Integrated GNSS/DR/Road Segment Information System for Variable Road User Charging

Fan Qin[1] Rui Sun[2, 3] Washington Yotto Ochieng[4] Shaojun Feng[4] Ke Han[4] Yuanqing Wang[1]

[1]Departmentof Traffic Engineering Highway School, Chang'an University, Xi'an 710064, China

[2]College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing, 211100, China

[3]State Key Laboratory of Geo-information Engineering, Xi'an，710054，China

[4]Department of Civil and Environmental Engineering, Imperial College London, SW7 2AZ, UK

Abstract

Road User Charging (RUC) is designed to reduce congestion and collect revenue for the maintenance of transportation infrastructure. In order to determine the charges, it is important that appropriate Road User Charging Indicators (RUCI) are defined. This paper focusses on Variable Road User Charging (VRUC) as the more dynamic and flexible compared to Fixed Road User Charging (FRUC), and thus is a better reflection of the utility of the road space. The main issues associated with VRUC are the definition of appropriate charging indicators and their measurement. This paper addresses the former by proposing a number of new charging indicators, considering the equalization of the charges and marginal social cost imposed on others. The measurement of the indicators is addressed by a novel data fusion algorithm for the determination of the vehicle state based on the integration of Global Navigation Satellite Systems (GNSS) with Dead Reckoning (DR) and road segment information. Statistical analyses are presented in terms of the Required Navigation Performance (RNP) parameters of accuracy, integrity, continuity and availability, based on simulation and field tests. It is shown that the proposed fusion model is superior to positioning with GPS only, and GPS plus GLONASS, in terms of all the RNP parameters with a significant improvement in availability.

KEY WORDS

1. Road User Charging Indicator. 2. Particle Filter. 3. GNSS Integration. 4. Intelligent Transportation Systems

1. Introduction

Severe road congestion resulting from rapid urbanization, motorization and poor urban planning has many social, economic, and environmental consequences (Boquet, 2011; Hu et al., 2015; Hu et al., 2016a; Hu et al., 2016b). While there are multiple means to address urban congestion at strategic, tactical and operational levels, Road User Charging (RUC) has been widely recognized as an effective way to alleviate congestion and raise revenue (Newbery,1988b). RUC can be categorized as Fixed Road User Charging (FRUC) and Variable Road User Charging (VRUC).FRUC charges each vehicle for using specific road segments or sub-networks regardless of the time spent in the charging zone and/or the travel activities; examples include tolled highways or bridges, and the Congestion Charging Zone (CCZ) in London (Ison and Rye, 2005; Richardson and Bae, 2008; Palma and Lindsey, 2011). VRUC, on the other hand, considers the specific road usage and related environmental and social impacts (Ochieng et al., 2010). Typical variable charges include distance-based road charging schemes for Heavy Goods Vehicles (HGV) (Cottingham et al., 2007; Palma and Lindsey, 2011).

For RUC to better reflect the utility of road space and its impact on the environment and society, Ochieng et al. (2008, 2010) proposed the concept of Variable Road User Charging Indicators (VRUCI). These indicators should be measurable with the required levels of accuracy and integrity in order not to result in incorrect charging (e.g. overcharging and under-charging), missed detection and false detection.

Currently, advanced technologies including networks of sensors and communication devices are widely applied in Intelligent Transportation Systems (ITS). These technologies including GNSS based positioning systems can be applied to meet the positioning and timing requirements of the location based indicators for RUC (Velaga and Panbourne,2014; Toledo-Moreo et al., 2010). In GNSS based RUC systems, the vehicle state (Positioning, Velocity and Time – PVT) or location determination function forms the basis for charging. In particular, the 4D positioning accuracy is a critical factor for identifying a vehicle's physical position (Zabic, 2009). This is because the positioning ambiguity arising from height inaccuracy could lead to incorrect physical location of a vehicle, especially for the vehicle on or beneath the viaduct. The quality of the state determination can be assessed based on the RNP parameters of accuracy, integrity, continuity and availability (Feng and Ochieng, 2007; Salos et al., 2010; Velaga and Sathiaseelan, 2011).

Research carried out by Transport for London (TfL) showed that only 58% of all the positioning data collected from GPS were adequate for RUC (TfL,2006), significantly below the requirement. However, the exploitation of new GPS signals and the addition of the Russian Global Orbit Navigation Satellite System (GLONASS) and in future the European Galileo and China's BeiDou systems have the potential to improve performance through improved satellite coverage, visibility and redundancy for the positioning (GINA, 2010). However, as evident from extensive field tests by

Zabic (2011) in Copenhagen, Denmark, the improvements from new signals and multiple constellations are unlikely to meet the requirements for RUC particularly in built environments. In such environments GNSS signal errors, weak geometry, road map errors and map-matching process errors have the potential to lead to vehicles being assigned to the wrong road segments with the consequences of incorrect charging (Velaga et al., 2012, Quddus et al., 2007; Toledo-Moreo et al., 2010).

In order to address the issues of Variable Road User Charging Indicators (VRUCI) and inadequate vehicle state estimation performance, this paper proposes a new definition of VRUCI and an integrated Particle Filter (PF) based GPS/GLONASS/DR/road segment information data fusion algorithm for VRUC.

2. Variable Road User Charging Indicators

The RUC indicators should capture all aspects of the utility of road space. Furthermore, they should as far as possible be independent and measurable. Using these criteria, Ochieng et al. (2010) identified the nine indicators listed in Table 1.

