논문 2009-46SC-3-4

INS/GPS 통합에 따른 관성 센서 에러율 감소 방법

(Inertial Sensor Error Rate Reduction Scheme for INS/GPS Integration)

Iftikhar Khan*, 백 승 현*, 박 경 린***, 강 성 민****, 이 연 석*****, 정 태 경**

(Iftikhar Khan, Seunghyun Baek, Gyungleen Park, Sungmin Kang, Yeonseok Lee, and Taikyeong Jeong)

요 약

GPS 와 INS 통합시스템은 저가 MEMS 기술의 결과에 따라 대중적으로 널리 사용되기에 이르렀다. 그러나 저가센서에 의한 현재의 성과는 관성센서의 큰 에러 때문에 여전히 낮은 실정이다. 이것은 제한된 도시환경 안에서의 비행범위 때문에 더욱 관련이 있다. 이러한 관성센서 에러를 줄이면서 동시에 위성의 활용성을 높이기 위하여 GPS 와 저가 INS 는 연성으로 결합되어 Kalman Filter 설계를 응용하여 상호 통합되어진다. 본 논문에서는 연성으로 결합된 Kalman Filter를 이용한 GPS/INS 센서 통합을 제공한다. 우리는 또한 경로의 기하학에 의해 또는 그 목적 시간 위치 따라 수학적으로 설명하는 ZH45C 궤도장치에 의한 산출된 기준 Wander Azimuth Strapdown Mechanization의 시뮬레이터 결과를 비교하여 검증하다.

Abstract

GPS and INS integrated systems are expected to become commonly available as a result of low cost Micro-Electro-Mechanical Sensor (MEMS) technology. However, the current performance achieved by low cost sensors is still relatively poor due to the large inertial sensor errors. This is particularly prevalent in the urban environment where there are significant periods of restricted sky view. To reduce the inertial sensor error, GPS and low cost INS are integrated using a Loosely Coupled Kalman Filter architecture which is appropriate in most applications where there is good satellite availability. In this paper, we present the GPS/INS sensor Integration using Loosely Coupled Kalman Filter approach. We also compare the simulation results of Wander Azimuth Strapdown Mechanization Scheme with the reference values generated by the ZH35C trajectory simulator that is describe mathematically either by the geometry of the path, or as the position of the object over time.

Keywords : Micro-Electro-Mechanical Sensor(MEMS), Loosely Coupled, Kalman Filter, Wander Azimuth Strapdown Mechanization.

* 학생회원, * 정회원, 명지대학교 통신공학과
(Dept. of Communication Eng. Myongji University, Korea)
*** 정회원, 제주대학교 전산통계학과
(Dept. of Computer Eng. Cheju National University, Korea)
**** 정회원, 중앙대학교 경영대학
(College of Business Administration Chung-Ang University, Korea)
***** 정회원, 군산대학교 전자정보공학
(Dept. of Electronics and Information Eng. Kunsan National University, Korea)

※ This research was supported by the MIC(Ministry of Information and Communication), Korea, under the ITRC(Information Technology Research Center) support program supervised by the IITA (IITA-2009-C1090-0902-0040). This research was supported by the Korea Science and Eng. Foundation (KOSEF) grant funded by the Koreagov.(MOST) (No.R01-2007-000-20599-0) and (No.M20809005636-08130900-63610). This work was financially supported by the Kunsan National University's Long-term Overseas Research Program for Faculty Member in the year 2007
접수일자: 2008년3월14일, 수정완료일: 2009년3월9일

I. Introduction

High accuracy and low cost are the two basic but conflicting requirements to be considered for vehicles requiring a navigation capability. The aim of this research is to develop low-cost and accurate INS/GPS aided inertial navigation system for land vehicles. The needs of safety, traffic control, fleet management, optimization of mass transit scheduling, require development of Autonomous Vehicle Positioning Systems (AVPS) for land vehicles such as buses, trains, cars, etc. The prime purpose of these systems is to determine continuously, in real time, the position of moving vehicles with satisfactory level of accuracy and reliability.

