INS/GNSS/Vehicle Speed Integration for Land Vehicles with Utilizing Zero-Velocity Information

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ABSTRACT

For highly precise positioning of land vehicles, in this paper, we present an integration method of the low-cost MEMS (Micro Electro Mechanical Systems) INS (Inertial Navigation System), GNSS (Global Navigation Satellite Systems) and vehicle speed information. In this paper, we develop the MEMS INS/GNSS/Vehicle Speed (VS) integration system by extending and refining our previous works [1] [2]. The VS is the vehicle speed obtained by counting the wheel rotation of the land vehicle. In the system, so-called the loosely coupled mechanization is applied. Thus, the three dimensional position, velocity, attitude of the vehicle and the three-dimensional accelerometer and gyro biases are estimated by the Kalman filter by using the measurement of GNSS and VS. And the estimated (predicted) INS errors are fed back to the INS calculations. In the previously presented method [2], once the system starts to calculate its navigation states (position, velocity, attitude and sensor errors), they are updated by the Kalman filter by using all the available measurements. However, the general GNSS point positioning method [3] is applied in the system, so the coordinate output by the receiver can move (jump) about several meters even if the vehicle is stopping. This can cause estimation errors in the Kalman filter, and consequently the performance of the system can be degraded. In this paper, therefore, we propose methods to improve the position accuracy by efficiently utilizing the zero velocity information [4]. The experiments have been carried out on country roads. Throughout the experiments, the proposed method can effectively fix the GPS position and provide accurate navigation consequently.

1 INTRODUCTION

In recent years, the self-driving system of the land vehicle has been paid much attention in a lot of research areas such as image sensing, sensor fusion and related signal processing. The autonomous positioning system is one of those technologies, and developing a low cost high precision system is much desired.

The MEMS (Micro Electro Mechanical Systems) IMU (Inertial Measurement Unit) is a natural choice because of its low cost, size and weight comparing with FOG (Fiber Optic Gyro) and RLG (Ring Laser Gyro). However, the MEMS IMU outputs contain much higher level errors such as high frequency noises, drift errors and scale factor errors, and they are accumulated with time by the integrating calculations of INS (Inertial Navigation System). Therefore, as well known, the integration with the external measurement of the position and velocity by GNSS (Global Navigation Satellite System) which has the characteristic of the long term stability is one of the important keys to hold the accurate navigation [5, 6]. However, the navigation errors very quickly grow when GNSS is unavailable.

To overcome the drawbacks of the MEMS IMU, in this paper, we develop the MEMS INS/GNSS/Vehicle Speed (VS) integration system by extending and refining our previous work [1] [2]. The VS is the vehicle speed obtained by counting the wheel rotation of the land vehicle. In the system, so-called the loosely coupled mechanization is applied. Thus, the three-dimensional position, velocity, attitude of the vehicle and the three-dimensional accelerometer and gyro biases are estimated by the Kalman filter by using the measurement of GNSS and VS. And the estimated (predicted) INS errors are fed back to the INS calculations [3, 7, 8].

In the previously presented method, as long as GNSS signals are available, the position information from the receiver is utilized to update the Kalman filter even if GNSS position jumps at the stopping point, for example in urban areas and tunnels. For that reason, when observed GNSS position is incorrect, the system is not able to correctly estimate the position. In this paper, because we focus on the land vehicle navigation, we can easily detect that the vehicle is stopping by the VS. Therefore, we propose the method to decrease the influence of varying GNSS position information, such that the GNSS position is fixed when the zero velocity is detected by the VS.

By using the real GNSS receiver, INS and the VS data, the performance of the proposed methods are examined. Also, comparing with the method in [2], the applicability of the proposed method is discussed.
2 INTEGRATION ALGORITHM [2]

In this paper, the INS, GNSS and the VS are combined as a data fusion system using the Kalman filter. The system works as a GNSS, the VS aided INS system, where the GNSS position and VS information are used to estimate and correct the INS errors and VS scale factor.