Table 1 Variable Road User Charging Indicators (VRUCI)

VRUCI
Geographic Area
Road Class
Distance Travelled
Pollutant Emissions
Vehicle Occupancy
Driver Behaviour
Time of Trip
Duration of Trip
Traffic Density

The geographic area and road class data are required to capture the spatial variations in the utility of road space. The real time travel information including travel distance, time of trip and duration of trip account for the temporal aspects of the use of road space. The traffic density data are needed to charge vehicles according to real network conditions (i.e. free flow or congested). The pollutant emissions are required to capture the impact of emissions on the environment and health. The effect of noise pollution should be included in addition to exhaust emissions. Furthermore, the indicator 'driver behavior' cannot be measured directly as it is affected by many factors, such as speed, acceleration, braking, gear changes, clutch pedal press. And these factors can be detected and measured related to the state of the car (Rendon-Velez et al., 2011). In practice, therefore, the factors that influence driver behavior should be measured separately. Furthermore, as the VRUC should be related to the amount of road use at the vehicle and traveler levels, vehicle occupancy should be included as an indicator. Therefore, Table 2 presents an improved list of indicators.

Table 2 Improved Variable Road User Charging Indicators (Improved VRUCI)for a Comprehensive Charging System

VRUCI (Ochieng et al., 2010)	Improved VRUCI (Measurable)
Geographic Area	Geographic Area
Road Class	Road Class
Distance Travelled	Distance Travelled
Time of Trip	Time of Trip
Duration of Trip	Duration of Trip
Traffic Density	Traffic Density
Pollutant Emissions	**Exhaust Emissions**
	Noise
Vehicle Occupancy	Vehicle Occupancy
Driver Behavior	**Speed**
	Acceleration
	Braking
	Gear Change
	Clutch Pedal Press

Besides the requirement for the indicators to be measurable, correlation should be accounted for in order to ensure independence. Therefore, two or more correlated variables can be combined into one factor in order to create an improved set of uncorrelated indicators. The approach based on the consideration of marginal social cost (Newbery, 1990) is used here to select independent indicators. According to Newbury (1990), there are four types of costs when a vehicle is travelling: road damage, congestion, accident externalities and environmental pollution. Therefore, the best charging scheme is where the charges equate to the marginal social cost each driver imposes on others. Based on this assumption, a charging scheme should be considered to be justified if the indicators influence these four costs.

The road damage caused by vehicles is manifest in the form of increased roughness of the surface (Newbery, 1988a)**.** This degree of damage depends on the characteristics of the vehicle and type of the road (paved or unpaved). For the indicators related to the road damage, road class is a variable indicator and should be 'measured' in real time. The vehicle type, on the other hand, for a certain type of vehicle, is a constant. For example, HGV can be considered as a kind of vehicle type indicator and the road damage charging contains the constant charging for the vehicle type "HGV" and other additional variables charging, such as travel distance etc. Hence, the only variable indicator associated with the cost of road damage is the road class.

According to Noordegraaf et al. (2009), congestion pricing is mainly specified as a differentiation in time and place. Thus the variable indicators for congestion cost are distance travelled, time of trip, duration of trip and traffic density. In addition, the charge should be closely related to the amount of road use and thus the vehicle occupancy is also a factor that needs to be considered.

The main variable indicator for accident cost is driver behavior and it appears as speed, acceleration, braking, gear change and clutch pedal press. However, the gear change and clutch pedal press indicators are correlated to the acceleration indicator. It is a fact that when you acclerate an manual transmission car, you need to take your foot off the accelerator, depress the clutch, change the gear and then the acceleration added, in all, you should change the proper gear level in according to how fast you are going. In addition, the acceleration indicator is highly correlated to noise, exhaust emission and speed. As we know, there is a very good correlationship between acceleration and speed. Acceleration is defiend as the rate of change of velocity of vehicle with respect to time, while the speed is measured in the same physical units of measurement as velocity, but does not contain an element of direction. In terms of the correlationship between acceleration and exhaust emission, Ericsson (2001) tested 30 driving familes for two weeks in Västerås, Sweden and indicated that rapid acceleration (>1.5 m/s2) resulted in a significant increase in the emission of HC, NOx and CO2. Rakha and Ding (2003) indicated that the aggressiveness of a vehicle stop, as represented by the vehicle's acceleration and deceleration level, does have a significant impact on vehicle emission rates. Specifically, HC and CO emission rates are highly sensitive to the level of acceleration when compared to cruise speeds in the range of 10 to 120 km/h. Furthermore in terms of the correlationship between the acceleration and the noise emission, Ouis (2001) pointed out that engine noise and vehicle exhaust noise are the two main sources of a vehicle noise. The data from the urban traffic experiment have shown that sudden accelerations have negative effects on traffic noise control (Waters, 1970). Therefore, by considering the correlations of these indicators, only the speed indicator, noise and braking indicators are selected. In addition, traffic density is an independent factor in the occurrence of incidents and accidents (af Wåhlberg 2004), and is included in the list of indicators.

The exhaust emissions of vehicles contain NOx, CO, CO2, HC and PM. These emissions and noise have a negative effect on the environment. Thus RUC should be levied according to their environmental pollution cost. Table 3 presents the variable road user charging indicators that are measurable, independent and capture the utility of road space.

Table 3 Variable Road User Charging Indicators (Measureable and Marginal Social Cost Based Low-Correlation VRUCI) for a Comprehensive Charging System

Cost Type	Identified VRUCI (Measurable and Marginal Social Cost based Low-correlation)
Road Damage Cost	Road Class
Congestion Cost	Distance Travelled
	Time of Trip
	Duration of Trip
	Vehicle Occupancy

	Traffic Density
Accident Externalities Cost	Traffic Density Speed Braking
Environmental Pollution Cost	Geographic area Exhaust Emissions Noise

Some of the indicators in Table 3 including road class, distance travelled, time of trip, duration of trip, and traffic density, can be determined from on-board positioning and motion sensors. In the following section, an integrated algorithm is designed to improve the current performance of the positioning sensors to underpin the measurement of the relevant variable road user charging indicators. The indicators that can be determined directly from the vehicle state estimation information include time of trip, duration of trip and speed. The indicators that can be derived, inferred from or require the state estimation information include road class, traffic density, geographic area, vehicle occupancy, braking, exhaust emissions and noise. Road class could be extracted by matching the state to the road network database. Traffic density is basically the number of vehicles unit distance of a road (n/L), which can also be expressed as the inverse of the average spacing of the number of vehicles, n, on the road segment. Geographic area can be determined based on the estimated state of the vehicle map matched to the road network spatial database. Although measurable using on-board sensors, it is important to determine the time at which the vehicle occupancy changes. Braking can be detected by the pedal pressure sensor. However, that data must be spatially and temporally referenced for behavioral and impact (e.g. an accident) analyses data of braking happen is also crucial to the accident identification. Exhaust emissions and noise can be measured by specific sensors. However, it is important that the pollutant species data are spatially and temporally referenced to determine the location and time of emission.

