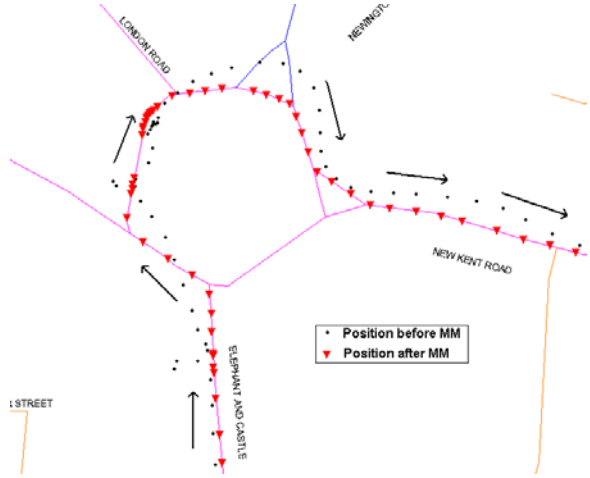
Each of the black round dots in the Figures (13 and 14) represents the vehicle position before MM. The arrow symbols in the figures show the path followed by the vehicle on the network.

The semi-major axis (i.e., *a*) and the semi-minor axis (i.e., *b*) of the error ellipse (see equation 1) can be seen to be between 20m to 50m and 15m to 46m respectively whenever IMP is required. The rectangular confidence region constructed from the major and minor axis of the error ellipse always contains one or more road segments. This is an indication that the vehicle was not traveling off the known road segments. The threshold values for the minimum speed is taken as 3m/sec, α is taken as 30^0, and β is taken as 35^0. These values are used to detect any maneuvers at junctions. 100% correct link identification is achieved for all scenarios.



(Presentation map scale 1 cm : 20 m)
Figure 13: Map Matching Results on Complex Urban Road Network

Each of the triangular symbols on the road segments represents the vehicle position after MM. 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). The optimal estimations (7) and (8) of easting and northing coordinates respectively.



(Presentation map Scale: 1cm: 24m)
Figure 14: Map matching results at roundabout

The MM algorithm was validated using a validation strategy explained in the previous section. GPS carrier phase observables were processed in relative mode to reduce errors. Therefore, the raw data was needed from both a reference (static) station and also from the geodetic receiver (roving). The applicable static station for this study was 'LOND' (located in London) which is an Ordnance Survey (OS) active station operating within the *UK National GPS Network* (http://www.gps.gov.uk). The raw data from this station for the 5th of July 2004 (at 15 s sampling interval), was extracted from the OS internet enabled data archives. All available data sets from the geodetic receiver and the reference station were processed in a *kinematic on-the fly* (KOF) post-processing mode using the *SkiPro GPS post-processing package*. The satellite positions were computed using broadcast ephemerides. The integer ambiguity (for GPS kinematic positioning) was resolved for all baselines involving all satellites in view (elevation cut-off 10^0), having detected and resolved all cycle slips at every 15s intervals.

The quality of positional data from carrier phase measurements largely depends on a reliable and correct determination of integer ambiguities. Unsuccessful ambiguity resolution, when passed unnoticed, may lead to unacceptable errors in the positioning results. Normally when processing an individual baseline, two types of double difference solutions result. One is a float solution in which the ambiguities are solved as real numbers, instead of integers, and the other is a fixed solution in which the ambiguities are fixed by basically exploring those integers close to the float solution of the ambiguities. Under normal circumstances, the fixed solution is better than a float solution. In open spaces and in static surveys, a fixed solution should be routine. However, float solutions cannot be avoided in kinematic surveys especially in the built-up urban areas. The variance-covariance matrix of the least squares estimation of the ambiguities contains the information necessary to

infer the quality and reliability of ambiguity estimation. The *SkiPro GPS post-processing package* used in this study gives a number of quality indicators for each position estimate, including the variance from the variance-covariance matrix. A threshold value for the standard deviation of the horizontal positioning can be used to select the float solution position estimates to use as reference or truth alongside ambiguity fixed position estimates.

