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Vehicle Localization with Global Probability Density Function for Road Navigation

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***Abstract*— This paper presents a novel approach of real-time vehicle's localization (position and orientation) estimation. Fusion of GPS, gyroscope, speedometer and visual data is employed here to provide real time and accurate localization information. Global Probability Density Function(PDF) is adopted to be the blending factor instead of general Kalman gain, which allows our approach to be robust and accurate for most of practical systematic problems, since the basic measurements from GPS may cause data drift or large infrequent data jumps during the fusion processing. Combining with visual data for lane shape recognition and tracking, our approach can provide as accurate as 3 to 5 meters RMS location accuracy at about 30Hz, with less then 35ms delay. This approach has been adapted to the direct visual navigation system in VICNAS.**

I. Introduction

MANY advanced safety and navigation applications require the precise localization information of vehicle. Global Positioning System (GPS) and inertial sensors are generally applied to provide localization information in these systems.

Previous research on self-positioning can be divided into three basic categories [3], [7]: stand-alone (e.g. odometer, inertial navigation), satellite-based (e.g. global positioning system), and terrestrial radio-based system (e.g. cellular networks). Other landmark-based or map-based approaches have also been proposed which use ultrasonic, sonar, or laser range sensors [2]. Recently, most of applications combine GPS data with inertial sensors [6], or vision sensors [4].

GPS-based vehicle localization algorithms are well studied and widely applied in in-vehicle navigation market since Pioneer® introduced the first commercial in-vehicle navigation system in 1990s. An on-road navigation system is generally defined as the integrated system that is mainly used to provide location and navigation information on the screen to help driving. Figure 1 shows an example of in-vehicle navigation system.

Localization algorithm in these state-of-the-art navigation systems generally takes advantages of the complementary characteristics of GPS, deduced reckoning (DR) and map matching technology with road network database. GPS data provides the absolute position, and DR sensors like inertial sensor, yaw rate sensor and odometer will provide supplemental position data when GPS signal is blocked or lost. Map Matching (MM) algorithm is usually applied for correcting vehicle's physical location to the nearest road position by assuming a vehicle is traveling on the road. Extended Kalman filter [9], particle filter [10] and other fusion algorithms are the most popular algorithms in navigation system to estimate vehicle's localization.

Major difficulties with respect to GPS and inertial sensor-based localization systems are the uncertainty of measurement error and data delay. Position accuracy will vary with GPS receiver's configuration (receiver and antenna), location (geographic latitude, as it influences HDOP, and surrounding objects possibly blocking reception or causing multi-path reception), satellite constellation status, and ionosphere conditions. Due to the cost issue, the accuracy of current low cost commercial GPS system is about 20 meters in Longitude/Latitude and 10 degrees in orientation. The output frequency is about 1 Hz. The delay problem of GPS measurement, namely, the delay between localization request time and response time is not constant, is the key issue that affects real-time applications. An average of 1 to 2 seconds delay from receiving GPS signal to location output is normal and even worse delay can be observed in urban area when map matching calculation is heavy. This delay will cause a very unstable estimation result of vehicle's location.

However, most of advanced safety and visual navigation [1] applications are required to control vehicle's movement real-timely or provide real-time indications for driving assistance. Real-time, high accurate and stable measurement of vehicle's position and orientation are vital to these

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applications, which are essentially unavailable from previous localization approaches.

In this paper, a real-time fusion approach for vehicle localization is presented. Data fusion is achieved by Kalman filter with global probability density function to deal with GPS's non-Gaussian distributed measure errors. It allows our approach to be robust and accurate for most of the practical problems in vehicle localization systems like slow data drift and large infrequent data jumps. At the same time, visual sensor based lane shape recognition and tracking compensates the offset displacement to road centreline.

The paper is outlined as follows: In Section II, global PDF based real-time vehicle localization algorithm is explained in detail. Implementation details in the application of visual navigation system (VICNAS) are introduced in Section III. Real outdoor test results are also presented. Finally, we give the conclusion and discuss the future perspective of our work.

Figure 1. Example of in-vehicle navigation system

II. GLOBAL PDF BASED REAL-TIME VEHICLE LOCALIZATION APPROACH

As described in Section I, real-time, high accurate and stable measurement of vehicle's position and orientation is vital to the applications like advanced safety and visual navigation systems, since it is required to control vehicle's movement or provide real-time indications for driving assistance.