Overall, the performance of the positioning system is critical to the measurement of the VRUC indicators. In the following section, an integrated algorithm is designed to improve the current performance of the positioning sensors, which is the underpinning technology for the VRUCI measurement.

3. Data Fusion Algorithm for the Measurement of VRUCI

The ability of locating and tracking a vehicle in space and time is fundamental to charge for real road use (Ochieng et al. 2010). The technology chosen to determine the state of each vehicle in real-time is therefore, critical. GNSS-based applications can provide real-time positioning information, which is fundamental for road user charging schemes. In this section, the required navigation performance for RUC and a novel data fusion algorithm exploiting GNSS, Dead Reckoning (DR) and road segment information are presented. The performance of the algorithm is tested using simulated and real data.

3.1.Required Navigation Performance for RUC

For the RUC scheme, GMAR (2010) has proposed a framework to measure the performance of GNSS-based road use metering systems at the service level. The quantitative and testable performance metrics have been derived, for testing and comparing the GNSS based metering products and services, including charging integrity and charging availability. However, the required navigation performance metrics are still to be derived from the service requirements and standardized.

At the technology level, accuracy, integrity, continuity and availability are the main parameters to capture the performance of a navigation system (Ochieng et al. 2003). Accuracy refers to the statistical distribution of position errors, velocity errors or speed errors (Peyret et al. 2015). Integrity is defined as the ability of a system to provide timely and valid warnings if the position errors exceed a certain alarm limit (Ochieng et al. 2003). Continuity risk is the probability that a navigation service available at the start of a specific operation is interrupted during the period of operation (Flament et al. 2010). Before selecting an appropriate navigation system to track vehicle location over time, an assessment of the candidate systems is required.

Although appropriate RNP values for RUC are still to be agreed, the targets in Ochieng et al. (2010) and Feng and Ochieng (2007) are adopted in this paper: accuracy 5m (95%); integrity risk 10-7, alarm limit 12.5m and availability 99.7%.

3.2.Algorithm Design

The designed integration algorithm has the merit of combing the vehicle positioning estimation with the lateral displacement estimation related to the road segment, which is critical for the RUCI measurements. The data fusion is based on a Particle Filter (PF) and precise motion models. The positioning and dynamic data from GNSS and DR sensors and road segment related information are input into the algorithm to estimate in real-time the positioning and attitude parameters. The PF is a non-parametric recursive Bayes filter, which uses a number N of weighted samples to approximate the probability density. It is designed to provide accurate and high integrity positioning and vehicle dynamic state estimation for the RUCI measurement. The steps for the particle filtering process are presented in the following sub-sections.

3.2.1. State Vector Definition

In the designed fusion algorithm, the state vector is presented in (1), where, x, y are the X-axis and Y-axis coordinates of the vehicle in the local coordinate system, h is the height coordinate of the vehicle in the local coordinate system. v is the vehicle's velocity along the heading, h is the vehicle's heading angle, ω is the vehicle's yaw rate, a is the vehicle's acceleration along the heading, β is the angle between the road segment and the local coordinates, d is the vehicle's lateral displacement within the road segment which is calculated to be the minimum distance between [x,y] and the road central line. The road centerline data is a set of points collected to represent the road centerline.

$$X = (\mathrm{x\ y\ h\ v\ \theta\ \omega\ a\ \beta\ d})^T \tag{1}$$

The state vector (1) is composed of two sub-state vectors, motion vector (2) and geometry vector (3).

$$A(t) = (\mathrm{x\ y\ h\ v\ \theta\ \omega\ a})^T \tag{2}$$

$$B(t) = (\mathrm{\beta\ d})^T \tag{3}$$

The parameters vary in time and the particles for each parameter within the state vector (1) during the operation of the PF are expressed as:

$\mathrm{X}_t^i(t = 0 \ldots n; i = 1 \ldots n)$ (4)

Where, X_t^irepresents the parameters in the state vector (1) with the particle number i at the time epoch t. The details of the initialization of the particles X_0^i for (2) and (3) are discussed below.

The filter begins with the initialization of the particles x_0^i, y_0^i and h_0^i in (4). The sphere region for the generation of particles is defined based on the GNSS a posteriori solution statistics. The mean value of the first accepted GNSS point is set as the origin and the standard deviation value is set as the radius of the sphere. The local coordinate variables x_0^i, y_0^i and h_0^i are randomly created following a Gaussian distribution. The initial heading velocity v_0^i is 0 as the static initial status of the vehicle is assumed. As there is no information of the initial heading, the values of θ are assumed as uniformly spread through the whole range of 360 degrees. The initial ω and a values are set as 0.

