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Uninterrupted Portable Car Navigation System Using GPS, Map and Inertial Sensors Data

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***Abstract*—This paper presents the development of car navigation system for portable navigation devices and car telematics applications. The objective was to develop a system that can provide uninterrupted reliable navigation even when GPS signals are not available. The approach uses digital maps, 3D accelerometer and one gyro for directional measurements to improve positioning availability and reliability in weak signal environment and during short GPS signal outages. This system does not require vehicle installation and can be easily transferred between vehicles. Loosely coupled extended Kalman filter and probabilistic map-matching algorithm provide optimally tuned navigation solution and continuous auto calibration of inertial sensors. A real-time prototype was built. The system accuracy performance was investigated using field tests in an urban environment.**

***Index Terms*—land vehicle navigation, driver assistance, map-matching, GPS, Kalman filtering**

I. Introduction

Accurate and uninterrupted position calculation is a key task for vehicle navigation and telematics applications. In most portable car navigation and telematics devices the position is calculated based only on GPS data. However, in urban canyons stand-alone GPS suffers signal masking and reflections of the signal from buildings, large vehicles, and other reflective surfaces. Driving tests in such metropolises as Hong Kong, Tokyo, and New York show that the chance of receiving four GPS satellites required for navigation can be as low as twenty percent of total driving time [1]. Even when four or more satellites are available, strong multipath effect might cause a positioning error of more than 100 m.

In order to obtain uninterrupted navigation data in urban environment, GPS can be augmented with a complementary navigation system that can work continuously in any type of urban environment [2], [3], [4]. This is known as an integrated navigation system. This article presents the development of integrated GPS/DR (Dead Reckoning) navigation system. A digital map database is used to update and verify the position given by the GPS or integrated GPS/DR navigation system. The process of improving navigation with the help of a map is called map-matching.

In this article we consider a DR configuration that consists of one gyro for directional measurements and 3D accelerometer. Both the gyro and accelerometers satisfy the requirements for mass market portable consumer devices: low cost, light weight, small power consumption. An odometer is not used because this requires additional car installation; our system is intended mainly for portable devices such as mobile phones, GPS-based peripherals and handheld GPS navigation devices.

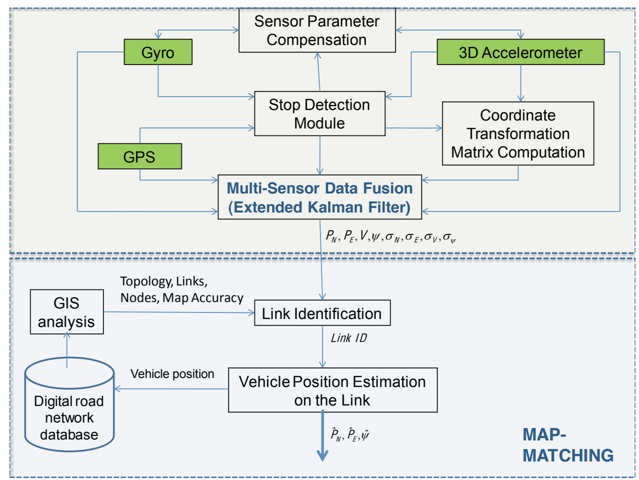

Fig. 1. Conceptual description of the navigation information sources and data flow for a portable car navigation system. The hardware elements are shaded (green).

This paper shows how GPS data can be augmented with DR sensor data using an Extended Kalman Filter (EKF) to achieve the required navigation performance in urban environment. In the proposed system the DR sensors are calibrated when GPS is available. If GPS signal is not available or GPS position accuracy suffers from multipath, the calibrated DR sensors are used to determine the position of the vehicle. The integrated GPS/DR navigation solution can be further improved using map-matching algorithm which in our case is based on particle filtering.

Field tests with real time prototype show that the proposed method improves vehicle positioning performance in high multipath signal environment and during short GPS signal outages.