The local measurement (inertial sensor) is integrated with global measurement (GPS data) to compensate and interpolate vehicle state vector (position and orientation) with Kalman Filter. Global probability density function (PDF) is adopted here to be the blending factor instead of general Kalman gain, which allows our approach to deal with data difference between reference measurement from GPS and information calculated by motion model.

A. *Vehicle State Vector*

Vehicle state $(x, y, ori)^T$ including position and orientation is the main parameter considered of on-road applications. Here, x and y are local plane coordinates transformed from global Longitude /Latitude data [12], and ori is the orientation angle.

The position accuracy provided by low cost GPS/DGPS unit in vehicle navigation system is closely related with satellites location and surrounding objects. In a wide-open area, it can generally provide 10 to 20 meters accuracy at about 1 Hz. After map matching process, an average of 4 to 5 meters accuracy can be achieved.

Since map matching outputs the closest road center line position and orientation, it can not present the exactly vehicle state on the road which always introduces a lateral offset and deviation angle referring to road center line. In this paper, the vehicle state vector is expressed as follows:

$$\begin{bmatrix} x \\ y \\ ori \end{bmatrix} = \begin{bmatrix} x_g \\ y_g \\ ori_g \end{bmatrix} + \begin{bmatrix} x_v \\ y_v \\ ori_v \end{bmatrix} \tag{1}$$

where $(x_g, y_g, ori_g)^T$ is the state estimation based on GPS/INS and odometer, $(x_v, y_v, ori_v)^T$ is the supplement vector by visual sensor to detect the lateral offset and deviation angle to road centred line.

Vehicle's motion on road can be generally treated as a rigid body motion (Figure 2). A general predication equation of vehicle state vector $\hat{X}_k = (\hat{x}_{g(k)}, \hat{y}_{g(k)}, \hat{ori}_{g(k)})^T$ is shown in equation (2). Vehicle state vector at time k can be estimated by the observation state at time k-1 and the fusion result of GPS/INS and odometer when sampling time is small enough.

$$\begin{bmatrix} \hat{x}_{g(k)} \\ \hat{y}_{g(k)} \\ \hat{ori}_{g(k)} \end{bmatrix} = \begin{bmatrix} x_{g(k-1)} \\ y_{g(k-1)} \\ ori_{g(k-1)} \end{bmatrix} + \begin{bmatrix} \Delta d \times \cos(ori_{k-1}) \\ \Delta d \times \sin(ori_{k-1}) \\ \Delta\varpi_{(k-1)} \end{bmatrix} \tag{2}$$

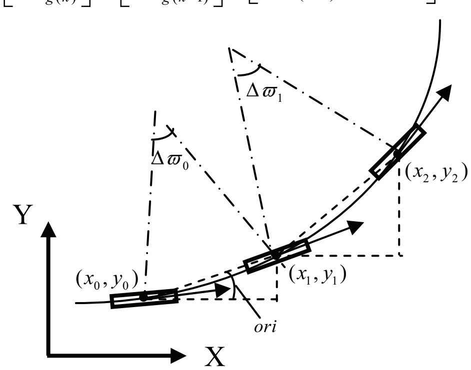


Figure 2. Motion model in world coordinate system

where $\Delta\varpi$ is the orientation variation, which can be derived directly from gyroscope's Yaw angle output. Δd is the displacement between sampling positions, which can be calculated by vehicle velocity from speedometer output as (3).

$$\Delta d = speed_k \times \Delta t \qquad (3)$$

Δt is the sampling time of gyroscope, which is normally less than 20ms.

B. Vehicle State Compensation with Global PDF

Vehicle state prediction based on equation (2) suffers with slow data drift as gyroscope and speedometer only provide differential data. This drift has to be recursively corrected upon each new GPS measurement comes.