3.2.2. Prediction

The prediction for (2) is based on vehicle kinematic motion models. Constant acceleration (CA) and Constant Turn Rate and Acceleration (CTRA) models, shown to provide reasonable approximation of motion, are used on straight/curved roads (Tsogas et al., 2005; Sun et al., 2015a; Sun et al., 2015b; Sun et al., 2016). Thus, for every particle in (2), the prediction models are applied during the filtering processing as in equation (4).

$$\begin{bmatrix} \mathrm{x}_{t+1}^i \\ \mathrm{y}_{t+1}^i \\ \mathrm{v}_{t+1}^i \\ \theta_{t+1}^i \\ \omega_{t+1}^i \\ \mathrm{a}_{t+1}^i \end{bmatrix} = \begin{bmatrix} \mathrm{x}_t^i + \Delta_\mathrm{x}^i \\ \mathrm{y}_t^i + \Delta_\mathrm{y}^i \\ \mathrm{v}_t^i + \Delta_\mathrm{v}^i \\ \theta_t^i + \Delta_\theta^i \\ \omega_t^i + \Delta_\omega^i \\ \mathrm{a}_\mathrm{t}^\mathrm{i} + \Delta_\mathrm{a}^\mathrm{i} \end{bmatrix} \tag{4}$$

Equation (5) is used for the prediction of the parameters in (3) based on the geometry relationship of the road segment.

$$\begin{bmatrix} \beta_{t+1}^i \\ d_{t+1}^i \end{bmatrix} = \begin{bmatrix} \beta_t^i \\ d_t^i + \sin(\beta_t^i)\,\Delta_x^i - \cos(\beta_t^i)\Delta_y^i \end{bmatrix} \tag{5}$$

Where, $\Delta_x^i \Delta_y^i \Delta_v^i \Delta_\theta^i\ \Delta_\omega^i \Delta_a^i$ are transition parameters calculated based on different vehicle motion models.

3.2.3. Update of Filter

For every input sample, the prediction cycle is applied. The filter update procedure is initiated by the validity test of the input sample. Once the validity is confirmed, the update of the particles in the prediction cycle ensues.

The test is based on the parameter d^i, i.e. $|d_t^i| < 3HR$ for validity, where $3HR$ is 3 times a half of the road width (1.5 times of the road width). The reason for specifying $3HR$ as the limit for the lateral displacement is that for a moving vehicle, it is not possible to suddenly move into a non-adjacent road within 1s. For example, for a vehicle on a 7m width road, if $|d_t^i|$ is greater than $3HR$ = 10.5m, then the position predicted based on the particle is on the non-adjacent road, which is unrealistic. If d_t^i is within this defined interval, the particle is considered to be valid and the parameter prediction for the next epoch$t+1$is undertaken.

The validity of the predictions should also fulfil the condition that only the predicted position for a particle $i$is still within the road width limits. Therefore, for every predicted d_{t+1}^i , if it complies with $|d_{t+1}^i| < 3HR$, then the predicted d_{t+1}^i is considered as valid and other predicted parameters in equation (1) are accepted also. If the predicted d_{t+1}^idoes not satisfy $|d_{t+1}^i| < 3HR$, then the other predictions based on this particle are invalid and the weighting of this particle$w_t^i$is set to zero. The validity of GNSS is then tested after every prediction cycle.

3.2.4. Normalization and Resampling

The weights of the particles are modified after every update phase and the normalization and resampling test phases of a PF are re-launched.

4. Simulation

The estimated positioning performance based on the PF with Constant Acceleration (PFCA) and PF with Constant Turn Rate and Acceleration (PFCTRA) models for simulated straight and curved roads are compared. The focus of the simulation test here was to capture the characteristics of the operational environment (i.e. open sky, suburban and urban). And with a GNSS simulator, the test can easily generate and run many different scenarios to verify the performance of the developed algorithm. Clearly, other characteristics that would require a larger dataset can be simulated as well. However, because of the availability data, effort was directed to the analysis of performance based on real-world data. The simulated GNSS data over a period of ten minutes, are generated by the Spirent GNSS simulator, the DR data and road segment data are created by the MATLAB software. In total 3 representative simulation test cases are created (Table 4). Test Case 1 represents a road with the open sky; Test Case 2 represents a highway with vehicle flows; Test Case 3 represents a light woodland area. The three positioning alternatives, data fusion PF algorithm, GPS/GLONASS and GPS only are analyzed for each test case. The vehicle speed is specified as 70km/h for the highway and 50km/h for the other roads.

Table 4 Simulation Test Cases

Test Cases	Time Duration (s)	Simulation Environment
Test Case 1	600	Open Sky
Test Case 2	600	Highway with Vehicle Flows
Test Case 3	600	Light Woodland Area

The analysis of the simulation results in terms of satellite coverage, accuracy, integrity, continuity and availability are presented in the following sub-sections.

4.1.Satellite Coverage

Satellite coverage is measured in terms of the number of visible satellites, which together with the user-satellite geometry are pre-requisites for positioning. Generally, three satellites are required for 2D positioning (longitude and latitude) and time determination, and a minimum of four satellites are required for 3D positioning (longitude, latitude and height) and time determination. For the road user charging service, especially in the graded roads, height accuracy is critical for the correct identification of the location of a vehicle.

The level of coverage is assessed here for positioning with GPS only and GPS/GLONASS. The numbers of visible GPS and GPS/GLONASS satellites in the three test cases are shown in Figure 1. It can be seen that there are always more than four satellites for both the GPS only and GPS/GLONASS constellations in these three test cases. In addition, by comparing with the simulation performance in the open sky test case, the number of visible GPS only and GPS/GLONASS satellites are lower in the highway (signal attenuated caused by proximate vehicles) and the light woodland test cases (signal attenuated caused by trees). Overall, the visibility of GPS/GLONASS satellites for positioning and time determination is significantly higher than that of GPS only.

