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MULTI-SENSOR DATA FUSION FOR FUTURE TELEMATICS APPLICATION

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ABSTRACT

In this paper, we present multi-sensor data fusion for telematics application. Successful telematics can be realized through the integration of navigation and spatial information. The well-determined acquisition of vehicle's position plays a vital role in application service. The development of GPS is used to provide the navigation data, but the performance is limited in areas where poor satellite visibility environment exists. Hence, multi-sensor fusion including IMU (Inertial Measurement Unit), GPS (Global Positioning System), and DMI (Distance Measurement Indicator) is required to provide the vehicle's position to service provider and driver behind the wheel. The multi-sensor fusion is implemented via algorithm based on Kalman filtering technique. Navigation accuracy can be enhanced using this filtering approach. For the verification of fusion approach, land vehicle test was performed and the results were discussed. Results showed that the horizontal position errors were suppressed around 1 meter level accuracy under simulated non-GPS availability environment. Under normal GPS environment, the horizontal position errors were under 40 cm in curve trajectory and 27cm in linear trajectory, which are definitely depending on vehicular dynamics.

Keywords: telematics, muti-sensor data fusion, land vehicle localization

1. INTRODUCTION

The next wave of motor vehicles will do more than transportation or commutation. In flourishing future telematics environment - the combination of telecommunications and informatics, our next vehicle will be a mobile office, a data center on wheels, a node on an E-commerce network, and a moving entertainment center. To supply the adequate contents for mobile driver, it is required to follow up super-power technology in following areas - mobile transmission and transfer rate of large volume data and determination of vehicle's position using satellite navigation (HILTECH 2001).

In that sense, the integration of a navigation-grade IMU and the GPS has lots of advantages, where navigation or position and attitude information is required. When it comes to land vehicle application and telmatics, integration is particularly required in urban canyon areas where the signal from the satellites is susceptible to blocking or detracting by high story building or trees. However, there are limitations of government restrictions and high price in using high performance IMU (Shin 2001). Therefore, recent research and study have emphasized on using low cost IMU and GPS integration by the benefit of computing power and low price of IMU.

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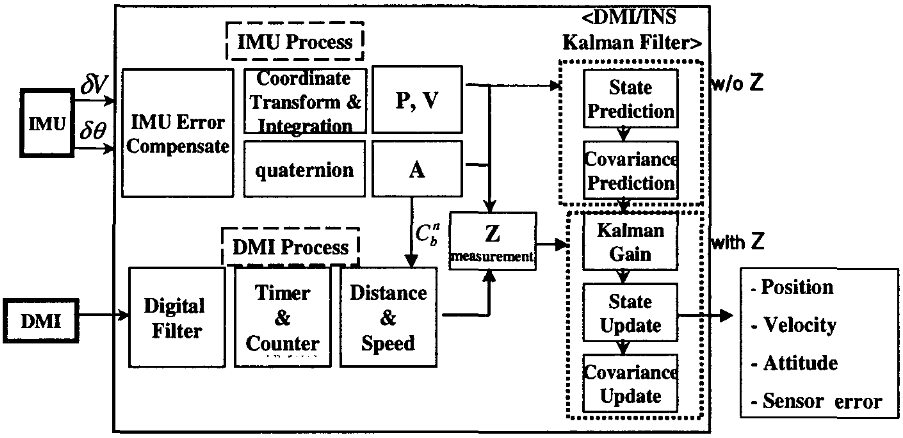

Figure 1. General Loosely Coupled Approach.

In this paper, we present a novel approach to integrate IMU and GPS under good satellite signal tracking environment and IMU/DMI integration under bad satellite signal reception. The implementation of this approach can provide better circumstances for future telematics based society.

This paper is organized as follows. In Section 2 and 3, basic ideas of integrating DGPS/IMU/DMI are introduced. Experimental results are covered in Section 4. Finally, conclusions are given in Section 5.