2.1 INS Error Model

The system dynamics model related to the INS errors is given by the differential equations of the INS mechanization. The INS mechanization applied in this paper is detailed in [9] and [10].

The position errors are modeled by

\[
\delta \lambda = - \frac{1}{R_M} \delta h + \frac{1}{R_M} \delta v_n \tag{1}
\]

\[
\delta \phi = (\phi \tan \lambda) \delta \lambda - \frac{\phi}{R_N} + \delta h \tag{2}
\]

\[
\delta h = - \delta v_d \tag{3}
\]

where \( \lambda, \phi, h \) are the latitude, longitude and height respectively. The symbols “\( \delta \)” in front of several components mean their errors. \( R_M \) is the meridian radius, and \( R_N \) is the normal radius of the earth. \( v \) is the velocity, and the subscripts \( n, e, d \) mean the axes in the NED (North-East-Down) coordinate system [8].

The velocity error \( \delta \mathbf{v} \) is modeled by

\[
\delta \mathbf{v}^n = - \mathbf{A}^n \delta \mathbf{\theta}^n - C^n_b \delta \mathbf{a}^b - (2 \mathbf{\Omega}^n_{en} + \mathbf{\Omega}^n_{en}) \delta \mathbf{v}^n
\]

\[
+ \mathbf{V}^n (2 \delta \mathbf{\omega}^n_{en} + \delta \mathbf{\omega}^n_{en}) + \delta \mathbf{a}^n \tag{4}
\]

where \( \mathbf{v}, \mathbf{\theta}, \mathbf{a} \) and \( \mathbf{g} \) are the three dimensional velocity, attitude, acceleration due to the non-gravitational specific force and gravity respectively. The superscripts “\( n \)” and “\( b \)” mean the NED and body coordinate systems respectively. \( \mathbf{C}^n_b \) is the coordinate transformation matrix from the body frame to the NED frame. \( \mathbf{A}^n \) and \( \mathbf{V}^n \) are the skew-symmetric matrices defined by the vector \( \mathbf{a}^n \) and \( \mathbf{v}^n \) respectively. \( \mathbf{\Omega}^n_{en} \) and \( \mathbf{\Omega}^n_{en} \) are the skew-symmetric matrices corresponding to the rotation rate of the Earth and angular velocity vector. The subscript “\( en \)” means the rotation rate of the ECEF(Earth-Centered, Earth-Fixed; \( e \)) frame with respect to the ECI(Earth-Centered Inertial; \( i \)) frame. Similarly, “\( en \)” means the NED frame with respect to the ECEF frame.

The attitude error model is

\[
\delta \mathbf{\theta}^n = - \mathbf{\Omega}^n_{in} \delta \mathbf{\theta}^i - \delta \mathbf{\omega}^n_{in} + C^n_b \delta \mathbf{\omega}^b \tag{5}
\]

where \( \mathbf{\Omega}^n_{in} \) is the skew-symmetric matrix defined by the angular velocity vector, \( \delta \mathbf{\omega}^n_{in} \) is the angular velocity error due to the position and velocity errors. In this formula, \( \delta \mathbf{\omega}^b \) represents the gyro bias.

In this paper, the accelerometer and gyro bias errors are modeled as the first order Markov processes respectively.

2.2 Measurement Models [2]

2.2.1 GNSS Measurement Model

The measurement equation which describes the relations between the GNSS position measurement and the system states can be established by subtracting the GNSS position from the INS position. The INS position is formulated by the sum of the true position plus the INS position error, and the GNSS position is modeled as the true position corrupted by the measurement noise. By subtracting the GNSS position from the INS position, the true position is canceled out and the INS position error is observed. The latitude error \( \delta \lambda \), the longitude error \( \delta \phi \) and the height error \( \delta h \) are observed as follows.