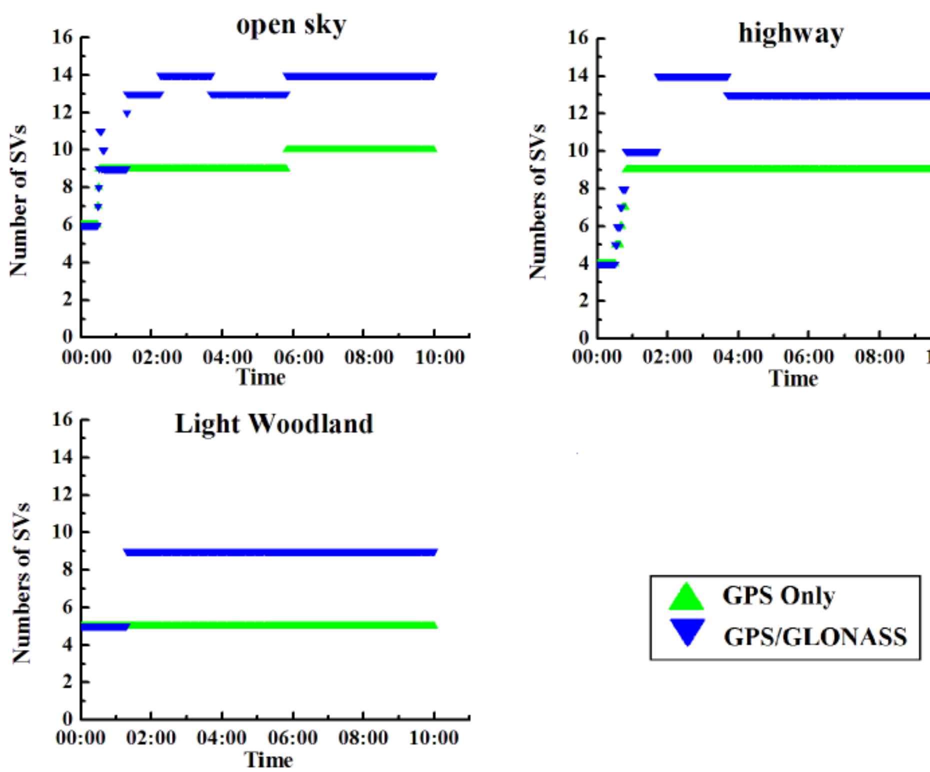

Fig.1 Numbers of Visible GPS and GPS/GLONASS Satellites in the Three Test Cases

4.2.Accuracy

In the simulation, the horizontal positioning results from GPS only, GPS/GLONASS and the data fusion PF algorithm, are compared with the reference trajectory to determine if the accuracy requirement of 5m (95%) accuracy can be fulfilled. A comparison of the position fixes from GPS only, GPS/GLONASS and the data fusion PF algorithm are shown in Figure 2. It is shown that the fusion model estimated results improve the accuracy of the positioning significantly compared to the GNSS only scenarios in these three test cases. The 95% percentile accuracy in the open sky test case is 1.24m (95%) for the data fusion PF algorithm and 2.11m (95%) for the GPS/GLONASS scenario. The corresponding value for the GPS only is 2.53m (95%). In the highway test case, the positioning accuracy is 2.03m (95%) for the data fusion PF algorithm, 2.74m (95%) in the GPS/GLONASS scenario, and 3.27m (95%) for GPS only. In the light woodland test case, the positioning accuracy is 4.82m (95%) for the data fusion PF algorithm, 8.34m (95%) for GPS/GLONASS and 10.31m (95%) for GPS only. Overall, the data fusion PF algorithm has significantly improved the positioning accuracy than the other GNSS only scenarios.

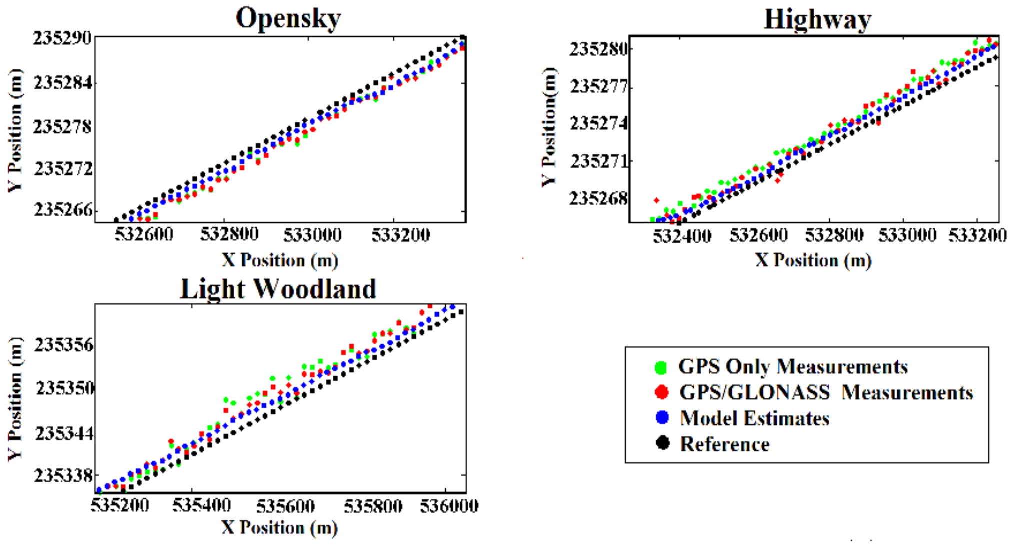

Fig.2 Comparison of the GPS Only, GPS/GLONASS and Data Fusion PF Algorithm with Respect to Reference

4.3.Integrity

Integrity is linked to mission (e.g. safety) criticality. In order to determine this parameter, redundant measurements are required (Ochieng, Flament 1996). Therefore, for 4D positioning at least five satellites should be available with good geometry for integrity monitoring. In the open sky test case, the number of satellites visible more than five for the whole simulation period for GPS only and GPS/GLONASS. In the highway test case, signal attenuate caused by the vehicle flows resulted in the visibility of at least five satellites being 94.31% of the time for GPS only and 96.83% for GPS/GLONASS. In the light woodland test case, more than five satellites are always visible during the simulation period for the GPS only and GPS/GLONASS scenarios.

In addition to redundancy, for safe operation the position error should not exceed the alarm limit of 12.5m. In particular, in the open sky test case, all the position fixes satisfy the alarm limit requirement for the data fusion PF algorithm, GPS/GLONASS and GPS only scenarios. In the highway test case, all the position fixes are within the alarm limit for the data fusion PF algorithm. However, the corresponding values for the GPS/GLONASS and GPS only scenarios are 98.67% and 97.33% respectively. In the light woodland test case, all the position fixes are within the alarm limit for the data fusion algorithm, while only 88.67% and 93.83% of the position fixes in the for GPS only and GPS/GLONASS, respectively are within the alarm limit. Overall, only the data fusion PF algorithm estimations can meet the alarm limit requirement in all these three scenarios.