2. GPS/IMI/DMI INTEGRATION ISSUES

GPS/IMU/DMI integration is required to meet the positioning accuracy and availability in a local area. There are basically two-integration approach based on extended Kalman filtering technique, namely loosely coupled and tightly coupled approaches. With regard to loosely coupled approach, it manages GPS, IMU and DMI as an independent system. GPS or DMI solution is fed back into Kalman filtering to estimate IMU errors. The errors in the derived position and velocity are modeled as white noise. In contrast, tightly coupled approach deals with GPS, IMU and DMI as one system and one sensor. Therefore, only single filter is adopted to complete the integration system (Brown & Hwang 1997).

With regard to DMI, the wheel rotation sensor is used. The wheel revolution from the sensor is transformed to measure total distance that a vehicle traveled. Given time information traveled, a forward velocity is determined. DMI is not subject to signal masking or outages. The positioning errors are accumulative with time. For the purspose of calibration of DMI sensor, the scale factor error is the most critical element as it affects the total distance traveled and the forward speed. Hence, adequate modeling for this error state should be designed as either a random constant or a first order Gauss-Markov process.

DMI plays a critical role in that process especially in loosely coupled method. When the land vehicle enters into GPS unfavorable environment, DMI provides an alternative measurement to calibrate and compensate a low cost IMU. The rest of the paper presents a design of GPS/IMU/DMI integration, the details of mathematical modeling and results obtained field practical experiment.

3. GPS/IMU/DMI INTEGRATION FILTER DESIGN

The integration of GPS/IMU/DMI is based on the concept of loosely coupled method and takes advantage of extended Kalman filter.

3.1 IMU Error Model

To construct the dynamic model for the Kalman filter requires mathematical error model of IMU and GPS systems. Several IMU error models have been derived, which are all equivalent. In this paper, the following error model is used. Error state vectors in the Kalman filtering scheme consist of navigation parameters, and accelerometer and gyroscope error states (Jekeli 2001). In this model, the errors modulated by the Earth's spin rate are neglected because of short-range application.

$$\begin{bmatrix} \dot{x}_i \\ \dot{x}_f \end{bmatrix} = \begin{bmatrix} F_{11} & F_{12} \\ O_{6\times9} & O_{6\times6} \end{bmatrix} \cdot \begin{bmatrix} x_i \\ x_f \end{bmatrix} + \begin{bmatrix} G \\ O_{9\times6} \end{bmatrix} \begin{bmatrix} W_g \\ W_A \end{bmatrix} \tag{1}$$

$$z(t) = H \cdot x(t) + v(t), \quad \nu \sim N(O,R) \tag{2}$$

where

$$x_i = [\delta\alpha \ \delta\beta \ \delta\gamma \ \delta Vn \ \delta Ve \ \delta\phi \ \delta\lambda]^T$$

$$x_f = [\delta Wn \ \delta Wn \ \delta Wn \ \delta fn \ \delta fn \ \delta fn \ k1 \ k2 \ k3]^T$$

$$w_i = [Wg \ Wg \ Wg \ Wa \ Wa \ Wa]^T$$

$$F_{11} = \begin{bmatrix} 0 & 0 & 0 & 0 & \cos\phi & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sin\phi & 0 & 0 \\ 0 & \frac{g}{r} & 0 & 0 & 0 & 0 & 0 \\ -\frac{g}{r\cos\phi} & 0 & -\frac{a}{r\cos\phi} & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix},$$

$$F_{12} = \begin{bmatrix} -C_b^n & O_{3\times3} & O_{3\times3} \\ O_{2\times3} & JD^{-1}C_b^n & JD^{-1}C_b^n diag(a^s) \\ O_{9\times3} & O_{9\times3} & \\ O_{2\times3} & O_{2\times3} & O_{2\times3} \end{bmatrix}$$

$$J = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \quad G = \begin{bmatrix} -C_b^n & O_{3\times3} \\ O_{3\times3} & C_b^n \\ O_{9\times3} & O_{9\times3} \end{bmatrix}$$

where $\delta\alpha, \delta\beta$ and $\delta\gamma$ are the orientation error vector, Vn and Ve are the velocity error vector, $\delta\phi$ and $\delta\lambda$ are the position error vector respectively. With regard to sensor errors, we considered gyroscope bias which denoted as $\delta\omega$, accelerometer bias and scale factor which denoted as δf and k, respectively. In this model, the errors are modulated by the Earth's spin rate is neglected because of short-range application.