In recent years, several AVPS systems have been developed that uses Global Positioning System (GPS). However, application of GPS in urban conditions presents serious problems due to blocking of satellite signals by tall buildings and trees. Reflection of the satellite signals from the buildings introduces additional errors. Also, GPS is unavailable in tunnels and for subway trains.

An alternative to the GPS approach is dead reckoning. Dead reckoning is based on continuous measurements of vehicle's heading and speed or traveled distance which are used to compute trajectory. These systems require initialization, i.e. starting position of the vehicle must be provided to the AVPS. Several existing dead reckoning systems use various sensors to measure direction of vehicle's motion. Specialized form of dead reckoning is Inertial Navigation System. Inertial navigation is based on measurements of the acceleration and the angular rotation of the vehicle by accelerometers and gyroscopes respectively[1].

The high cost of inertial sensors and strict maintenance requirements restricted applicability of the inertial navigation systems in the past to high-end military applications. They have been used for applications where their utilization was justified by the unique system requirements. Recent advances in the development MEMs based relatively inexpensive and small inertial sensors lead to the development of inertial navigation systems (INS) for civilian land vehicles. Inertial navigation system calculates the velocity and position of a vehicle by integrating the measurements of gyroscope and accelerometer. Since MEMS based IMU has inherent sensor biases and drifts, so when we integrate the measurements of gyroscope and accelerometer, the error also gets integrated and the error starts to accumulate and the position accuracy reduces with passage of time and the system becomes unstable.

A combination of an INS with GPS is advantageous. It provides position estimates at a higher update rate and a smaller position error than a stand-alone INS or GPS system. Usually, the INS acts as the main navigation system since it is self contained, and if available, GPS position estimates are used to correct the errors in the INS.

In this paper we have presented the GPS/INS Integration Scheme using Loosely Coupled Kalman Filter Algorithm. In Section II we have introduced the general navigation equations. In Section III we have discussed the Strapdown Inertial Navigation System (SINS) Mechanization algorithm. In Section IV we have presented the INS System Error Model. In Section V we have presented Loosely Coupled Kalman filter algorithm. In Section VI, we have presented the simulation results of Wander Azimuth Strapdown Inertial Navigation Mechanization Scheme and loosely coupled Kalman filter algorithm.

II. General Navigation Equations

Navigation mechanization refers to the equations and procedures used with a particular inertial navigation system in order to generate position and velocity information. We begin our discussion by noting that the differential equation of motion of inertial navigation of vehicle relative to an inertial frame can written in vector as[2~3]

$$\dot{R} = V \quad (1)$$

$$\left[\frac{dV}{dt}\right]_I = A + g_m(R) \quad (2)$$

where R = geocentric position vector, V = velocity of the vehicle relative to the inertial frame = $[V_X V_y V_Z]$

A = non-gravitational specific force, gm(R) = gravitational acceleration due to mass attraction.

Now we wish to express the earth centered inertial acceleration in terms of the specific force and the gravitational acceleration.

$$\ddot{R}^I = C_P^I A^P + g_m^I(R)$$

We need to refer the position and velocity of the vehicle to an earth-fixed coordinate system which rotates with the earth.

$$\left[\frac{dR}{dt}\right]_I = \left[\frac{dR}{dt}\right]_E + \Omega \times R = V + \Omega \times R$$

$$V = V_{xI} + V_{yJ} + V_{zK} \quad (4)$$

Where Ω is the angular rate of the earth relative to the inertial frame. V is the true velocity of the vehicle with respect to the earth. It should differentiating Eq. (4) with respect to the inertial coordinates.

$$\left[\frac{d^2R}{dt^2}\right]_I = \left[\frac{dV}{dt}\right]_I + \Omega \times V + \Omega \times (\Omega \times R) \quad (5)$$

The output of the accelerometer gives quantities that are measured along the platform (or system axes). Differentiation or integration of these components is therefore carried out with respect to the platform axes. The derivative of the velocity V with respect to the platform axes is an essential quantity and can be related to the derivative with respect to inertial space by the expression.

$$\left[\frac{dV}{dt}\right]_I = \left[\frac{dV}{dt}\right]_P + \omega \times V \quad (6)$$

