Realization of an Adaptive Hybrid Low-cost GPS/INS Integrated Navigation System with Switched Position-Domain and Range-Domain Filtering Strategy

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ABSTRACT

GPS receivers are widely used in navigation and positioning, due to the global availability of GPS signals, its low cost and low power consumption. However, it does not work sufficiently in all signal environments. This raises the need to integrate GPS with other sensor systems (for instance, the inertial navigation system (INS)) to have a robust, continuous navigation solution regardless of the environment. The combination of the complementary characteristics from the GPS and INS provides overall an enhanced navigation performance. With the emergence of the micro-electromechanical systems (MEMS) based low-cost inertial measurement unit (IMU), cost-effective GPS/INS integrated navigation systems became of high interest. In this paper, the system performances of loosely- and tightly-coupled low-cost GPS/INS integrations are analyzed. An adaptive hybrid low-cost GPS/INS integration system architecture is proposed. Simulation and test results are presented based on using an RF GPS signal simulator and synthetic IMU data.

KEYWORD

GPS/INS, Kalman filter, MEMS-based IMU, Low-cost, Adaptive hybrid, Online computational burden

INTROUDCTION

GPS/INS integration architectures have been introduced in literatures (e.g., [1], [2], [3]), and they are generally classified as loosely-coupled, tightly-coupled and deeply-coupled (or ultra-tightly coupled) integration. The loosely-coupled integration system uses the position and velocity measurements as inputs to the integration algorithm. In a tightly-coupled system, the pseudo-range and pseudo-range rate raw measurements are used to correct the state of the navigation filter. In the deeply-coupled integration, not only the GPS aiding of INS, but the INS aiding of GPS tracking loops is implemented. In the loosely-coupled integration considered in this paper, the least-squares estimator has been used for the GPS receiver, instead of using an 8-state Kalman filter to prevent from the cascading filtering problems (details are given in [1], [2]) caused by mutual feedbacks from two Kalman filters. When using the least-squares estimator, it has the advantage of simplicity with low online computational burden, and a completely independent GPS navigation solution. But signals from at least four satellites are required to obtain a GPS navigation solution. For the integration Kalman filter, the accurate error covariance information is needed for the optimal estimation, but it is not available from the least-squares estimator.

The GPS/INS tightly-coupled integration, which performs comparable or better than its loosely-coupled counterpart in terms of both accuracy and robustness, is implemented by a centralized Kalman Filter. For the centralized integration, the sensor raw measurements rather than the navigation solutions are input to the integration Kalman filter. All systematic errors and noise sources of the navigation sensors are modelled in the same filter. This ensures that all error correlations are accounted for, all measurements are optimally weighted, and the full information is used to estimate each error [1]. However, all sensors need to be modelled correctly, and the system must be carefully designed. The main disadvantage of centralized integration is that it requires a high processor load, and there are no available independent subsystem navigation solutions. Sequential processing normally can be used to avoid the matrix inversion in the calculation of the Kalman gain to reduce the online computational load. But generally, it is not possible to optimally process the integrated measurements (for instance, the carrier phase Doppler shift from PLL) sequentially without estimating additional states which are related to the integrated process noise over the integration interval [4]. The methods of optimal sequential processing of the integrated measurements without adding additional states can be found in Ref. 4. Currently they are not considered in this adaptive hybrid system.

From the former analysis, we know that for the integration with low-cost MEMS-based IMUs (especially for the sensors with the price tag about 100-200$), the filter update rate (or we say, the IMU error calibration rate) is important for the accuracy of the integrated navigation solutions. The INS estimates need to be corrected by the GPS measurements due to its fast position drift over time. It is mainly caused by the gyro bias error (the large turn on biases combined with high sensor noise), because the gyros bias will cause a linear increase tilt error and make the wrong projection of the gravity on to the horizontal plane as acceleration error. After double integrations, it becomes the position drift [5].

ADAPTIVE HYBRID NAVIGATION SYSTEM

In order to improve the accuracy and robustness of the navigation solution, and optimize the processing efficiency, an adaptive hybrid integrated navigation system has been designed.

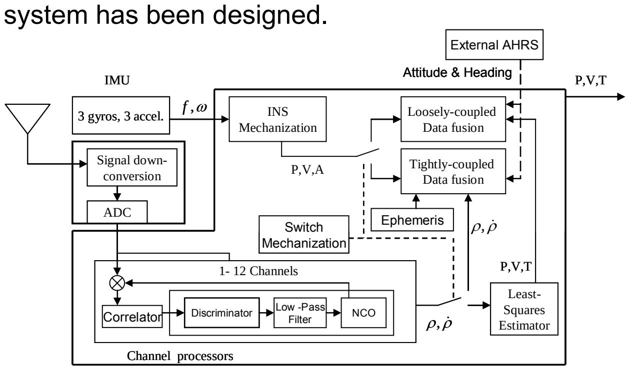

Fig. 1: Framework of the low-cost GPS/INS adaptive hybrid navigation system.