4.4.Continuity

Continuity risk is the probability that the navigation system available at the start is interrupted during a specified period of operation (Ochieng, Flament 1996). This interruption and lack of guidance information occurs in these situations: lack of accuracy, position outage, integrity alert and false alert. As the sample is not large enough in these three simulation test cases, the position errors exceeding the alarm limit and position outages are proxies for continuity risk. From the results, there is no position outage problem for each simulation test case because the visible satellites are always more than four for all the scenarios. Since the requirement for integrity risk is 10^{-7}, the allowable number of interruptions is 10^{-7}*600=6*10^{-5}, effectively zero for each test case (600 positioning outputs in each test case). From the statistical analysis of the simulation results, no interruption exists in the open sky test case for all the GPS only, GPS/GLONASS and data fusion PF algorithm scenarios during the simulation period. In the highway test case, the numbers of interruption are 16, 8, 0 for GPS only, GPS/GLONASS and the data fusion PF algorithm respectively. Therefore, it can be concluded that the proposed algorithm has the lowest continuity risk. In the light woodland test case, the numbers of the interruptions are 68, 37 and 0 for GPS only, GPS/GLONASS and the proposed fusion algorithm, respectively. Overall, the proposed data fusion PF algorithm provides superior continuity than GPS only and GPS/GLONASS measurement in all the three test cases.

4.5.Availability

The navigation service is available if accuracy, integrity and continuity requirements are satisfied (Ochieng, Flament 1996). Therefore, a navigation system is available for the RUC scheme only if its accuracy, integrity and continuity requirements are satisfied. From the results statistical analysis in in terms of the accuracy, integrity and continuity performance for designed test cases, the service availability is 100% in the open sky test case, for the GPS only, GPS/GLONASS and the proposed data fusion PF algorithm scenarios. In the highway test case, the proposed data fusion algorithm service availability is 100%, while the availability for GPS only and GPS/GLONASS is 97.33% and 98.67% respectively. In the light woodland test case, the availability values for the GPS only scenario, GPS/GLONASS scenario and the new data fusion PF algorithm scenario are 88.67%, 93.83% and 100% respectively. From the simulation results, the proposed data fusion PF algorithm has the best service availability at 100%. The next section uses real data to verify the simulation results.

5. Field Test Validation

The field test is to validate the simulation results. In road transport, it is difficult to define the specific Period of Operation (PoP) in a similar manner to air transport. Thus, every positioning fix is considered as a PoP during the field test. The field test route was designed to be representative of the relevant spatial characteristics including open spaces, trees, tall buildings on one side, tall buildings on both sides, tunnels and bridges. Therefore, the chosen route in London was from Chiswick park station southbound to Heathrow Tunnel and then back to Imperial College road. The total duration of the route was 90 minutes (15:00 to 16:30). The field test route is representative of the operational environment and consists initially of a suburban segment (Cromwell road, predominantly medium rise buildings), an urban segment (around the Hammersmith areas consisting of buildings and multi-grade roads) and open highway (from Hammersmith to Heathrow airport), shown in Figure 3.

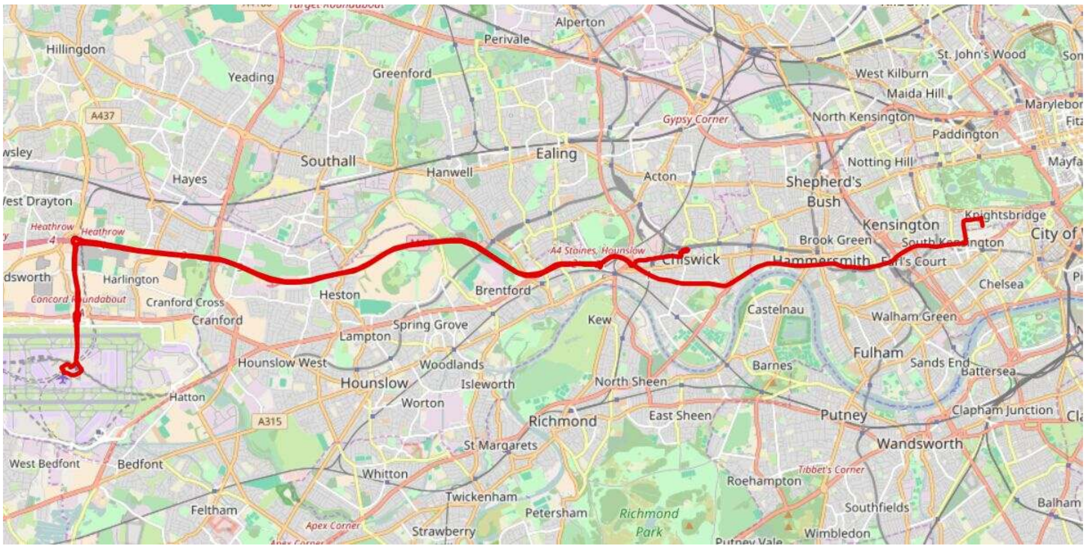

Fig. 3 Field Test Route

For the data collection the equipment used were the Leica Viva GNSS GS15 receiver, mounted on the roof of the test vehicle for the Real-Time Kinematic (RTK) GPS and GLONASS data collection. The position data refresh rate is 1Hz. The low cost u-blox DR sensor was used to output the attitude and acceleration information of the vehicle. The measurements from the RTK GPS/GLONASS data were combined with DR and road segment data in the PF. The 'truth' trajectory was determined using post-processed data from a high grade GNSS/IMU system from iMar and measured with a 1Hz frequency. The results for GPS only, GPS/GLONASS, and data fusion PF algorithm are presented below.