In our test route, both fixed and float solutions were obtained corresponding largely to open and built-up areas respectively. However, the positioning quality indicator in the form of the standard deviation of the horizontal position given by the *SkiPro GPS post-processing package* was used to select good float solutions used with the fixed solutions to provide the reference (truth) of the vehicle trajectory. It was found that the values of the standard deviation of the horizontal position were always less than 0.03 if the positioning fixes were from the fixed solutions. In the case of the float solutions, this value varied from 0.4 to 26.0. To select a threshod value for the standard deviation, which could identify good carrier phase observations by the float solutions of the ambiguities, the position fixing data from both solutions was overlaid onto a high resulotion digital base map (Figure 15).

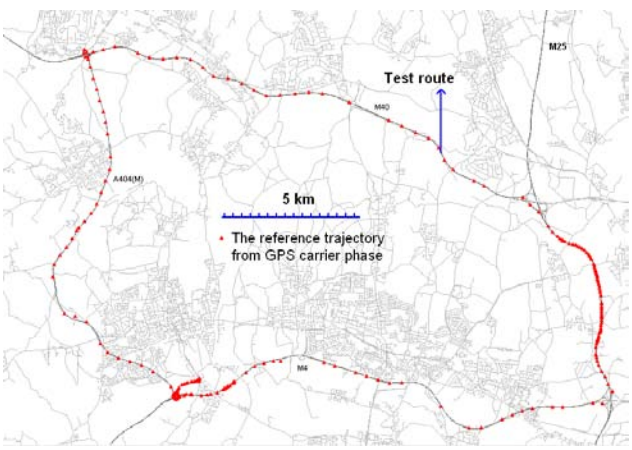


Figure 15: The Reference Trajectory of the Vehicle from GPS Carrier Phase Observables

The positioning fixes from the float solutions were sometime offset by more than 20m from the road centerline when the standard deviation was large. It was found that the postioning fixes identified by a threshold value of 2.0 aggreed reasonably with the positioning fixes from the fixed solutions relative to the road centerline. Therefore, this threshold value of the standard deviation was employed to select all good carrier phase observations from GPS.

Based on the reference of the vehicle trajectory obtained from the GPS carrier phase measurements, a set of correct links on which the vehicle was traveling is identified. Another set of links is identified for the corresponding epochs from the MM results. From this a 100% correct link identification was achieved by the new MM algorithm. In terms of physical location of the vehicle, different categories of horizontal positioning errors could be derived. The errors associated with the positions from the GPS C/A code-ranging augmented with DR are shown in Figure 16. The maximum horizontal error of this category is 34m i.e., all GPS positions are within 34m relative to the truth positions. The average error is 7.01m and the standard deviation is 6.23m. The root mean square (RMS) of the easting component of this error is 8.84m and the northing component is 7.79m.

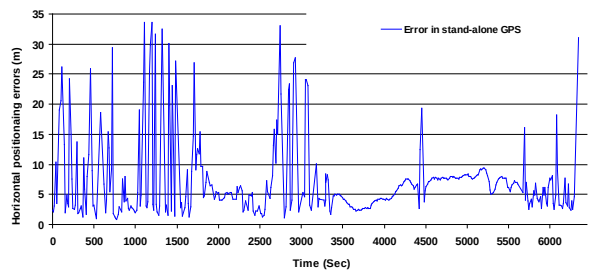


Figure 16: Horizontal Errors of Stand-alone GPS Positions Relative to the Reference (truth) of the Vehicle Trajectory

The next step is to compute the horizontal errors associated with the positions estimated from the MM results. This is shown is Figure 17.

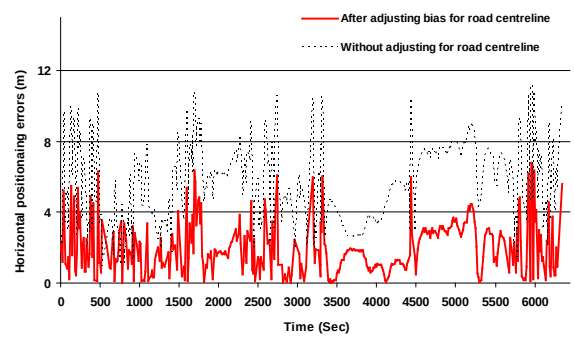


Figure 17: Horizontal Errors of Positions from the MM results Relative to the Reference (truth) of the Vehicle Trajectory

The errors are calculated by equation (10). It was found that all MM positions on the road centerline are within 11m (maximum error) of the truth positions of the vehicle. The average of the errors is now 5.6m and the standard deviation is 2.26m whereas the RMS of the easting component of the error is 5.12m and the northing

component of the error is 6.37m. Therefore, a significant improvement in the estimation of the vehicle positions on the map is achieved by the MM algorithm.