Similar with other tracking problems, a Kalman fiter works well for prediction and correction problem in the linear Gaussian situations, if the highly restrictive Kalman gain assumptions hold. The compensation state vector is expressed in equation (4) at GPS sampling time *i*:

$$\mathbf{C}_i = \mathbf{K}_i(\mathbf{X}_i - \mathbf{H}\hat{\mathbf{X}}_i) \qquad (4)$$

where $\boldsymbol{C}_i = (Cx_i, Cy_i, Cori_i)^{\mathrm{T}}$ is the compensation state vector, $\boldsymbol{K}_i$ is the Kalman gain matrix, $\hat{\mathbf{X}}_i$ is the predicted state vector provided by (2) and $\mathbf{X}_i$ is the GPS measurement.

Unfortunately, it is very hard to calculate the Kalman gain in the practical application without related update functions. Even if these functions could be acquired, it will increase the complexity and computational expense. Moreover, GPS measurement is an obvious non-gaussian distributed data with uncertain data drift and large infrequent data jumps. If the general linear Kalman gain vector is used to calculate the compensation state vector, the overall state vector will be unstable because of the GPS bias, which can be always observed in urban area.

In this paper, we propose a global Probability Density Function (PDF) based approach to calculate compensation state vector. PDF from Bayesian perspective is required as a recursive factor between prediction and update instead of traditional Kalman gain in order to stabilize the state vector from sudden or/and large measurement variation. The compensation state vector is expressed as follows:

$$\mathbf{C}_i = (1 - \mathbf{P}_i)(\mathbf{X}_i - \mathbf{H}\hat{\mathbf{X}}_i) \qquad (5)$$

where P_i is the probability vector and it can be derived as a gaussian density probability.

$$\boldsymbol{P}_i = \frac{1}{\sqrt{2\pi}\delta_{\Delta_i}} \exp\{-\frac{(\Delta_i - \overline{\Delta}_i)^2}{2\delta_{\Delta_i}{}^2}\}. \qquad (6)$$

where $\mathbf{\Delta}$ is the prediction error $\mathbf{\Delta}_i = \mathbf{X}_i - \mathbf{H}\hat{\mathbf{X}}_i$. $\overline{\mathbf{\Delta}}$ is the mean value of prediction error and $\delta_\Delta{}^2$ gives the standard deviation. $\overline{\mathbf{\Delta}}$ and $\delta_\Delta{}^2$ are statistical constant by variable $\mathbf{\Delta}$.

With the introduction of PDF concept, the compensation vector $\mathbf{C}_i$ is normally distributed with mean $\overline{\mathbf{\Delta}}$ and variance $\delta_\Delta{}^2$ (standard deviation δ_Δ). The new GPS measurement data would be taken into consideration through weighted probability from PDF function. It will largely eliminate the random bias from GPS.

Furthermore, by local PDF calculation like equation (6), a long time drive on straight road will cause PDF's over-centralization since map matching's performance is good in this case and the standard deviation of predication error will be extremely small. PDF's over-centralization to a certain value will weaken its effectiveness since it will neglect the normal variations on orientation and position like lane change or slow turn. In this paper, we take a global probability limitation into consideration. The probability calculated in eq.(6) will be saturated to a certain limitation depending on the performance of GPS and related digital map.

Finally, the vehicle state is estimated by the result of predicted state and compensation. The vehicle state function is expressed as:

$$\begin{bmatrix} x_{g(k)} \\ y_{g(k)} \\ ori_{g(k)} \end{bmatrix} = \begin{bmatrix} \hat{x}_{g(k)} \\ \hat{y}_{g(k)} \\ o\hat{r}i_{g(k)} \end{bmatrix} + \begin{bmatrix} C_x \\ C_y \\ C_{ori} \end{bmatrix} \qquad (7)$$

where $(C_x, C_y, C_{ori})^T$ is the compensation state vector based on last GPS measurement.

Figure 3 shows the result of vehicle state's error and compensation respectively, where "---" line is the error between prediction and measurement and the "----" line is the compensation during update. Comparing with a simple low pass filter or general Kalman filter, the global PDF based approach provides an effective compensation by stabling the state vector recursively in low vibration while keeping a close track to the prediction error.