Where ω is the angular rate of the platform with respect to inertial space. Substituting Eq. (6) into Eq. (5) result in

$$\left[\frac{d^2R}{dt^2}\right]_I = \left[\frac{dV}{dt}\right]_P + (\omega + \Omega) \times V + \Omega \times (\Omega \times R) \quad (7)$$

Substituting Eq. (7) into Eq. (2) gives the expression

$$A = \left[\frac{dV}{dt}\right]_P + (\omega + \Omega) \times V + \Omega \times (\Omega \times R) - g_m(R) \quad (8)$$

Since the centripetal acceleration of the earth term $\Omega \times (\Omega \times R)$ is a function of position on the earth only it can be combined with the mass attraction gravity term to give the apparent gravity vector as

Ⅲ. SINS Mechanization

INS mechanization is the process of determining the navigation states (position, velocity and attitude) from the raw inertial measurements through solving the differential equations describing the system motion. IMU measurements include three angular rate components provided by the gyroscopes and denoted by the 3x1 vectors w_{ib}^b well as three linear acceleration components provided by the accelerometers and denoted by the 3x1 vector f b. Mechanization is usually expressed by a set of differential equations and typically performed in the local level frame defined by the local east, north and ellipsoid normal[4].

$$\begin{pmatrix} \dot{r}^l \\ \dot{v}^l \\ \dot{R}_b^l \end{pmatrix} = \begin{pmatrix} D^{-1}v^l \\ R_b^l f^b - (2\Omega_{ei}^l + \Omega_{el}^l)v^l + g^l \\ R_b^l(\Omega_{ib}^b - \Omega_{il}^b) \end{pmatrix} \quad (13)$$

Where

r^l is the position vector in the local level frame including the latitude ψ, the Longitude (λ), and the ellipsoidal height (h)

v^l is the velocity vector in the local level frame $(v_{east}, v_{north}, v_{up})$

$$v^l = ((R_N + h).\dot{\lambda}\cos\varphi, (R_M + h).\dot{\varphi}, \dot{h}) \qquad (14)$$

R_b^l is the transformation matrix from body to local frame as a function of attitude components

g^l is the gravity vector in the local level frame

$$g^l = G^l - \Omega_{ie}^l \Omega_{ie}^l r^l \qquad (15)$$

$\Omega_{ib}^b, \Omega_{il}^b$ are the skew-symmetric matrices of the angular velocity vectors $\omega_{ib}^b, \omega_{il}^b$ respectively.

$$\omega_{lb}^b = \omega_{ib}^b - R_l^b \omega_{il}^l \qquad (16)$$

$$\omega_{ib}^b = \bar{\bar{\omega}}_{ib}^b - d_{ib}^b \qquad (17)$$

D^{-1} is a 3x3 matrix whose non zero elements are functions of the user's latitude φ and ellipsoidal height (h).

$$D = \begin{bmatrix} 0 & 1/(R_M + h) & 0 \\ 1/(R_N + h)\cos\varphi & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}. \qquad (18)$$

Figure.2 shows the SINS mechanization block diagram. First of all we have to convert the specific force calculated by the accelerometer in body frame f^b in to Earth centered earth fix frame f^e.

The computation involved to implement the system described in equation (1) includes the processing of angular rate measurements implied in the term Ω_{ib}^b and the specific force term f^b as shown in Fig.1. Firstly, gyro drift corrections are applied to the measured body rates with respect to inertial space by using equation (17). The corrected angular rate

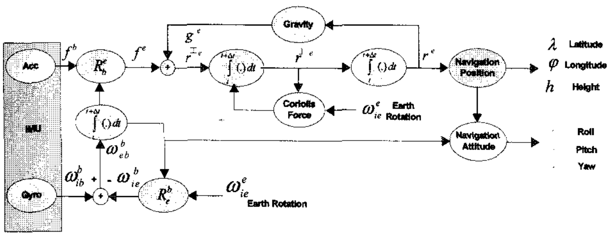


그림 1. SINS 메카니즘의 블럭도

Fig. 1. SINS Mechanization Block Diagram.