The horizontal errors were also calculated after correction for the road centerline using equation (13). This is also shown in Figure 17. The maximum horizontal error is now only 6m implying that the final positions of the vehicle are within 6m of its true positions. The average of these horizontal positioning errors is 2.03m and the standard deviation is 1.48m. The RMS of the easting component of this error is now only 3.03m and the northing component is 4.03m. Therefore, a further improvement in the estimation of the vehicle position can be achieved after adjusting for the road centerline.

Clearly the quality of the vehicle positions estimated from the MM algorithm largely depends on the quality of the digital base map. If a good digital network map is not used in the MM process, the positions estimated from the MM process may get worse than the positions from stand-alone GPS.

Most of the MM algorithms in the literature (e.g., Greenfeld, 2002, White et al., 2000, Quddus et al, 2003) used epoch-by-epoch heading information from GPS in order to identify the correct link among the candidate links. Therefore, one can compare the GPS heading and the GPS/DR heading with the actual link heading which is calculated from the map data whereas the actual link is identified by the GPS carrier phase observations. The results are shown in Figure 18.

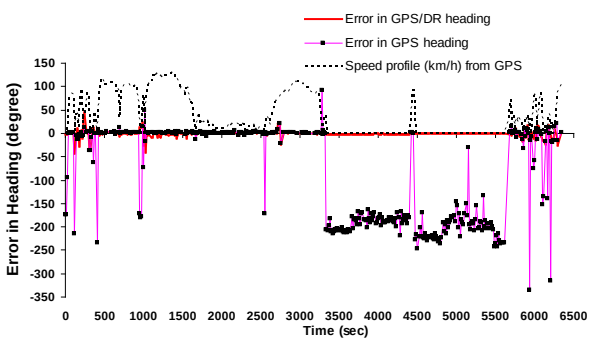


Figure 18: Errors in GPS and GPS/DR Heading Relative to the Truth Link Heading

The heading from the stand-alone GPS is significantly different from the true heading. The difference is higher when the speed of the vehicle is very low. On the other hand, the vehicle heading from the integration of GPS/DR is very close to the true heading. Therefore, the heading derived from the stand-alone GPS SPS should be used with caution within MM algorithms.

CONCLUSION

The integration of low cost DR sensors and GPS was achieved employing an EFK algorithm. This integrated navigation system gives continuous vehicle position fixes (including urban canyons, streets with dense tree cover and tunnels). However, the vehicle positions derived from the integrated system do not always map to the actual vehicle position. Therefore, a novel MM algorithm was developed and demonstrated. This algorithm was validated using a higher accuracy reference (truth) of the vehicle trajectory as determined by high precision positioning achieved by the carrier phase observable from GPS

Probabilistic approaches were applied in the MM algorithm for both identification of the actual road segment on which the vehicle was traveling and the determination of the vehicle position. The algorithm was tested on various complex urban roadways and traffic scenarios with a relatively high-resolution digital map of the road network. The validation results revealed that about a 100% correct link identification was achieved by the MM algorithm. It was found that the horizontal position of the vehicle estimated from GPS C/A code-ranging deviated at most from 34m of its true positions, with an average error of about 7m. The horizontal position of the vehicle was 11m from its true position after the application of the MM algorithm indicating that MM improved the mapping of vehicle positions on a link. The average horizontal error was 5.6m. The estimate is further improved to within 6m in the estimation of the vehicle positions after adjusting MM results for the road centerline, with an average error of 2m.

One of the interesting findings, therefore, was that the matching of the vehicle positions on the road centerline introduced additional error. If a good digital map is not used in MM algorithms, the estimation of the vehicle positions may become worse than the positions from GPS C/A code-ranging. Another finding was that the vehicle heading derived from the stand-alone GPS was significantly different from the true heading of the link especially at very low speed. Therefore, the heading information needs to use MM algorithms carefully.

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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