3.2 IMU/GPS Integration

In this paper, we adopted following GPS/IMU integration approach. The detailed description of integration scheme is depicted in Fig 1. This fusion approach includes a 17 state Kalman filter that is to calibrate IMU and a navigation equation that is to transform angular velocity and linear acceleration to attitude, velocity and position. The estimated errors from Kalman filter components are fed back to update the inertial solution and sensor measurements (Farrel & Barth 1999). The

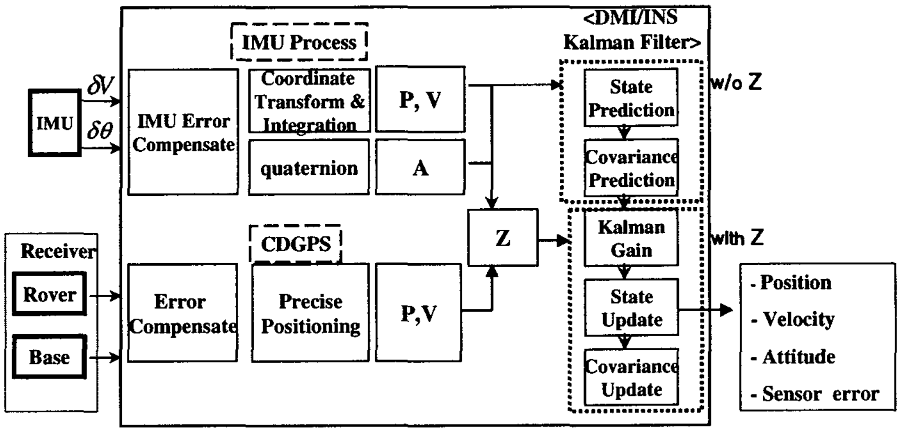

Figure 2. Multi-Data Fusion during GPS Signal Blockage.

position and velocity from GPS are considered as measurements and observation vector is as follows (Kim et al. 2002).

$$Z = \begin{bmatrix} V_{ins} \\ P_{ins} \end{bmatrix} - \begin{bmatrix} V_{GPS} \\ P_{GPS} \end{bmatrix}, \quad H = \begin{bmatrix} 0_{ix3} & I_{ix2} & 0 \\ 0_{ix3} & 0 & I_{ix2} \end{bmatrix} \tag{3}$$

3.3 IMU/DMI Integration

From DMI, the information of pulse and time interval representing distance traveled can be acquired. The accuracy of DMI is limited by distance measurement and that system requires having initial location and attitude conversion matrix as containing relative positioning. The detail data flow is depicted in Figure 2. The measurement of DMI should be converted to navigation frame and offset vectors between sensors are considered. Hence, the observation is as follows.

$$Z = [V_{ins}] - C_b^n[Speed] + (\Omega_{\mathrm{ie}} + \Omega_{\mathrm{en}})C_b^n \Delta P, \quad H = [0_{ix3} \quad I_{ix2}] \tag{4}$$

where ΔP represent sensor displacement vector, Ω_{ie} represents the rotation rate of the Earth, and Ω_{en} represents the rate of change of position.

4. EXPERIMENTAL RESULT

In order to verify the reliability of GPS/IMU/DMI integration, field test was performed for 30 minutes in a trajectory chosen from a suburb of DaeJeon. The test vehicle consists of single Trimble GPS receiver, single Litton 200 IMU, and DMI, which mounts directly to the vehicle's right side rear wheel. Raw IMU and DMI measurements were recorded at 200 Hz, while dual-frequency GPS data were logged at 1 Hz. During the experimental test, there were more than 6 visible satellite signals available.