measurements are then used to compute the transformation matrix, between the body and navigation frames, which is required to transform the specific force measurements from the accelerometers. This transformation matrix, R_b^l, must be continuously updated in order to follow the vehicle dynamics. As the specific force contains all the sensed accelerations, the Coriolis acceleration, gravitational and centrifugal accelerations must be removed in order to extract correct vehicle velocity and position. The Coriolis acceleration is a function of the vehicle velocity while the sum of gravitational and centrifugal acceleration is the gravity which can be approximated by the free-air normal gravity. The corrected specific force now represents the vehicle acceleration, and can be integrated to get the vehicle velocity increments.

Ⅳ. INS System Error Model

INS system error model is developed in the form of a stochastic linear vector differential equation given by

$$\dot{x}(t) = F(t)x(t) + G(t)w(t) \qquad (19)$$

where

x(t)=the error state vector

F(t)=the system dynamics matrix

G(t)=input matrix (coupling between the navigation parameter error and the inertial sensor)

w(t)=vector of white noise forcing functions

The error state vector is

$$x = [\delta\lambda\ \delta\varphi\ \delta h\ \delta V_E\ \delta V_N\ \delta V_Z\ \psi_E\ \psi_N\ \psi_Z] \qquad (20)$$

where $\delta\lambda$, $\delta\phi$ & δh are longitude, latitude & height errors respectively; δV_E, δV_N & δV_Z are the errors in east, north & up components of velocities; ψ_E, ψ_N, ψ_Z are the east, north & up component of attitude errors.

The INS error system dynamics matrix F can be defined as follows :[2]

$$F=\begin{bmatrix} 0 & \rho_z\cos\phi & -\rho_N/R\cos\phi & 1/R\cos\phi & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_E/R & 0 & 1/R & 0 & 0 & 0 & 0 \\ 0 & 0 & -K_1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & A_{42} & A_{43} & A_{44} & \omega_z+\Omega_z & -\omega_N+\Omega_N & 0 & -f_z & f_N \\ 0 & A_{52} & A_{53} & -2\omega_z & -K_z & \rho_E & f_z & 0 & -f_E \\ 0 & -2\Omega_z V_E & A_{63} & 2\omega_N & -2\rho_E & 0 & -f_N & f_E & 0 \\ 0 & 0 & -\rho_E/R & 0 & -1/R & 0 & 0 & \omega_z & -\omega_N \\ 0 & -\Omega_z & -\rho_N/R & 1/R & 0 & 0 & -\omega_z & 0 & \omega_E \\ 0 & A_{92} & -\rho_N/R & \tan\phi/R & 0 & 0 & \omega_N & -\omega_E & 0 \end{bmatrix} \tag{21}$$

Notation Used in Matrix F

$$\Omega_N = \Omega\cos\phi, \quad \Omega_z = \Omega\sin\phi, \quad \rho_E = -V_N/R,$$
$$\rho_N = -V_E/R, \quad \rho_Z = -V_E/\tan\phi/R, \quad w_E = \rho_E,$$
$$w_N = \rho_N + \Omega_N, \quad w_Z = \rho_Z + \Omega_Z, \quad K_Z = V_Z/R,$$
$$A_{42} = 2(\Omega_N V_N - \Omega_Z V_Z) + \rho_N V_N/\cos^2\phi,$$
$$A_{43} = \rho_Z\rho_E - \rho_N K_Z, \; A_{44} = -\rho_E\tan\phi - K_Z,$$
$$A_{52} = -2\Omega_N V_E - \rho_N V_E/\cos^2\phi,$$
$$A_{53} = \rho_N\rho_Z - \rho_E K_Z, \; A_{63} = 2g/R - \left(\rho_N^2 + \rho_E^2\right),$$
$$A_{92} = \omega_N - \rho_Z\tan\phi$$

The basic INS error model can be described by the equation

$$\dot{\delta x_I} = F_I\delta x_I + w_I \tag{22}$$

The nine-state INS error model is the minimum useful configuration for three-dimensional applications and represents the baseline INS error model. In a more complete INS model, the error dynamics are driven additionally by gyroscope and accelerometer errors.