\[
y_1 = \lambda^i - \lambda^g \tag{6}
\]

\[
y_2 = \phi^i - \phi^g \tag{7}
\]

\[
y_3 = h^i - h^g \tag{8}
\]

where \( \lambda^i \equiv (\lambda + \delta \lambda), \phi^i \equiv (\phi + \delta \phi) \) and \( h^i \equiv (h + \delta h) \) are the latitude, longitude, height indicated by the INS, and \( \lambda^g \equiv (\lambda - n_1), \phi^g \equiv (\phi - n_2) \) and \( h^g \equiv (h - n_3) \) by the GNSS, and \( n_1, n_2 \) and \( n_3 \) are the GNSS errors to be assumed as the zero-mean Gaussian white noises. The minus signs in front of \( n_1, n_2 \) and \( n_3 \) are just for convenience of expression.

2.2.2 VS Measurement Model

In this paper, we assume that the land vehicle does not sideslip, and we can observe the vehicle speed (VS) along with X axis of the body frame. In Fig. 1, the observed VS is shown by \( \mathbf{v}_x \), and X and Y axis of the body frame are shown by \( X_B \) and \( Y_B \) respectively. The observed VS, i.e. \( \mathbf{v}_x \), includes errors due to small slips of tire and the error of the scale factor which converts the wheel rotation into the vehicle’s speed. They can

![Fig. 1: Vehicle speed obtained from tire rotation](attachment:image.png)
be regarded to be in proportion to the vehicle’s speed
\[ v_x = (1 + \delta \gamma) v_x \]  
(9)
where \( v_x \) is the true speed along with \( X_B \) axis, and \( \delta \gamma \) represents the scale factor error. By using the transformation matrix \( C^n_B \), the VS is transformed into the NED frame, then we have

\[
\begin{bmatrix}
\tau_n \\
\tau_e \\
\tau_d
\end{bmatrix} = C^n_B
\begin{bmatrix}
\tau_x \\
0 \\
0
\end{bmatrix}
\]  
(10)

The matrix \( C^n_B \) is calculated in the INS computations, and it includes the small attitude errors \( \delta \theta_n, \delta \theta_e \) and \( \delta \theta_d \), which are the components of the vector \( \delta \Theta^B_n \) in Eq. (5). Therefore, from Eqs. (9) and (10), the true velocity can be expressed as follows:

\[
\begin{bmatrix}
v_n \\
v_e \\
v_d
\end{bmatrix} = \frac{1}{1 + \delta \gamma}
\begin{bmatrix}
1 & 0 & -\delta \theta_d & -\delta \theta_e & \delta \theta_d \\
0 & 1 & -\delta \theta_d & -\delta \theta_e & \delta \theta_d \\
-\delta \theta_e & -\delta \theta_n & 1 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
\tau_n \\
\tau_e \\
\tau_d
\end{bmatrix}
\]  
(11)

where \( I_3 \) denotes the 3 \( \times \) 3 identity matrix.

On the other hand, the INS velocity can be formulated by the sum of the true velocity and the INS velocity error.

\[
\begin{bmatrix}
v^i_n \\
v^i_e \\
v^i_d
\end{bmatrix} = \begin{bmatrix}
v_n + \delta v_n \\
v_e + \delta v_e \\
v_d + \delta v_d
\end{bmatrix}
\]  
(12)

where the superscripts “\( \cdot \)" in the left hand side show INS indicated values. Therefore, by substituting Eq. (12) into Eq. (11), we have the measurement equations related to the VS and INS error states as follows.