C. Visual Compensation

The offset calculated by visual analysis is necessary to correct vehicle position from road center line to its exact lane position.

$$\begin{cases} x_{v(k)} = (W - d_{(k)}) \times \mathbf{cos}(\frac{\pi}{2} + ori_{w(k)} + \theta_{(k)}) \\ y_{v(k)} = (W - d_{(k)}) \times \mathbf{sin}(\frac{\pi}{2} + ori_{w(k)} + \theta_{(k)}) \end{cases} \qquad (8)$$

where *W* is road width in one direction, which is provided by the digital road map. $d_{(k)}$ is the offset to the leftmost roadside, $\theta_{(k)}$ is the deviation angle to road center line. $d_{(k)}$ and $\theta_{(k)}$ can be calculated from lane tracking result.

An efficient algorithm [11] of road model for lane recognition and tracking by EKF was applied to retrieve road shape parameters as well as vehicle state parameters including pitch angle, lateral offset, deviation angle and camera's height. Figure 4 shows the result of lane detection and virtual green lanes based on road parameters are shown on the image.

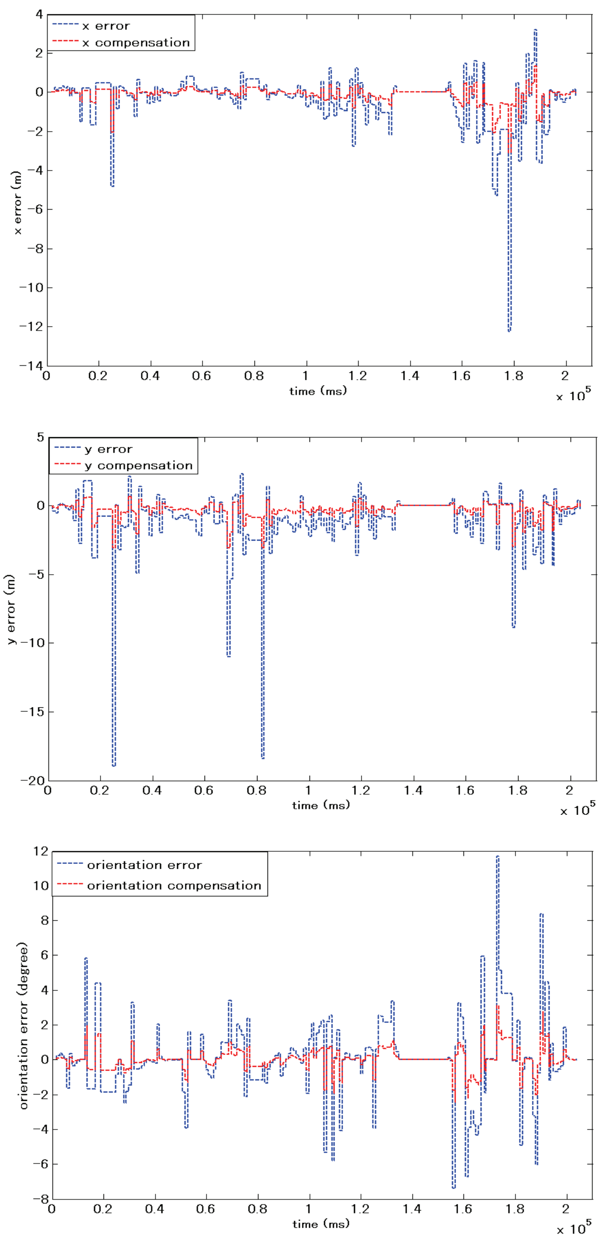


Figure 3. Vehicle state compensation result based on global PDF

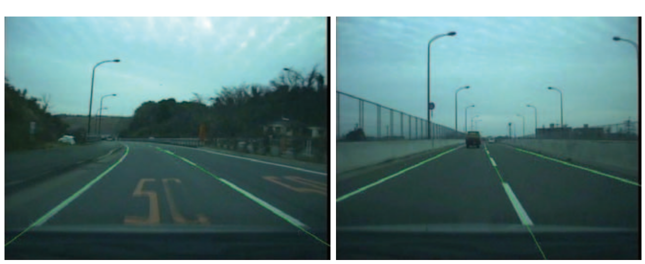


Figure 4. Examples of lane detection

III. IMPLEMENTATION ON VISUAL NAVIGATION

With the development of voice guidance and dynamical traffic information exchange techniques, recent vehicle navigation systems will guide you with voice instructions well in advance of your next move along a pre-planned route. However with a traditional navigation system, drivers still have to compare by himself the road scene ahead with his digital map to determine which lane to take or, at which intersection to turn. It is not only inconvenient, but also even dangerous in some cases, especially during the high-speed driving in dense traffic roads. A new concept of direct visual navigation and its prototype system – Vision-based Car Navigation System (VICNAS)[1] was proposed by the authors to overcome this problem. As shown in Figure 5, VICNAS employs Augmented Reality technique to superimpose virtual direction indicators and traffic information bulletins upon the real driver's view.

