Multi-model Switching for Car Navigation Containing Low-Grade IMU and GPS Receiver

Seong Yun Cho, Byung Doo Kim, Young Su Cho, and Wan Sik Choi

ABSTRACT—This letter presents a filter for a car navigation system integrating a low-grade inertial measurements unit (IMU) and a global positioning system receiver. The filter is designed according to the state variables to be estimated and the usable measurements. The usable measurements change from case to case, and the estimative state variables also change due to the measurements; therefore, multiple models must be used for real environmental maneuvers. In this letter, four models for land navigation are chosen and switched by rearranging the system matrix and resetting the error covariance matrices.

Keywords—Car navigation, INS/GPS integrated system, multi-model switching.

I. Introduction

The typical car navigation system consists of a global positioning system (GPS) receiver, digital map, and navigation computer. However, GPS signal is only partially available in the urban environment. To provide seamless position information, a car navigation system can adopt a dead reckoning/GPS integrated system, which can be accomplished using an odometer, magnetic compass, accelerometer, gyro, and so on [1], [2]. In this letter, an inertial navigation system (INS)/GPS integrated system is adopted for car navigation. The INS and the GPS can be integrated using a proper filters such as a Kalman filter. Due to the nonlinearity of the systems, a nonlinear filter must be selected, such as the extended Kalman filter, or the sigma point Kalman filter [1], which is designed according to the state variables to be estimated and the measurement information. In a real environment, several cases occur, such as stop, run, GPS signal blockage, and so on. In each case, the usable measurements are different, and the estimative state variables change according to the measurements [3]; therefore, different models must be used in each case [4]. In this letter, four models are designed for four different cases, and a model switching (MS) method is used for continuous filter driving. This filter, incorporating MS, can prevent incorrect estimation of unobservable state variables and can reduce the computational burden.

II. Design of Multi-model Switching

The proposed INS/GPS filter is designed with four different measurement models and MS as shown in Figs. 1 and 2. Figure 1 shows a block diagram of the INS/GPS system. The filter consists of four models based on a GPS receiver and additional information extracted from the INS and the IMU. Model 1 (M1) is the *0-velocity model*, model 2 (M2) is the *15th state INS/GPS model*, model 3 (M3) is the *19th state INS/GPS model*, and

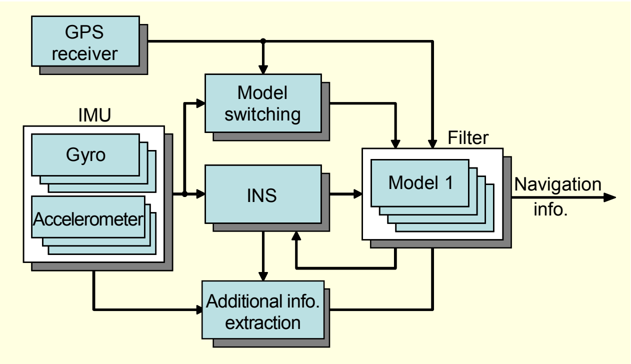

Fig. 1. Block diagram of the INS/GPS system.

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Seong Yun Cho (phone: + 82 42 869 1636, email: sycho@etri.re.kr), Byung Doo Kim (email: bdkim@etri.re.kr), Young Su Cho (email: choys@etri.re.kr), and Wan Sik Choi (email: choiws@etri.re.kr) are with the Telematics & USN Research Division, ETRI, Daejeon, Rep. of Korea.

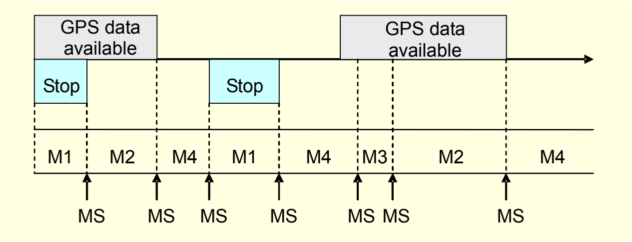

Fig. 2. Scenario for model switching.

model 4 (M4) is the *constrained INS model*. The MS is performed by using the information obtained from the GPS receiver and the IMU. The scenario for MS is described in Fig. 2.