\[
y_4 \equiv v^i_n - \tau_n
\]
\[
= (1 + \delta \gamma) \delta v_n + \tau_e (\delta \theta_d) - \tau_d (\delta \theta_e) - \delta \gamma v_n + n_4
\]  
(13)

\[
y_5 \equiv v^i_e - \tau_e
\]
\[
= (1 + \delta \gamma) \delta v_e - \tau_n (\delta \theta_d) + \tau_d (\delta \theta_e) - \delta \gamma v_e + n_5
\]  
(14)

\[
y_6 \equiv v^i_d - \tau_d
\]
\[
= (1 + \delta \gamma) \delta v_d + \tau_e (\delta \theta_d) - \tau_c (\delta \theta_e) - \delta \gamma v_d + n_6
\]  
(15)

where \( n_4, n_5 \) and \( n_6 \) are unmodeled measurement errors and/or approximation errors, and they are assumed to be zero-mean Gaussian white noises in this paper. In this paper, the VS scale factor error \( \delta \gamma \) is modeled by the first order Markov process and is simultaneously estimated by the Kalman filter.

### 2.3 Measurement Models with Zero-Velocity Information

In the previous method [2], if GNSS signals are available, the position information from the receiver is always utilized to update the Kalman filter even when the vehicle is stopping. However, as we have mentioned in Section 1, even if the vehicle is stopping, the GNSS position result moves about several meters in general case. Moreover, in the worst case, the moving distance can reach about several tens of meters due to effects of multipath, ionosphere and so on. In such case, i.e. the observed GNSS position is incorrect, the system is not be able to correctly estimate the position. Therefore, in this paper, we propose the method to fix the GNSS position information and to utilize the fixed position for the measurement update of the Kalman filter. Fig. 2 shows the proposed measurement update procedure. Firstly, the system judges whether vehicle is stopping or not by using the vehicle speed. Here, we assume that the zero velocity \( \overline{\dot{v}_c}(k) = 0 \) is detected at time \( k \). Then the GNSS position is fixed to the GNSS position information at time \( k \), i.e. \( \lambda^g_{k,x} = \lambda^g(k) \), \( \phi^g_{k,x} = \phi^g(k) \), \( h^g_{k,x} = h^g(k) \). And the fixed positions \( \lambda^g_{k,x}(k), \phi^g_{k,x}(k), h^g_{k,x}(k) \) are utilized in the measurement update in the Kalman filter. After the measurement update, the new measurement of the VS \( \overline{\dot{v}_c}(k + 1) \) and the GNSS \( \lambda^g(k + 1), \phi^g(k + 1), h^g(k + 1) \) are obtained. Then the system judges again whether stopping or not. If the vehicle continues to stop, the fixed positions \( \lambda^g_{k,x}(k), \phi^g_{k,x}(k), h^g_{k,x}(k) \) are utilized again in the measurement update at time \( k + 1 \). On the other hand, if the vehicle starts to move, the new GNSS position results \( \lambda^g(k + 1), \phi^g(k + 1), h^g(k + 1) \) are utilized in the measurement update.

**Fig. 2: Procedure of the proposed method**

#### 2.3.1 GNSS Measurement Model

From Eqs. (6) to (8) and Fig. 2, when the vehicle is stopping, the INS position is formulated by the sum of the true position plus the INS position error, and the GNSS position is modeled as the true position corrupted by the measurement noise, where it is fixed to the position indicated by the receiver when the zero velocity is detected (at the time of \( k \) in Fig. 2). Similarly to the previous GNSS measurement model, by subtracting the GNSS position from the INS position, the true position is canceled out and the INS position error is observed as follows.
\[ y_7 = \lambda^i - \lambda_{\text{fix}}^i = (\lambda + \delta\lambda) - (\lambda - n_7) = \delta\lambda + n_7 \tag{16} \]
\[ y_8 = \phi^i - \phi_{\text{fix}}^i = (\phi + \delta\phi) - (\phi - n_8) = \delta\phi + n_8 \tag{17} \]
\[ y_9 = h^i - h_{\text{fix}}^i = (h + \delta h) - (h - n_9) = \delta h + n_9 \tag{18} \]

where \( \lambda_{\text{fix}}^i \equiv (\lambda - n_7) \), \( \phi_{\text{fix}}^i \equiv (\phi - n_8) \) and \( h_{\text{fix}}^i \equiv (h - n_9) \) by the GNSS, and \( n_7 \), \( n_8 \) and \( n_9 \) are the GNSS error to be assumed as the zero-mean Gaussian white noise. The minus sign in front of \( n_7 \), \( n_8 \) and \( n_9 \) are just for convenience of expression. The other definitions are similar to Subsection 2.2.1.