5.1.Satellite Coverage

The number of visible satellites for GPS only and GPS/GLONASS scenarios are shown in Figure 4. It can be seen that because of signal blockage, there were four occasions in which the number of GPS satellites dropped below four: the first from15:04 to 15:07 (signal blockage caused by trees), the second around 15:13 to 15:22(signal blockage caused by trees), the third from 15:50 to 15:55 (signal blockage caused by trees and an overhead bridge), and the fourth from 16:05 to 16:10(signal blockage caused by the Heathrow tunnel and trees). For the GPS/GLONASS scenario, satellite visibility improved significantly during the field test.

Figure 5 shows the visibility of GPS and GPS/GLONASS satellites expressed as a percentage of the field test duration. These results indicate that the visibility of at least four satellites was 88.16% and 95.29% for the GPS only and GPS/GLONASS scenarios respectively. For integrity, the basic requirement for failure detection in 4D positioning should be at least five satellites (Ochieng et al., 1999). From Figure 5, the visibility of at least five satellites was 86.01% for the GPS only and 93.71% for

GPS/GLONASS scenarios respectively. Overall, due to signal blockage the number of visible satellites is lower in the real field test than in the simulation results due to the latter's complexity in capturing accurately the relevant spatial elements.

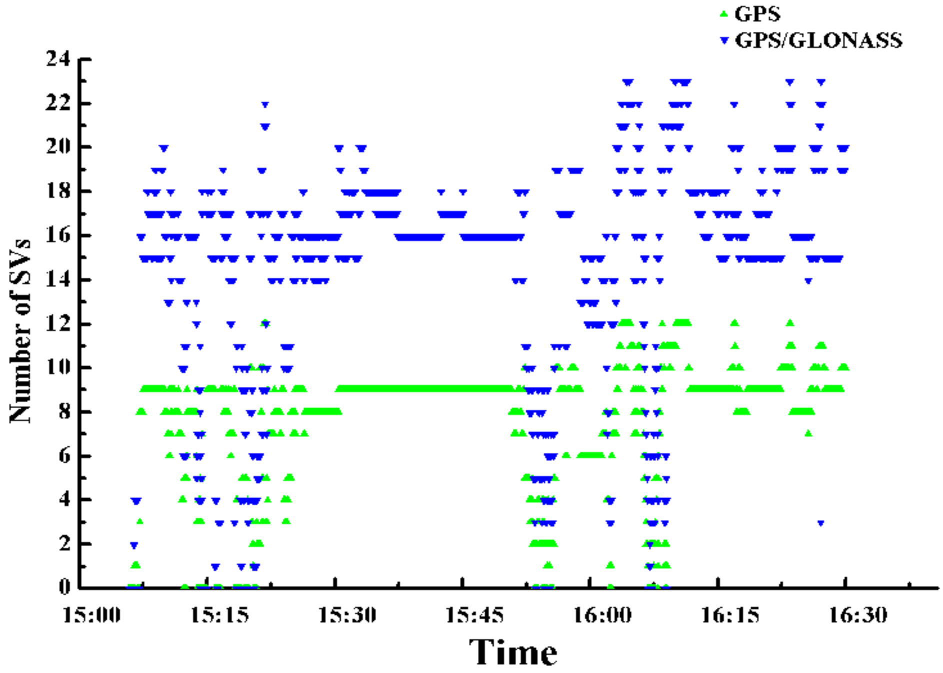

Fig.4 Number of Visible Satellites in both GPS only and GPS/GLONASS scenarios

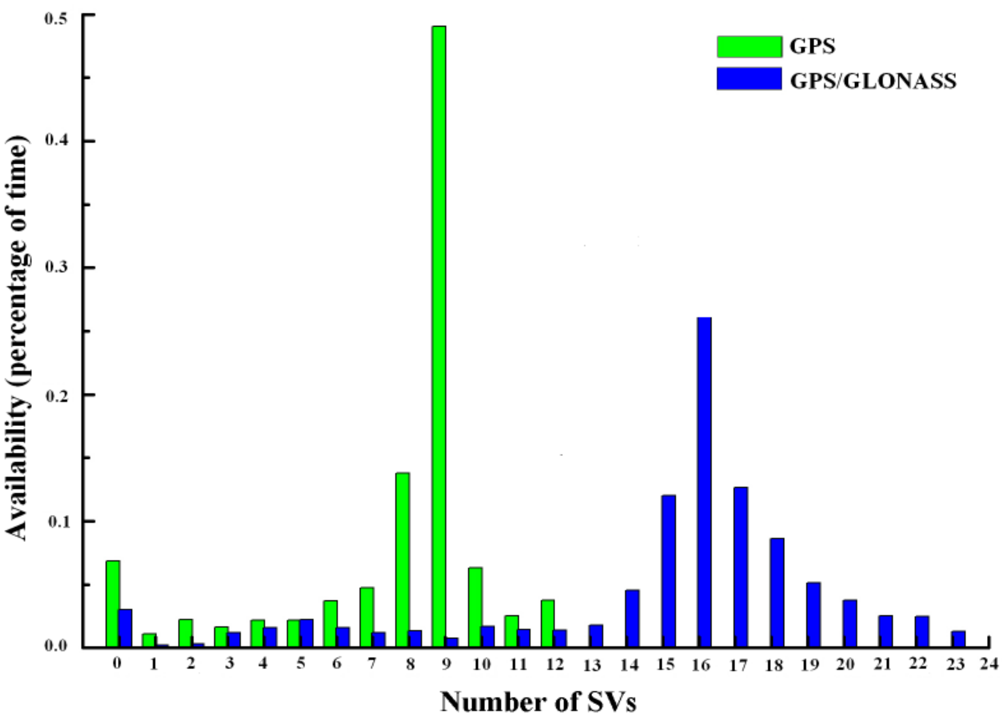

Fig.5 GPS and GPS/GLONASS Satellites Availability

5.2.Accuracy

The position errors arising from the use of GPS only measurements, GPS/GLONASS measurements and the data fusion PF algorithm are shown in Figure 6. It can be seen that the results for the GPS/GLONASS scenario are closer to the reference than the GPS only results (e.g. point 1 and point 2). Furthermore, the GPS/GLONASS scenario has a higher position fix density (e.g. points 3 and 4) than GPS only. The results from the data fusion algorithm while providing a 100% position fixing density (points 7 and 8) improves the accuracy significantly (points 5 and 6) compared to the GPS only and GPS/GLONASS scenarios.