V. Kalman Filtering

a. Algorithm

The navigation algorithm integrates the INS mechanization equations (see Equation 1) to yield the parameters on the left-hand side, namely the position, velocity, and attitude (PVA) of the vehicle. The algorithm takes into account the Earth's rate of rotation and gravity. The navigation algorithm by itself is seldom useful since the inertial sensor errors (mainly sensors biases) and the fixed-step integration errors will cause the PVA solution to diverge quickly. The navigation algorithm must account for these error sources in order to be able to correct the estimated PVA. The most common estimation algorithm used in integrated INS/GPS is the Kalman Filter (KF). The KF exploits a powerful synergism between GPS and IMU measurements. In this integration scheme, the GPS derived positions and velocities are used as the update measurements for the IMU derived PVA. The KF error state vector in this case includes the navigation parameters as well as the accelerometer and gyroscope error states.[4~6]

According to linear system theory, the dynamics of a linear system can be represented be a state space model given by

$$x = Fx + w \tag{23}$$

$$z = Hx + v \tag{24}$$

Where x is an nx1 state vector, F is an nxn system dynamic matrix , w is an nx1 system noise vector, z is an mx1 observation vector, H is an mxn design matrix, m is the number of measurement & n is the number of the states Eq (6) is the dynamic equation and Eq (7) is the observation equation. Since the implementation of the estimation process is done on a computer, the discrete form is generally more convenient to use. Corresponding to equations (6) and (7), the discrete system equations are derived as follows:

$$x_{k-1} = \psi_{k+1}x_{k+}\omega_k \tag{25}$$

$$z_k = Hx_k + v_k \tag{26}$$

Where, k denotes epoch t_k, ϕ is the nxn state transition matrix, x_k is the state vector at a discrete epoch k, z_k is the observation vector at a discrete epoch k, w_k & v_k are system driving noise and observation noise at epoch k.

For a stationary system, the state transition matrix

ψ is :

$$\psi = e^{F\triangle t} \tag{27}$$

and can be approximated by a Taylor series expansion over a short time interval

$$\phi = I + F\triangle t \tag{28}$$

Where I is the identity matrix. Kalman filtering is a two-step recursive process. The first step is prediction by the system model i.e.,

$$x_k(-) - \psi_{k,k-1} x_{k-1}(+) \tag{29}$$

$$P_k(-) = \psi_{k,k-1} P_{k-1}(+) \psi^T_{k,k-1} + Q_{k-1} \tag{30}$$

and the second step is the measurement update of the system model. The elements of the update process are as follow:

Kalman gain matrix:

$$K_k = P_k(-) H_k^T \left[H_k P_k(-) H_k^T + R_k \right]^{-1} \tag{31}$$

Error covariance update:

$$P_k(+) = \left[I - K_k H_k \right] P_k(-) \tag{32}$$

State update:

$$x_k = x_k(-) + K_k \left[z_k - H x_k(-) \right] \tag{33}$$

Where $\hat{x}_k$ is the estimated state vector , $v_k = z_k - H_k \hat{x}_k(-)$ is the innovation vector, P_k is the nxn covariance matrix of the state vector, R_k is the $m \times m$ covariance matrix of the measurement noise, K_k is the $n \times m$ Kalman gain matrix & Q_k is the $n \times n$ covariance matrix[7~9].

A priori information including the initial value of the state x0 and the initial error covariance matrix, P_o will only influence the transit process of a Kalman filter but not the steady state, i.e., theoretically a priori information will not affect the estimation optimality of the Kalman filter.

The measurement noise covariance matrix, R, which describes how well the measurement noise is modeled, is one of the important factors related to the estimation quality. The system noise covariance, Q, which defines the extent to which the prediction should be trusted, is another important factor that affects the estimation quality.

b. Loosely Coupled Mode

Inertial navigation systems in principle permit autonomous operation. However, due to their error propagation properties, most applications require high-terminal accuracy and external aiding is usually utilized to bound the INS errors. Fig. 2 shows a loosely coupled integrated configuration with a feedback loop.