### 2.3.2 VS Measurement Model

From Eq. (9), when vehicle is stopping, \( \tau_x \) is modeled as follows.

\[ \tau_x = 0 \tag{19} \]

Therefore, from Eqs. (10) to (12) and Eq. (19), we have the measurement equations related to the VS and INS error states as follows.

\[ y_{10} = v_{n}^i = \delta v_n + n_{10} \tag{20} \]
\[ y_{11} = v_{e}^i = \delta v_e + n_{11} \tag{21} \]
\[ y_{12} = v_{d}^i = \delta v_d + n_{12} \tag{22} \]

where \( n_{10}, n_{11} \) and \( n_{12} \) are unmodeled measurement errors and/or approximation errors, and they are assumed to be zero-mean Gaussian white noises. The other definitions are similar to Subsection 2.2.2.

#### Table 1: List of state variables

| No. | Symbol | Description |
|-----|--------|-------------|
| 1   | \( \delta\lambda \) | Latitude error |
| 2   | \( \delta\phi \) | Longitude error |
| 3   | \( \delta h \) | Height error |
| 4   | \( \delta v_n \) | \( N \)-axis velocity error |
| 5   | \( \delta v_e \) | \( E \)-axis velocity error |
| 6   | \( \delta v_d \) | \( D \)-axis velocity error |
| 7   | \( \delta \theta_n \) | \( N \)-axis attitude error |
| 8   | \( \delta \theta_e \) | \( E \)-axis attitude error |
| 9   | \( \delta \theta_d \) | \( D \)-axis attitude error |
| 10  | \( \delta a_x \) | \( X_B \)-axis accelerometer bias |
| 11  | \( \delta a_y \) | \( Y_B \)-axis accelerometer bias |
| 12  | \( \delta a_z \) | \( Z_B \)-axis accelerometer bias |
| 13  | \( \delta \omega_x \) | \( X_B \)-axis gyro bias |
| 14  | \( \delta \omega_y \) | \( Y_B \)-axis gyro bias |
| 15  | \( \delta \omega_z \) | \( Z_B \)-axis gyro bias |
| 16  | \( \delta\gamma \) | VS scale factor error |

### 2.4 State Space Model for Kalman Filter

From Subsections 2.1 and 2.2, the state vector \( \mathbf{x} \) which is estimated by the Kalman filter is defined as follows,

\[ \mathbf{x} \equiv [\delta\lambda, \delta\phi, \delta h, \delta v_n, \delta v_e, \delta v_d, \delta \theta_n, \delta \theta_e, \delta \theta_d, \delta a_x, \delta a_y, \delta a_z, \delta \omega_x, \delta \omega_y, \delta \omega_z, \delta\gamma]^T \tag{23} \]

where the description for each component is shown in Table 1. With appropriate discretization of Eqs. (1) to (5), we have the following linear state equation.

\[ \mathbf{x}_{k+1} = F_k \mathbf{x}_k + \mathbf{w}_k \tag{24} \]

where \( F_k \) is the 16 \times 16 known matrix, \( \mathbf{w}_k \) is the zero-mean Gaussian white noise process with covariance matrix \( \mathbf{Q}_k \). The components of \( F_k \), especially for the INS errors, are detailed in [9]. The measurements are \( y_1 \) to \( y_6 \) in Eqs. (6) to (8), (13) to (15), thus we define

\[ \mathbf{y} \equiv [y_1, y_2, \ldots, y_6]^T \tag{25} \]
\[ \mathbf{n} \equiv [n_1, n_2, \ldots, n_6]^T \tag{26} \]