The 95th percentile accuracy values are 4.92 (95%) for the data fusion PF algorithm, 7.84m (95%) for GPS/GLONASS and 13.74m (95%) for GPS only.

Overall, the field test results confirm those from the simulation that the data fusion PF algorithm provides the best accuracy and meets the requirement for the measurement of the VRUCIs.

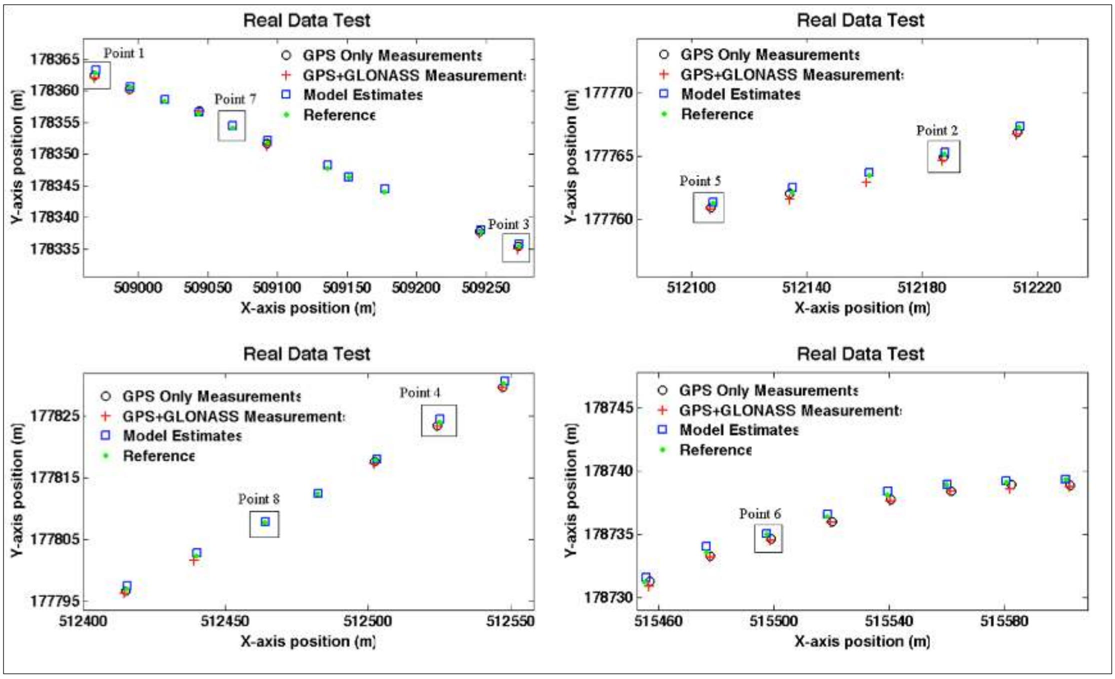

Fig.6 Comparison of the GPS Only, GPS/GLONASS and Fusion algorithm with Respect to Reference in Filed Test

5.3.Integrity

For the integrity monitoring requirement, the number of more than five satellites for the GPS only and GPS/GLONASS scenarios are 86.01% and 93.7% respectively. In terms of the alarm limit requirement, all the position fixes are within the alarm limit in data fusion PF algorithm scenario, while the corresponding values for the GPS/GLONASS and GPS only scenarios are 97.82% and 95.12% respectively.

From the results it is concluded that only the data fusion PF algorithm estimations can meet the alarm limit requirement in both simulation and field test results compared to other GNSS only scenarios.

5.4.Continuity and Availability

The two major issues considered in the continuity risk is the alarm limit and position outage. According to the continuity risk requirement, the allowable number of interruptions is 10^{-7}*5400=54*10^{-5} (5400 possible position fixes in the field test), effectively zero. The position outages occur when there are less than four visible satellites. From the test sample and results the continuity risk is zero for the data fusion PF algorithm. For the GPS/GLONASS scenario, the continuity risk is 6.8%, as there are 254 interruptions due to position outage and 117 due to position errors exceeding the alarm limit. For the GPS only scenario, the continuity risk is 16.7%, as there are 639 interruptions due to position outage and 263 due to position errors exceeding the alarm limit. It should be noted that there are more position outages and lower accuracy positioning fixes in the field test than are in the simulation. The reason is that the real test environment is more complex (i.e. tunnel overfly bridge tall buildings and trees will result in the GNSS signal loss lock during the field test) and difficult reflect accurately in simulation.

Overall, from results of the performance measured in terms of accuracy, integrity, continuity analysis, the proposed data fusion PF algorithm provides the best service availability at 100%, compared to 93.2% for GPS/GLONASS and 83.3% for GPS only. Therefore, based on the simulation and field tests, the proposed fusion algorithm can meet the RNP requirements for RUC.

6. Conclusions

This paper has proposed a new definition of Variable Road User Charging Indicators (VRUCI) by considering the equalization of the charges and the marginal social cost that each driver imposes on others. The indicators are measurable and are as far as possible independent. Because many of the indicators are related to the vehicle state, a Particle Filter (PF) data fusion algorithm exploiting GNSS, DR and road segment information has been developed for state estimation and shown to achieve the RNP requirements for RUC. Future work should collect more field test samples in a heavily built environment area for further validation of the proposed PF data fusion algorithm and address the integration of the European Galileo and Chinese Beidou systems in addition to assessing the benefits of the new GPS signals including L2C, and terrestrial signals of opportunity such as WiFi based positioning and map-matching.

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