1. Measurement Models

The main frame for the system matrix of the filter is the 15th state model [5]. The state vector includes position error, velocity error, attitude error, accelerometer bias, and gyro bias. When a vehicle stops, secure information, the zero velocity of the vehicle, can be adopted as a measurement:

$$z(k) = V^n(k) - \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T = \delta V^n(k). \tag{1}$$

When the vehicle moves, three situations can be considered. If GPS signal is not available, the non-holonomic constraints of a vehicle (for example, the velocity of the vehicle on the axes perpendicular to the forward direction which is nearly zero [4]) are used as a measurement. To construct the measurement model, the relations between the body-frame velocity and navigation-frame velocity must be considered:

$$\begin{aligned} &\hat{V}^b = \left(\hat{C}_b^n\right)^T \hat{V}^n \\ \Leftrightarrow\ & V^b + \delta V^b = \left(C_b^n\right)^T \left(I + (\phi^n \times)\right)\left(V^n + \delta V^n\right), \end{aligned} \tag{2}$$

where δV^i is the i-frame velocity error, $\phi^n \times$ is the skew symmetric matrix of the attitude error vector, and C_b^n is the direction cosine matrix.

The velocity error on the body-frame can be approximated as

$$\begin{aligned} \delta V^b &\cong \left(C_b^n\right)^T \delta V^n + \left(C_b^n\right)^T (\phi^n \times) V^n \\ &= \left(C_b^n\right)^T \delta V^n - \left(C_b^n\right)^T (V^n \times) \phi^n. \end{aligned} \tag{3}$$

Therefore, the measurement model for the constrained INS model is designed as

$$z(k) = V_{yz}^b(k) - \begin{bmatrix} 0 & 0 \end{bmatrix}^T = \delta V_{yz}^b(k), \text{ and} \tag{4}$$

$$\begin{aligned} H(k) = \Bigg[& \begin{matrix} c_{12} & c_{22} & c_{32} \\ c_{13} & c_{23} & c_{33} \end{matrix} \ \Bigg\vdots \ \begin{matrix} -c_{22}V_D + c_{32}V_E \\ -c_{23}V_D + c_{33}V_E \end{matrix} \\ & \begin{matrix} c_{12}V_D - c_{32}V_N & -c_{12}V_E + c_{22}V_N \\ c_{13}V_D - c_{33}V_N & -c_{13}V_E + c_{23}V_N \end{matrix} \ \Bigg\vdots \ \begin{matrix} 0_{1\times3} \\ 0_{1\times3} \end{matrix} \Bigg], \end{aligned} \tag{5}$$

where H is the measurement matrix, and c_{ij} denotes the components of the direction cosine matrix.

When the GPS signal becomes available, the constrained INS model is still used for some time determined previously because the GPS data is not reliable in this term. After this section, GPS position information is used as a measurement:

$$z(k) = P_{INS}(k) - P_{GPS}(k). \tag{6}$$

2. Model Switching Rule

Figure 3 shows the system matrix and error covariance matrix according to the models. If the vehicle stops, M1 is used. The stop condition of the vehicle is estimated using accelerometers. The flowchart for stop detection is shown in Fig. 4, where a_x and a_z are accelerometer outputs of the x-axis and z-axis, respectively, and δ_x, δ_z, and δ_N are adjustable threshold values. In this case, the position error, accelerometer bias (x, y), vertical axis attitude error, and gyro bias cannot be estimated. Only 8 states are estimated using the reduced system matrix (M1). If the vehicle moves and GPS signal is not available, M4 is used. The position error is not estimated, so only 12 states are estimated using the reduced system matrix (M4). Then, M3 is used for some time set in advance. In this case, the sensor biases are not estimated, and the 9th system matrix is used (M3). During M4, position error is accumulated despite the constrained INS model. If the sensor biases are included in the state vector to be estimated, false biases can be estimated due to the position error. After M3, M2 is used with the full system matrix while GPS signal is available. It uses only the value corresponding to the area shown in Fig. 3 with update and propagation of the error covariance matrix.