Fig. 3 shows a vehicle trajectory used for validation of integration approach. In this chapter, we deliberately selected three different environments. In case I section, we simulated that there was GPS signal blockage and analyzed the IMU/DMI fusion errors. In case II and III, we analyzed the IMU/GPS prediction errors with respect to different vehicle dynamic such as curve and linear trajectory. For performance analysis, we compared the result of commercial post-processing S/W

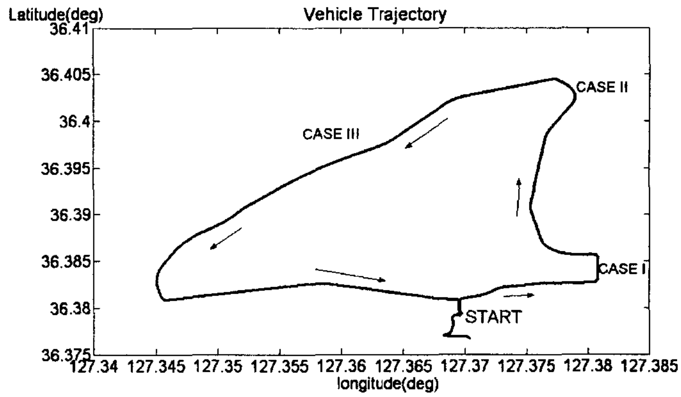

Figure 3. Vehicle Trajectory with GPS signal outage position.

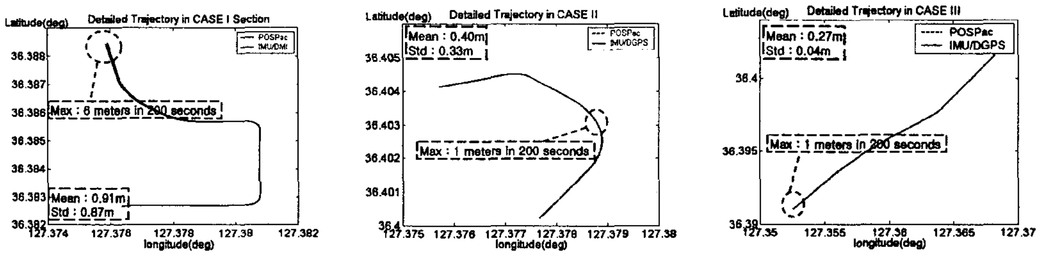

Figure 4. Detailed Trajectory in Case I, II and III.

POSPac^{TM}. It computes and integrates carrier phase GPS solution and inertial data in forward and reverse time processing to heighten the data accuracy, which has around 1-2 cm level accuracy under GPS favorable environment (Mostafa 2001). Figure 4 shows the detail trajectories of case I, II and III and horizontal positioning errors in each cases. The results of IMU/GPS or IMU/DMI integration approaches were denoted in black line and results of POSPac^{TM} were illustrated in red dotted line. Our fusion approach provided similar result with POSPac^{TM}.

For the analysis, we simulated GPS adverse operational environment in case I section because of the analysis of IMU/DMI integration performance. In case I, the mean positioning errors are successfully suppressed below 1 meters although maximum positioning errors went up to 6 meters in 200 seconds. Therefore, our fusion approach successfully verified that it could meet the requirements of land vehicle navigation around meter level accuracy. In case II and III, where GPS favorable environment supported, mean positioning errors are under 40 cm. As expected, the position errors are more related to vehicle maneuver. Especially, the smaller errors were indicated in linear vehicle maneuver. Table 1, 2 and 3 summarize mean and standard deviation positioning errors in each case.

5. CONCULSION

As the vehicle enters GPS unfavorable environments such as urban canyon, the IMU cannot provide enough information for telematics and land vehicle navigation. To overcome this drawback

Table 1. Positioning error in Case I.

	East	North
Mean (m)	0.814	0.410
Std (m)	0.572	0.658

Table 2. Positioning error in Case II.

	East	North
Mean (m)	0.304	0.148
Std (m)	0.143	0.038

Table 3. Positioning error in Case III.

	East	North
Mean (m)	0.145	0.138
Std (m)	0.032	0.658

of low cost IMU, we present an approach to integrate IMU, GPS and DMI utilizing velocity calculated from odometer sensors. The measurements were fed back into the Kalman filter to reduce and compensate IMU errors and improve the performance during GPS signal blockage. Preliminary test results were presented to show the effectiveness for telematics application. The contribution of this paper is that we introduce another modality to integrate low cost IMU, GPS and DMI for telematic applications, even though further simulations and algorithm refinements are required.

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