When the vehicle is stopping, the measurements are \( y_7 \) to \( y_{12} \) in Eqs. (16) to (18), (20) to (22), thus we define

\[ \mathbf{y} \equiv [y_7, y_8, \ldots, y_{12}]^T \tag{27} \]
\[ \mathbf{n} \equiv [n_7, n_8, \ldots, n_{12}]^T \tag{28} \]

In this case, because the VS scale factor error \( \delta\gamma \), which is the 16th component of the state vector, is related to the only VS measurement, it is removed from the state variable. Then the measurement equation can be expressed as follows,

\[ \mathbf{y}_k = \mathbf{h}_k(\mathbf{x}_k) + \mathbf{n}_k \tag{29} \]

where \( \mathbf{h}_k \) is the known function, and the covariance matrix of \( \mathbf{n}_k \) is defined as \( \mathbf{R}_k \). The nonlinearities appear in Eqs. (13) to (15) as the products of \( \gamma \) and the velocity errors \( \delta v_n, \delta v_e \) and \( \delta v_d \). Therefore, in this paper, the Extended Kalman filter (EKF) [12] is applied.

### 3 EXPERIMENTAL RESULTS

The experiment was conducted on Nov. 3, 2015. From 00:47 to 01:57 (UTC), i.e. totally 4,200 seconds, a test car ran on suburban roads in Iida City, Nagano, Japan. In the experiment, the MEMS INS board AU7595 (Tamagawa Seiki) [13] equipped with the GNSS receiver NEO-7P (Ublox) was installed in the car, and IMU data and GPS position data were collected at 100 [Hz] rate and 1 [Hz] rate respectively. The following results were obtained by offline calculations. The specifications of the IMU are shown in Table 2.

#### Table 2: Specifications of IMU [13]

| Component | Bias (rms) | Scale factor (p-p) |
|-----------|-----------|--------------------|
| Accelerometer | 0.098 m/s^2 | ±0.5 % |
| Gyro | 0.098 m/s^2 | ±0.5 % |
As follows on applying integration navigation, initial estimation error variances of Kalman Filter, variances of system noises and variances of observation noises are shown Tables 3 to 5. They were determined from the specifications of IMU shown in Table 2. It should be noted that the values in Tables 3 to 5 are strongly depend on the specifications of IMU.

Table 3: Initial estimation error variances

| Source                     | Covariance                  | Unit |
|----------------------------|-----------------------------|------|
| Latitude error             | (10/6378137)^2              | m^2  |
| Longitude error            | (10/6378137)^2              | m^2  |
| Height error               | 10.0^2                      | m^2  |
| N-axis velocity error      | 1.0^2                       | m^2/s^2 |
| E-axis velocity error      | 1.0^2                       | m^2/s^2 |
| D-axis velocity error      | 1.0^2                       | m^2/s^2 |
| N-axis attitude error      | 0.05^2                      | rad^2 |
| E-axis attitude error      | 0.05^2                      | rad^2 |
| D-axis attitude error      | 0.05^2                      | rad^2 |
| X_B-axis accelerometer bias| 0.12                        | m^2/s^2 |
| Y_B-axis accelerometer bias| 0.12                        | m^2/s^2 |
| Z_B-axis accelerometer bias| 0.12                        | m^2/s^2 |
| X_B-axis gyro bias         | 0.0002^2                    | rad^2/s^2 |
| Y_B-axis gyro bias         | 0.0002^2                    | rad^2/s^2 |
| Z_B-axis gyro bias         | 0.0002^2                    | rad^2/s^2 |
| VS scale factor error      | 0.01^2                      | m^2/s^2 |