II. Integration concept

The proposed car navigation system includes different types of navigation sensors and technologies. Our concept of data fusion from multiple sensor technologies is shown in Fig. 1. This methodology comprises several stages of data processing:

- Inertial sensors data for stop detection
- Inertial sensor data for position, velocity and heading computations (DR computations)

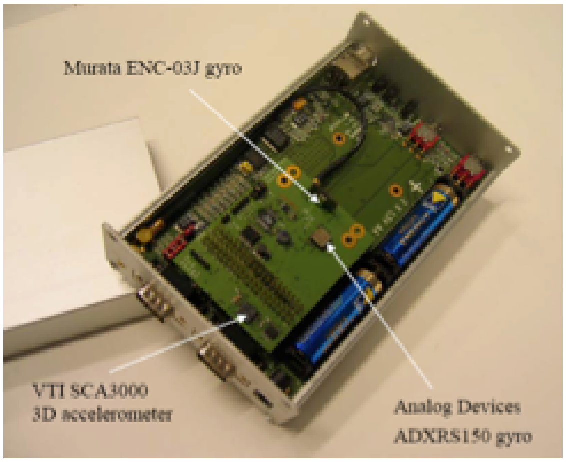

Fig. 2. Evaluation and software development kit. GPS receiver chip is on the opposite side of the PCB.

- Calibration of inertial sensors when vehicle is stationary
- Integrated GPS/DR navigation
- Map-matching

The above concept of integrating GPS, DR and map-matching will be explained in sections III–V.

III. Description of real-time prototype

To evaluate the performance of our integrated GPS/DR navigation system and map-matching algorithm, a real time prototype was built. One Analog Devices ADXRS150 yaw-rate gyro [5], and VTI Technologies SCA3000 3D accelerometer [6] were selected as the dead reckoning sensors to augment IT03 L1 GPS receiver by Fastrax [7], which is based on the Atheros chipset [8]. The inertial sensors are mounted on a separate sensor board which is connected to the Fastrax IT03 evaluation kit via SPI bus available on I/O card terminal connectors as shown in Fig. 2. Murata gyro can be also used as a cheaper alternative to the ADXRS150 gyro.

This evaluation kit allows convenient real time data fusion between the GPS and inertial sensors. In this arrangement the GPS receiver is the core of the system and is responsible for both making its own measurements, and for time tagging of the inertial sensor measurements. The integrated GPS/DR solution is computed at rate of 5 Hz and represented in NMEA 0183 format. The map-matching algorithm is implemented on the PC which is connected to the evaluation board via serial port. We are working now on the real-time implementation of our map-matching algorithm on Nokia N800 with Linux OS.

IV. Integration of GPS and DR

A. Kalman Filter

The real time data fusion algorithm employs an extended Kalman filter to combine computed GPS position, velocity, and heading with the acceleration and heading rate measurements provided by the 3D accelerometer and heading gyro. The EKF uses the values of the filter states to predict the future states through a dynamic model which is based on dead reckoning equations to estimate position, velocity, and heading. The dynamic model is given by

$$\dot{x} = \begin{bmatrix} \dot{P}_N \\ \dot{P}_E \\ \dot{v} \\ \dot{\Psi} \end{bmatrix} = f(x) = \begin{bmatrix} v\cos\Psi \\ v\sin\Psi \\ a_L \\ w \end{bmatrix}, \tag{1}$$

where P_N and P_E are the vehicle north and east positions, respectively, Ψ is the vehicle heading, w is the measured heading rate, v is the speed over ground, and a_L is the measured vehicle acceleration in the longitudinal direction. The vehicle frame longitudinal acceleration is calculated by transforming three-dimensional acceleration vector measured by accelerometers in the sensor frame into vehicle frame and calculating projection of the transformed vector on vehicles longitudinal axes. It also includes the effect of gravitational forces because of unknown road grade. It is defined by

$$a_L = a + b_L + g\theta + n \tag{2}$$

where a is the vehicle longitudinal acceleration, g is the gravitational constant, θ is the road grade and b_L is the longitudinal acceleration error. To properly model accelerometer and gyro measurement errors and unknown road grade the state vector is augmented with two additional states: gyro bias, δw, and acceleration bias and misalignment, δa, which includes unknown road grade,

$$x = [P_N, P_E, v, \Psi, \delta w, \delta a]^\top. \tag{3}$$

The observation vector is calculated by taking the difference between GPS and DR corresponding positions and velocities, and in some cases heading. The measurement update can take the following forms:

- vehicle position, velocity, and heading,
- vehicle position and velocity,
- or velocity, only in the case of the zero velocity update (ZUPT).

The position accuracy of a single frequency L1 GPS receiver is approximately 10 m in the horizontal axis and 15 m in the vertical axis. A single frequency L1 GPS receiver determines velocity based on the Doppler shift of the GPS carrier wave. The velocity accuracy in the horizontal axis can reach 2-5 cm/s and in the vertical axis 4-10 cm/s 1-σ standard deviation of the stochastic errors [9]. The accuracy of GPS depends heavily on satellite geometry and multipath errors. In this project, the update rate of the GPS receiver was set to 1 Hz to reduce the amount of computations in the processor. The GPS velocity measurements can be also used to determine vehicle heading. If there is no vehicle sideslip, the heading can be calculated as

$$\Psi^{GPS} = \arctan\frac{v_E^{GPS}}{v_N^{GPS}} \tag{4}$$

where v_E^{GPS} and v_N^{GPS} are the east and north GPS velocity measurements, respectively. The standard deviation of the heading error can be approximated by

$$\sigma(\Psi^{GPS}) = \frac{\delta v^{GPS}}{v^{GPS}}. \tag{5}$$

The GPS heading is calculated only when a vehicle has sufficient speed. This threshold is determined empirically and in the current project a threshold of 2.5 m/s was used.

B. Alignment and Calibration

In order to assist GPS with the gyro and accelerometers, initialization procedures have to be completed: initial alignment and calibration. The initial alignment procedure includes horizontal alignment based on the accelerometers outputs, yaw angle estimation, and azimuth alignment using external heading information. The initial calibration includes estimation of the accelerometer bias and misalignment, and also calibration of the gyroscope bias. The horizontal alignment and calibration are implemented in real time and can be performed at any time when vehicle is stationary. The yaw angle between sensor frame and vehicle frame can be estimated when vehicle is accelerating with constant direction [2]. It takes about 20 seconds to complete all these procedures in fully automatic mode. There is no need for the user to take any special actions. During and after the alignment the portable navigation device has to be fixed into a cradle. The system has the capability to re-initialize alignment and calibration parameters at any time when it is not moving. The need for re-computation of alignment parameters may arise due to change in orientation of the device during the drive which can be detected by the algorithm. This change in orientation can affect the gyro scale factor. The need for re-computation of accelerometer and gyro calibration parameters is caused by changes of accelerometer and gyro bias mainly because of temperature variations.

C. Stop detection

The stationary state is detected by a stop detection module based on accelerometers output. Our stop detection algorithm is based on the observation that during a complete stop the variance of the accelerometer signal is markedly smaller than when the vehicle is moving. This algorithm can work in all types of vehicles and has the ability to calibrate itself in a brief learning phase during GPS availability. The real-time version of stop detection algorithm is based on signal detection analysis of accelerometer variance data within a moving window. Unlike the algorithm described in [10] where stops are reliably detected only after 15 seconds delay, our algorithm detects stops almost immediately. The stop detection algorithm will be described in more detail in a future paper.