When the model is changed, the MS term is performed first. The measurement error covariance matrix and the process error covariance matrix are changed according to the measurement

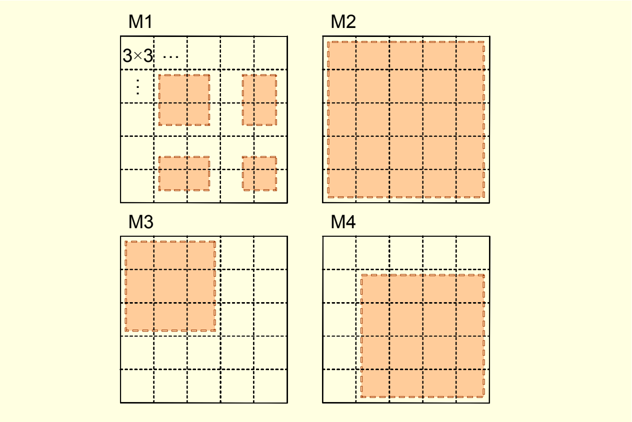

Fig. 3. System matrix and error covariance matrix according to models.

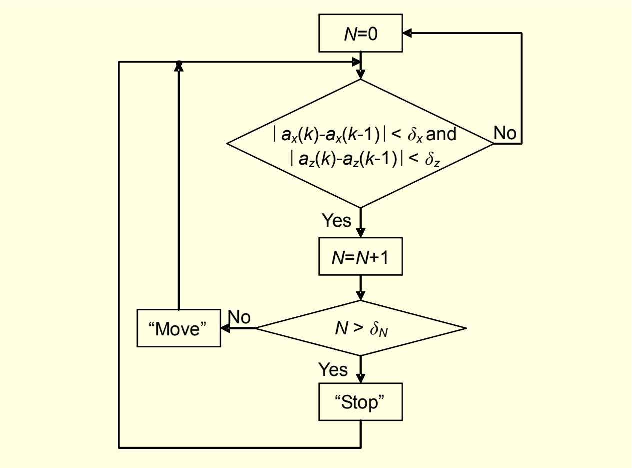

Fig. 4. Flowchart for stop detection.

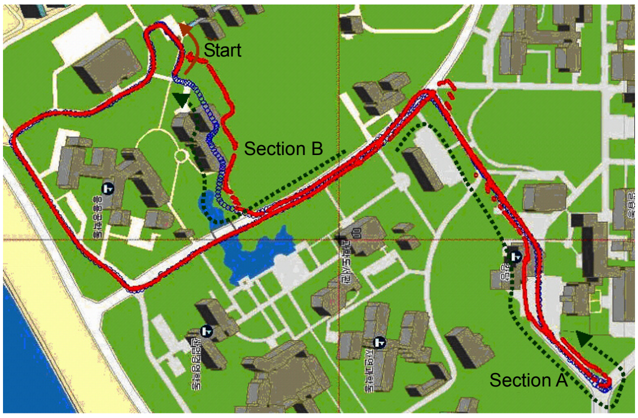

Fig. 5. Experimental result 1.

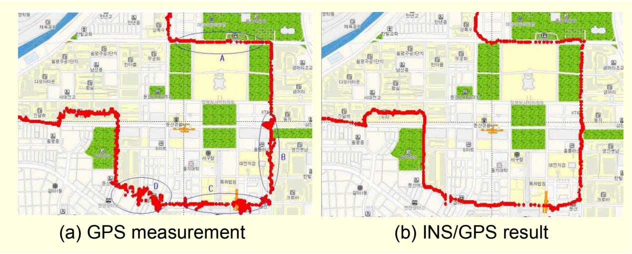
(a) GPS measurement
(b) INS/GPS result

Fig. 6. Experimental result 2.

and the state vector, respectively. The off-diagonal elements of the state error covariance matrix are reset by force. Thus, an error covariance matrix of the 15th state can be implemented continuously by using the allocated area shown in Fig. 3 on the measurements and resetting the off-diagonal elements.

III. Experimental Results

To verify the performance of the proposed INS/GPS integrated system, experiments were performed. Figure 5 shows the results. The blue dotted line denotes the true trajectory, and the red line denotes the INS /GPS result. We assume that GPS signal is unavailable in section A and section B marked by dotted lines. The 0-velocity model is used before starting. The INS/GPS 15th state model is adopted before the vehicle enters section A and when it is between section A and section B. The constrained INS model is used in section A and section B. The INS/GPS 9th state model is used some time after the vehicle leaves section A.

Continuous and reliable position information is provided using the proposed system. Figure 6 shows that GPS measurement is not reliable in the urban environment; however, the INS/GPS containing the proposed filter can provide smoothed and error reduced position information.

IV. Conclusion

Multi-model switching for the INS/GPS system was investigated. Four models were designed and were changed according to the scenario by rearranging the system matrix and resetting the error covariance matrices. The performance was examined by experiments, and showed good results.

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