In a loosely coupled system, the GPS receiver has its own Kalman filter to process pseudo range or Doppler measurements which are used to calculate positions and velocities. GPS-derived positions and velocities are combined with INS positions and velocities to form the error residuals which are sent to the navigation Kalman filter. This filter corrects the INS in a feedback manner, and the effects of biases and drifts, as well as misalignment errors, will be significantly decreased. The features of a loosely coupled aiding approach include: (1) it allows maximum use of off-the-shelf hardware and software that can be easily assembled into a cascaded system without major development; and (2) the feedback of the error states to the inertial navigation system will bound the INS errors.[4]

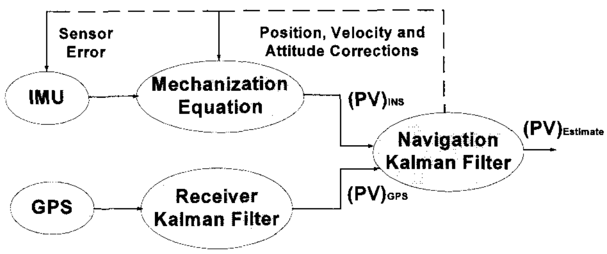


그림 2. 연성결합의 통합 방법
Fig. 2. Loosely Coupled Integration Approach.

VI. Simulation Results

We have done simulation of wander azimuth

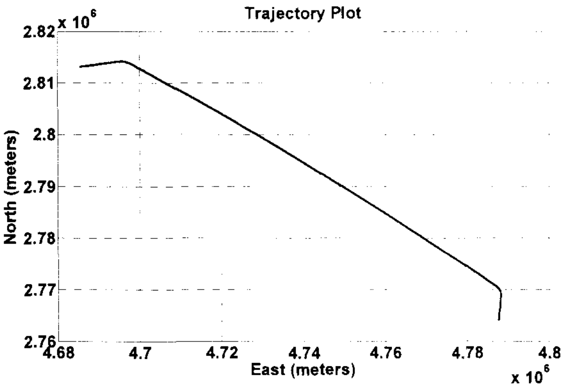


그림 3. Trajectory 플롯
Fig. 3. Trajectory Plot.

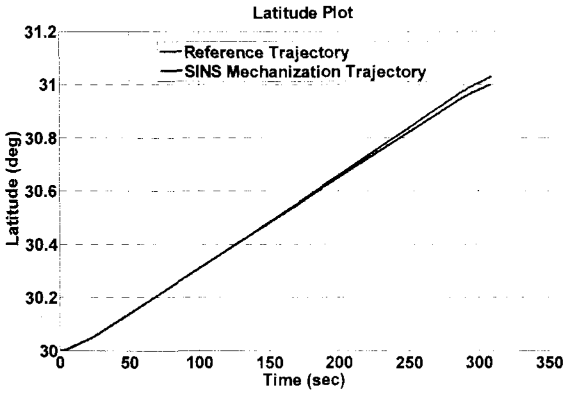


그림 4. Latitude 플롯
Fig. 4. Latitude Plot.

strapdown inertial navigation scheme. We have used ZH35C.exe simulator[7] to generate the SINS reference mechanization trajectory & the raw data for strapdown inertial navigation mechaniztion scheme. We have used the raw data generated by the ZH35C.exe simulator in wander azimuth strapdown mechanization scheme. We have implemented the wander azimuth mechanization scheme using MATLAB 7.01 m-file format. The plot in Fig 3 shows the North vs East trajectory plot in meters. The plot in Fig.4. compares the Latitude values generated by "wander azimuth mechanization scheme" with the "reference trajectory" generated by the ZH35C simulator. There is small latitude error in the wander azimuth mechanization scheme design by us. The plot in Fig.5 compares the longitude values generated by "wander azimuth mechanization scheme" with the "reference trajectory" generated by the ZH35C simulator. Longitude plot also shows very

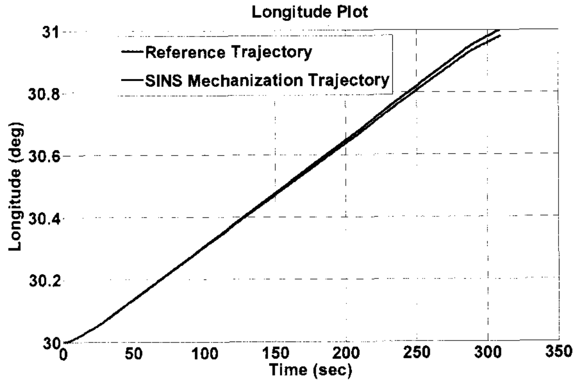


그림 5. Longitude 플롯
Fig. 5. Longitude Plot.

small error.