Table 4: Variances of system noises

| Source                     | Variance                  | Unit |
|----------------------------|---------------------------|------|
| Latitude error             | 0.0                       | rad^2 |
| Longitude error            | 0.0                       | rad^2 |
| Height error               | 0.0                       | m^2   |
| N-axis velocity error      | 0.017                     | m^2/s^2 |
| E-axis velocity error      | 0.017                     | m^2/s^2 |
| D-axis velocity error      | 0.017                     | m^2/s^2 |
| N-axis attitude error      | 0.000088                  | rad^2 |
| E-axis attitude error      | 0.000088                  | rad^2 |
| D-axis attitude error      | 0.000088                  | rad^2 |
| X_B-axis accelerometer bias| 0.00017                   | m^2/s^2 |
| Y_B-axis accelerometer bias| 0.00017                   | m^2/s^2 |
| Z_B-axis accelerometer bias| 0.00017                   | m^2/s^2 |
| X_B-axis gyro bias         | 0.000116                  | rad^2/s^2 |
| Y_B-axis gyro bias         | 0.000116                  | rad^2/s^2 |
| Z_B-axis gyro bias         | 0.000116                  | rad^2/s^2 |
| VS scale factor error      | 0.001                     | m^2/s^2 |

Table 5: Variances of observation noises

| Source                     | Variance                  | Unit |
|----------------------------|---------------------------|------|
| Latitude                   | 1.0                       | m^2   |
| Longitude                  | 1.0                       | m^2   |
| Height                     | 2.0                       | m^2   |
| N-axis Vehicle Speed       | 0.1                       | m^2/s^2 |
| E-axis Vehicle Speed       | 0.1                       | m^2/s^2 |
| D-axis Vehicle Speed       | 0.1                       | m^2/s^2 |

Although the word “GNSS” has been used in the previous sections, only GPS system was utilized in this experiment. The INS board has the CAN (Controller Area Network) communication interface and the VS information from the car is also collected. The test course was in the open sky environment, thus 7 to 11 satellites were available throughout the experiment as shown in Fig. 3. Fig. 4 shows the car trajectory obtained by the INS/GPS integrated system, i.e. the system without the VS measurement. A lap of the rectangular test course was approximately 1.5 [km], and the car ran about 5 laps for 70 minutes. The maximum speed of the car was about 14 [km/h]. In Fig. 4, yellow circles are stopping points (3 points) of the vehicle. Because car ran 5 laps, the car stopped totally 3 × 5 = 15 times. The stopping time at each point was about 90 seconds. In order to examine the proposed method, the GPS position data while the vehicle was stopping were artificially degraded such that the uniformly distributed random

Fig. 3: Number of visible satellites

Fig. 4: Test course trajectory obtained by INS/GPS integration
numbers between $-0.0002 \ [\text{deg}]$ to $0.0002 \ [\text{deg}]$ were added to the GPS position every 20 [sec]. The value of $0.0002 \ [\text{deg}]$ in the latitude and longitude is about 20 [m], and this is the typical value for the multipath and inospheric effects. Fig. 5 shows the horizontal position results of the degraded GPS position. Fig. 6 shows the horizontal position results of the INS/GPS/VS integration of the previously presented method [2]. From Fig. 6, we can see that there exist position jumps of several meters due to the degraded GPS position data at stopping points. And, Fig. 7 shows the horizontal position results of the INS/GPS/VS integration of the proposed method. The upper two plots in Fig. 8 show the position errors in East and North directions respectively. The blue lines show the results of the previous method [2], and the red lines show the results of the proposed method. From these plots, we can see there exist about 4 [m] and 8 [m] error in each direction with the previous method. On the other hand, by using the proposed method, the position error can be decreased to almost zero. The "error" was calculated as the difference from the results of the INS/GPS (not degraded) integration. By comparing the position error and vehicle speed, only while the vehicle stops, it is clear that the position error occurs by the previous method.

4 CONCLUSION

In this paper, the MEMS INS/GNSS/VS integration system has been developed by applying the EKF. In order to effectively utilize the zero-velocity information of the vehicle, the system fixed the GPS position while the vehicle is stopping. From the experimental results, we can see that the proposed method can effectively utilize the zero-velocity information of the vehicle, and continuously keep the navigation accuracy even when the GPS information are incorrect.
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