V. MAP-MATCHING

The digital road network map is another important component of our positioning system. A map database is a source of valuable information that can be used to improve the accuracy of the position given by the GPS/DR navigation system and calibrate the DR sensors. Map-matching algorithms usually consist of two steps: identification of the road link where vehicle is most likely travelling and estimation of vehicle position on the selected road link[9]. We used the map matching algorithm which is based on probabilistic Bayesian theory to select a correct road segment on which the vehicle is travelling. This approach is mainly based on the proximity between the position fix and the road, the difference between the estimated vehicle heading and the current segment heading from the map data, and vehicles position, velocity and heading prior to the current moment. The determination of the vehicle location on the segment is a challenging task, especially considering the errors associated with both the digital map and navigation sensors. When the vehicle is travelling on a straight road the orthogonal projection of the position fix onto the selected road segment is used to calculate the vehicle location on the segment. In this case only cross track error can be deduced by map-matching. But when the vehicle is travelling on a curved road or turning at an intersection, along track errors can also be reduced [9].

Our map-matching algorithm is built on the Bayesian framework and uses particle filtering. Because it is Bayesian, it does not associate a single specific street to a position fix, but computes a probability for every street on the map, and it is incremental [11], that is, it processes one single GPS/DR fix at a time rather than trying to identify a trajectory on the map from a sequence of fixes.

A. Model

We are interested in obtaining the sequence of streets or street segments[1] travelled by the vehicle given all the information provided by the GPS receiver and the INS sensors, namely, position, velocity, and heading. Thus, we aim at approximating the *a posteriori* pdf $p(s_{:t}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t})$, which contains all the information to estimate that sequence. Here $s_{:t}$ stands for the set $\{s_0, s_1, \cdots, s_t\}$.

Using Bayes' theorem and straightforward manipulations, we have

$$\begin{aligned} &p(s_{:t}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t}) \propto p(\mathbf{x}_t|s_{:t}, \mathbf{x}_{:t-1}, \Psi_{:t}, v_{:t})\times \\ &\times p(\Psi_t|s_{:t}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t}) p(s_t|s_{:t-1}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t})\times \\ &\times p(s_{:t-1}|\mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t}), \end{aligned} \tag{6}$$

where s_t is the street segment on which the vehicle is moving at discrete time t, and $\mathbf{x}_t$, Ψ_t, and v_t are, respectively, the position, heading and speed given by the GPS/DR system.

In order to compute $p(s_{:t}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t})$ we make several assumptions. Each assumption is connected with one or several terms in (6) and will be discussed briefly in the following.

We will start by considering that if the current street, s_t, is known, the heading given by the positioning system is independent of the previous travelled segments and previous GPS/DR fixes (position, heading, and velocity). Using the above notation, this can be written as

$$p(\Psi_t|s_{:t}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t}) = p(\Psi_t|s_t, v_t). \tag{7}$$

The dependency of the heading on the speed in (7) models the degradation of the heading measurement given by a GPS receiver as speed decreases.

[1] A street is modelled as a sequence of connected straight segments since this is the way in which most digital maps store the information.

To simplify the last two terms in (6), we also assume that the speed of the vehicle is independent of the current and any previously travelled streets, that is,

$$p(v_t|s_{:t}, \cdot) = p(v_t|\cdot). \tag{8}$$

This is a fair assumption if the digital map does not provide any information of speed limits. With this assumption, it follows that

$$p(s_t|s_{:t-1}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t}) = p(s_t|s_{:t-1}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t-1}) \tag{9}$$

and

$$p(s_{:t-1}|\mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t}) = p(s_{:t-1}|\mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t-1}). \tag{10}$$

Thus, in order to simplify computation of $p(\mathbf{x}_t|s_{:t}, \mathbf{x}_{:t-1}, \Psi_{:t}, v_{:t})$, we consider that the probability of $\mathbf{x}_t$ only depends on the current street, s_t, that is

$$p(\mathbf{x}_t|s_{:t}, \mathbf{x}_{:t-1}, \Psi_{:t}, v_{:t}) = p(\mathbf{x}_t|s_t). \tag{11}$$

Then, using equations (7), (9), (10), and (11), we can rewrite (6) as

$$\begin{aligned} p(s_{:t}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t}) \propto\, & p(\mathbf{x}_t|s_t)p(\Psi_t|s_t, v_t)\times \\ & \times p(s_t|s_{:t-1}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t-1})\times \\ & \times p(s_{:t-1}|\mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t-1}). \end{aligned} \tag{12}$$