Since all the virtual indicators and overlay graphics have to be aligned properly with the real road scene from driver's view, the accuracy of navigation that VICNAS can provide absolutely depends on the accuracy of the estimated vehicle state vector, which means localization accuracy directly determines the visually-perceived performance of this AR system.

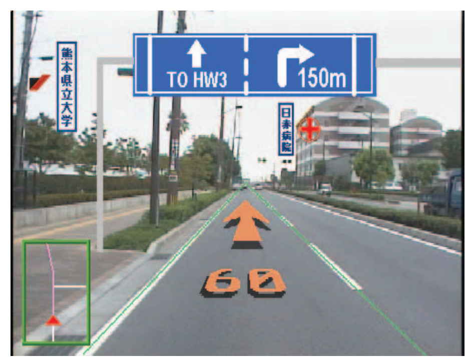


Figure 5. Vision-based Road Navigation System: VICNAS

A. System Setup

All components in our system are off-the-shelf products on the market: a Teli CCD COLOR CAMERA was mounted on the front roof of test vehicle, image sequences were captured in NTSC format at the frame rate of 30fps, GPS data (Pioneer® AVIC-DR2030ZZ) and inertial data (Gyroscope: Datatec®GU-3024 & CAN: Kvaser® USBcan II HS/LS) were sent to PC's serial port and recorded at the frequency of 1Hz and 60Hz separately; Zenrin® Z-Map Town II (1/25,000) was used as the 2D road map.

Outdoor test environment includes the most general road types (express toll-way, city highway, downtown street and countryside road), different lane structures (one-way or two-way, 1~6 lanes, with or without central separators) and shapes (straight, curve, S-curve). Tests were also carried out in no GPS signal area like tunnels and road under overpass. The following navigation information is extracted from the digital map: 1) road nodes location and segment attributes (name, level, lane info, etc.); 2) intersection location, names and crossing angles of the roads intersected; 3) landmarks, buildings and other value-added objects information (hospitals, gas stations, shopping centers, restaurants, etc.).

All information is dynamically extracted according to the current location (within certain range) and driver's preference. Icons are generated depending on its category: road information such as speed limits, direction indicators are modeled as virtual road paintings and are located on the road surface, road names and intersection information are modeled as virtual traffic bulletins mounted on a certain height above the road. All these Points Of Interests (POIs) are visible along the driving route and no occlusion is considered in the perceived performance tests.

B. *Vehicle State Estimation Results*

To evaluate the performance of our approach, the state-of-art in-vehicle navigation system (Pioneer® AVIC -DR2030ZZ) is used to compare with our approach. The estimation results of vehicle state are shown in Figure 6, in which the measurement data from navigation system is marked as "■" points, and "●" points are data fusion result by our approach.

As described above, high building, signal random reflection in urban area and weak signal plus imprecise digital map in mountain area will significantly affect accuracy of GPS. Even for commercial hybrid (GPS+DR+ MM) navigation system, many segmented GPS tracks still can be observed from Figure 6(a).

Comparing with navigation system's output, estimation results of our approach correctly compensate the vehicle state and follow the trajectory based on "■" points in real time. Moreover, it successfully solved GPS's measurement delay problem which can be observed in the enlarged part in Figure 6(a) and Figure 6(b). The estimation points "●" present the right state much more precisely and timely comparing with navigation system output. The estimation results verified that our approach is more precise, efficient and adaptive to the visual navigation application.