The plot in Fig. 6 compares the simulation results of "Loosely coupled Kalman filter" with the "reference trajectory". In Fig. 6, we have compared the latitude trajectory estimated by the Kalman filter v/s reference trajectory. We have also shown the error plot in the same figure. From Fig. 6 we can see that Kalman filter tracks the reference trajectory till there is GPS signal outage occurs. As soon as GPS measurement updates are absent due to blockage of GPS signal, the Kalman filter estimate trajectory starts to diverge from the reference trajectory.

There is GPS outage starting from 38sec to 49sec. From Fig.6 it is evident that Kalman filter trajectory diverges whenever there is GPS signal outage occurs. Similar results are shown for the longitude plot in Fig. 7. There is GPS signal outage starting from 41sec to 50sec. From Fig. 7 it is also evident that longitude estimates from Kalman filter diverges whenever there is GPS signal outage occurs.

Ⅶ. Conclusion

In this research paper we have compared the results of "Wander Azimuth Strapdown Inertial Navigation Mechanization Scheme" with the "Reference Strapdown inertial navigation mechanization scheme" values generated by the "ZH35C.exe" trajectory simulator. The results from the wander azimuth mechanization scheme designed

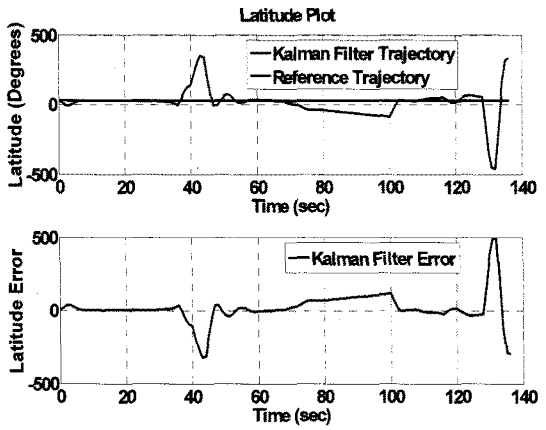


그림 6. Kalman 필터 Latitude 플롯
Fig. 6. Kalman Filter Latitude Plot.

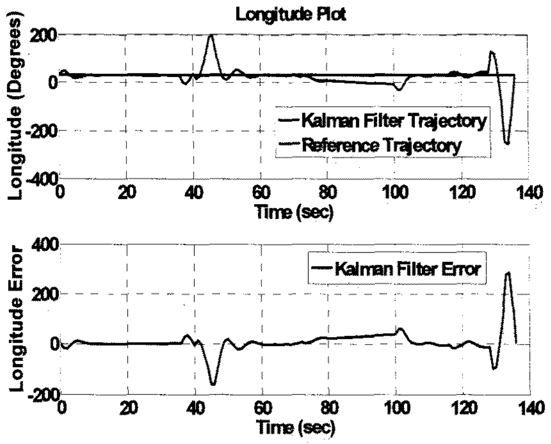


그림 7. Kalman 필터 Longitude 플롯
Fig. 7. Kalman Filter Longitude Plot.

by us is almost same with the reference values generated by the simulator. Then we have shown the simulation results of the loosely coupled Kalman filter. The simulation results for

GPS/INS integration using loosely coupled Kalman filter shows that the estimated values for latitude and longitude have very small errors as compared to standalone INS system. There is small error in position due to outage of GPS signals.