Leaving aside the recursive part of (12), we still need to provide a way to compute the first three pdf's on the right-hand side of that equation. The first two pdf's can be either defined *ad-hoc* or estimated during a training phase of the algorithm. We assume the *a priori* probability of s_t is

$$\begin{aligned} & p(s_t|s_{:t-1}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t-1}) = \\ & = \begin{cases} (1-\alpha)/|\mathcal{S}_{t-1}|, & s_t \in \mathcal{S}_{t-1} \\ \alpha/|\mathcal{S} - \mathcal{S}_{t-1}|, & \text{otherwise} \end{cases} \end{aligned} \tag{13}$$

where $\mathcal{S}$ is the set of all streets, $\mathcal{S}_{t-1}$ is the set of streets connected to s_{t-1} (note, $s_{t-1} \in \mathcal{S}_{t-1}$), and $0 \leq \alpha \leq 1$ is a design parameter, that stands for the probability of the current street not being connected to the previous one. This could happen during the algorithm initialization or due to errors in the digital map (a missing street, for example).

The computational burden of the algorithm can be reduced if only the streets located up to a certain radius from the current GPS/DR position fix (the *road cache*) are taken into account.

Further details on the definition of the probabilities involved in (12) will be given in a follow-up paper.

B. Particle filtering

The idea behind sequential Monte Carlo (SMC) methods, also known as particle filtering (PF), is the recursive approximation of probability distributions of interest by using samples and weights [12]. Most PF methods rely on the principle of importance sampling (IS) [13] to build an empirical aproximation of the desired pdf by drawing samples from a different distribution known as importance function or proposal pdf.

In order to approximate $p(s_{:t}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t})$, we will use a proposal function of the form

$$\begin{aligned} q(s_{:t}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t}) = & \, q(s_t|s_{:t-1}, \mathbf{x}_{:t}, \Psi_{:t}, v_{:t}) \\ & \times q(s_{:t-1}|\mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t-1}). \end{aligned} \tag{14}$$

If we have M samples,

$$s_{:t}^{(1)}, s_{:t}^{(2)}, \cdots, s_{:t}^{(M)} \sim q(s_{:t}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t}), \tag{15}$$

and assign them appropriate normalized weights computed according to the IS principle,

$$w_t^{(i)} \propto \frac{p(s_{:t}^{(i)}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t})}{q(s_{:t}^{(i)}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t})}, \tag{16}$$

then an approximation of the probability of interest is

$$\hat{p}(s_{:t}^{(i)}|\mathbf{x}_{:t}, \Psi_{:t}, v_{:t}) = \sum_{i=1}^{M} \delta(s_{:t} - s_{:t}^{(i)}) w_t^{(i)}. \tag{17}$$

It is straightforward to obtain estimates of the sequence of travelled streets from the pdf in equation (17).

The recursive decomposition of the importance function in (14) allows to obtain a sample of the sequence of travelled streets up to time t, $s_{:t}^{(i)}$, from the sequence of travelled streets up to time $t-1$, $s_{:t-1}^{(i)}$, by simply drawing a sample, s_t, from the marginal proposal $q(s_t|s_{:t-1}, \mathbf{x}_{:t}, \Psi_{:t}, v_{:t})$. We will define the latter as

$$q(s_t|s_{:t-1}, \mathbf{x}_{:t}, \Psi_{:t}, v_{:t}) = p(\mathbf{x}_t|s_t)p(\Psi_t|s_t, v_t), \tag{18}$$

and the weight update equation that results in this case is

$$w_t^{(i)} = p(s_t^{(i)}|s_{:t-1}^{(i)}, \mathbf{x}_{:t-1}, \Psi_{:t-1}, v_{:t-1}) w_{t-1}^{(i)}. \tag{19}$$

A more thorough explanation on the use of particle filtering to solve the map-matching problem given the model depicted in section V-A will be presented in the aforementioned follow-up paper.