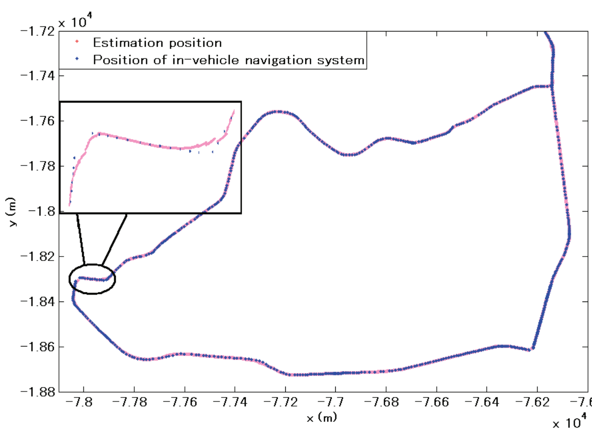
C. *Visual Perceived Performance Test*

Once vehicle's position and orientation are estimated, we converted the position and POIs' latitude/longitude data (which were based on Tokyo Datum) to the Euclidean planar coordinate system. With the calculated camera's extrinsic parameters, POIs' WCS coordinates were transformed to the camera based CCS coordinates and then projected to the image plane. An icon will be rendered on each POI's projection position. Icon's size and orientation is determined by POI's CCS coordinates. The movie files of evaluation results can be downloaded from the following web site:

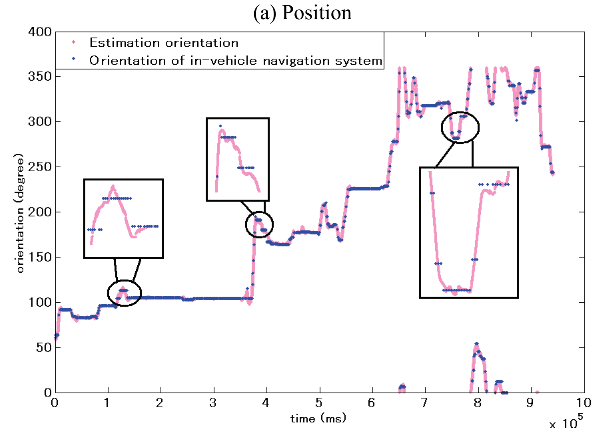
http://navi.cs.kumamoto-u.ac.jp/~hu/ITS/image/.

Figure 7 shows some superimposing results by projecting the virtual objects on the real image overlay. Although the store is occluded and driver could see straight, the icon of store could still be see-through to the scene for guidance (Fig.7 (a)) when vehicle is in heavy traffic. The distance to the intersection is shown in Fig.7 (b) and the direction of crossing could also be shown by ICON along the preplanned route. Even no GPS signal in tunnel, the exit of tunnel could still be shown precisely (Fig.7 (c)) based on our global PDF based state estimation approach.

Figure 8 shows an image sequence when test vehicle was turning left and the virtual POI indicator (railway station) kept perfectly pace with scene movement. It shows that our vehicle state estimation is very precise without delay.



(a) Position

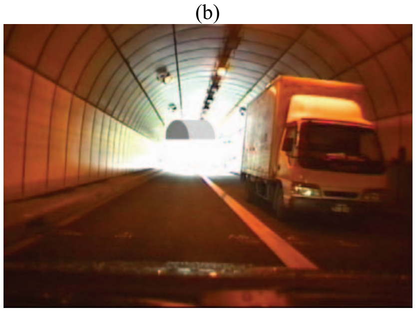


(b) Orientation

Figure 6. Comparison result of vehicle's state between GPS and estimation

(a)

(b)



(c)

Figure 7. Superimposing results of virtual indicators onto real images

Figure 8. Image sequence of POI indicator (railway)

IV. CONCLUSION

This paper presents a real-time data fusion approach for vehicle localization to adaptive stabilization of uncertain GPS localization system. Our approach is based on the fusion of GPS, gyroscope and speedometer to compensate and interpolate vehicle state vector (localization and orientation) with Extended Kalman Filter. The global probability density function (PDF) is adopted to be the blending factor instead of general Kalman gain function, which allows our approach to be robust and accurate for most of practical problems like slow data drift, large infrequent data jumps. The algorithms proposed in this paper are implemented in our visual navigation application and validated with the experimental results of real road tests under different conditions and types of road.

In the future we would like to extend the algorithm for higher accuracy localization with the method of visual pattern matching between navigation information and visual cues on the road.

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