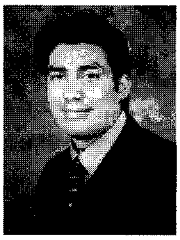
Ⅷ. Future Work

To enhance the positional accuracy of GPS/INS integrated system we are currently working on GPS/INS integration using Neural Network based loosely coupled Kalman filter algorithm. Neural network will compensate the errors caused by the outage of GPS signals and enhance the positional accuracy of current navigation system.

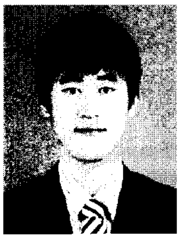
References

[1] A. Brandt, J.F. Gardner, "Constrained Navigation Algorithms for Strapdown Inertial Navigation Systems with Reduced Set of Sensors", Proceedings of the American Control Conference, Philadelphia, Pennsylvania, June 1998.
[2] Zhang Chang Yun "Class Notes on Inertial Navigation". Baihang University 2003.
[3] R. M. Rogers, "Applied Mathematics in Inertial Navigation Systems", AIAA Education Series, pp71-80, June 2000.
[4] X. Zhang, "Integration of GPS with a Medium Accuracy IMU for Metre-Level Positioning", Department Of Geomatics Engineering , University Of Calgary, Master Thesis, pp 35-39, 47,51-56, May 2003.
[5] M.S.Grewal and A.P.Andrews, "Kalman Filter Theory & Practice using Matlab", John Willey & Sons Inc, pp 121-122, Second Edition, 2001.
[6] R. G. Brown, "Random Signal Analysis & Kalman Filter ", John Willey & Sons Inc, pp 195-200, 1983.
[7] "The Data Generator ZH35C.exe (SINS Simulation program ", Automatic Control Department of Beijing University of Aeronautics and Astronautics, Beijing, China.

저 자 소 개



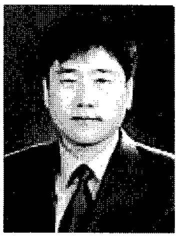
이프티칼 칸(학생회원)
2008년~현재 ITS, Pakistan
2006년~2008년 명지대학교 석사 졸업
2004년 NED University of Eng. & Tech., Karachi, Pakistan
2000년 D.J Sindh Govt. Science College, Karachi, Pakistan
1998년 F.G Public School Malir Cantt, Pakistan
<Area of Interest: Integrated Inertial Navigation System and Embedded Architecture Design



백 승 현(학생회원)
2009년~현재, 명지대학교 석사과정 재학
2006년~2009년, 명지대학교 학사.
<주관심분야 : 회로설계, 방송기기 설계>

박 경 린(정회원)
1998년~현재, 제주대학교 전산통계학과 교수
1993년~1997년, University of Texas at Arlington, Ph.D.
1989년~1992년, University of Texas at Arlington, MS
<주관심분야 : 텔레메틱스, 통신시스템, 데이터 방송>

강 성 민(정회원)
2003년~현재 중앙대학교 경영대학 부교수
1997년~2003년 LG CNS, 엔드루 컨설팅 선임 컨설턴트
1994년~2001년 University of Texas at Austin,
1992년~1994년 Carnegie Mellon Univ. (MBA)
1989년~1992년 Carnegie Mellon Univ. (B.S)
<주관심분야 : 전자상거래, 모바일 컴퓨팅, 지식경영>



이 연 석(정회원)
1993년~현재, 군산대학교 전자정보공학 교수
1987년~1993년 서울대학교 제어계측공학 박사
1980년~1984년 서울대학교 제어계측공학 석사
1980년~1984년 서울대학교 제어계측공학 학사
<주관심분야 : 항법 및 유도 제어, 비선형 시스템 분석>

정 태 경(정회원)
2006년~현재, 명지대학교 통신공학과 조교수
2004년~2006년 Univ. of Delaware, joint collaboration with NASA GSFC, Research Associate
2000년~2004년 University of Texas at Austin, Ph. D.
1998년~2000년 University of Texas at Austin, M. S.
2001년~2002년 IBM Austin Research Laboratory.
1999년~2001년 Cisco Systems. Inc.
<주관심분야 : 통신회로설계, DxB, 고성능 시스템 설계>