C. Position accuracy enhancement

The above procedure allows to identify the street segment in which the vehicle is moving, but we still need to find out its position on that segment. This is a challenging task, especially taking into account the errors associated with both the digital map and the navigation sensors. Given a position fix and its corresponding segment, we assume the true position of the vehicle is the point on the latter that is the closest to the former. More sophisticated (and complex) approaches [14] could be used here based on the above map-matching procedure.

VI. Experimental Results

The system was tested in a real driving environment that included tunnels, parking garages, urban canyons, and road interchanges. Typical performance during these road tests is presented in this section. In Figures 3–4, the blue line is a DGPS computed trajectory which is a reference trajectory in our case. The position error of Novatel DGPS receiver didn't exceed 0.5 m during the test. The green line is the GPS/DR integrated solution. During GPS outages it will be the DR only

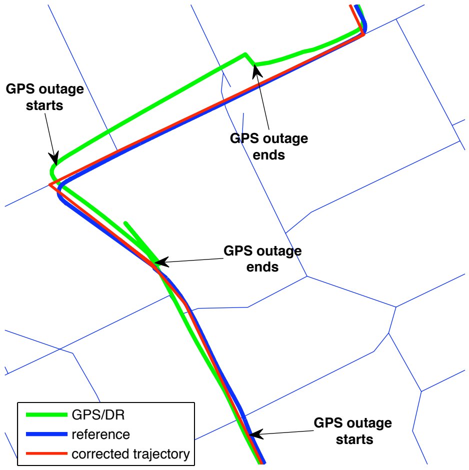

Fig. 3. Reference trajectory, uncorrected GPS/DR trajectory, and GPS/DR trajectory corrected using our map-matching particle filter.

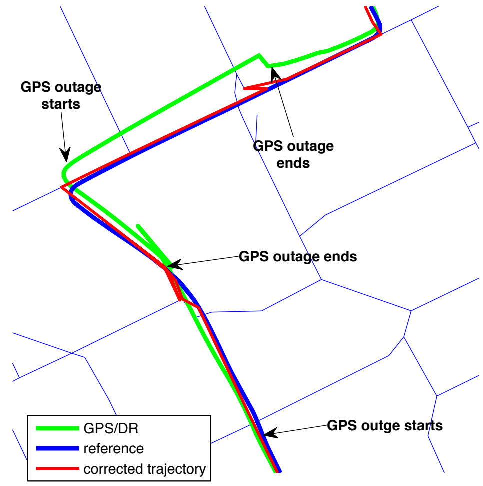

Fig. 4. Reference trajectory, uncorrected GPS/DR trajectory, and GPS/DR trajectory corrected using Mahalanobis map-matching scheme.

solution. The red line corresponds to a corrected solution after map-matching algorithm was applied. We have implemented two different versions of map-matching algorithm: one is based on probabilistic approach implemented in a form of particle filter which is described in this paper, another is based on calculation of Mahalanobis distance between road segments and a vehicle [15], [11]. The performance of particle filter based algorithm (Fig. 3) is superior to the second approach (Fig. 4). This test shows that the combined GPS/DR solution provides significant improvement; accurate position, velocity, and heading information were available even in the absence of GPS signal.

VII. Conclusion

This paper has shown that low-cost inertial sensors and map-matching algorithm can significantly improve GPS positioning by continuing to output position during short GPS outages with sufficient accuracy for most of car navigation applications. The integrated GPS+MEMS system has also demonstrated improvement of position and velocity accuracy in high multipath urban canyon environment and the ability to provide continuous output of the vehicle heading even when vehicle is not moving. This is useful when we apply the map-matching algorithm. This device does not require any installation in the vehicle. It works in all vehicles and can be easily transferred between vehicles. Finally, it should be noted that our design is suitable for portable navigation devices since the cost, size and power consumption of inertial sensors meet the requirements for mass market consumer electronics.

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