In this proposed adaptive hybrid low-cost GPS/INS integration system (the architecture is shown in Fig. 1), the loosely-coupled integration (least-squares estimator with 15-state Kalman filter) is set to be the default mode (as shown in Fig. 2). That is, when the receiver operates in open sky condition, a high filter recursive rate and faster response to IMU errors can be achieved (1 Hz filter update rate).

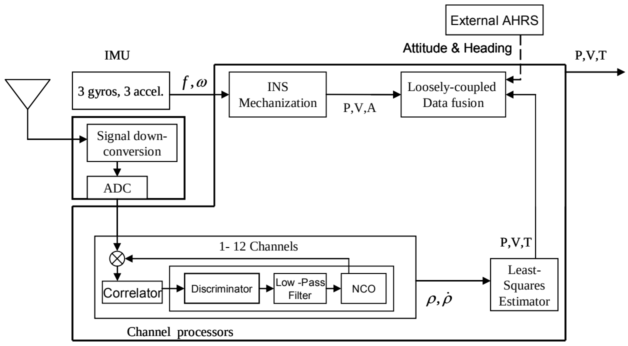

Fig. 2: Default mode

When the system moves under challenging signal conditions, the tightly-coupled integration (17-state Kalman filter) will be triggered with the filter initialized by the loosely-coupled integrated navigation solutions (as shown in Fig. 3).

In the Kalman filter used for the GPS/INS integration, state propagation and update occur at the high rate at which the IMU measurements are available (for instance, in our case at 100 Hz), but the Kalman gain calculation, covariance propagation, and update where the bulk of Kalman computations are performed at a much lower rate. The computational burden is further determined by the order of the Kalman filter state space and observation models. For the tightly-coupled integration, we set the filter update rate to be 0.5 Hz due to its high online computational load.

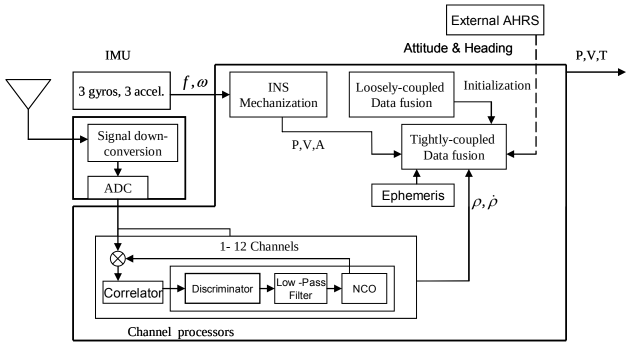

Fig 3: Enhanced mode

A switching mechanism between the loosely- and tightly-coupled integration is used which is based on the number of tracked satellites. In the conducted simulations in this paper, the switching happens when the tracked satellites number is below 4.

The external attitude and heading reference system (AHRS) is optional. This redundant attitude information could be derived from horizontal reference instruments, and the heading information from, for instance, a magnetic compass. The attitude and heading measurements derived from a low-cost GPS receiver with single antenna are challenging. However, higher quality real-time velocity information (from carrier phase Doppler shift), especially when it is available at high sample rates such as 10 Hz has the potential for precision guidance [6].

SYSTEM ERROR STATE SPACE MODEL

The low-cost gyroscopes are usually not able to sense the Earth's rotation, so that the gyro-compassing for alignment in azimuth is not feasible. Transport rate and Coriolis terms can be neglected in the strap-down processing.

In the loosely-coupled GPS/INS integration architecture, the following *n*-frame *error state system model* is used for the integration Kalman filter:

$$\underbrace{\begin{bmatrix} \Delta\dot{\mathbf{x}} \\ \Delta\dot{\mathbf{v}} \\ \Delta\dot{\boldsymbol{\psi}} \\ \Delta\dot{\mathbf{b}}_a \\ \Delta\dot{\mathbf{b}}_\omega \end{bmatrix}}_{\Delta\dot{\mathbf{x}}_c} = \underbrace{\begin{bmatrix} O & I & O & O & O \\ O & O & F_{23} & R_b^n & O \\ O & O & O & O & -R_b^n \\ O & O & O & O & O \\ O & O & O & O & O \end{bmatrix}}_{F} \cdot \begin{bmatrix} \Delta\mathbf{x} \\ \Delta\mathbf{v} \\ \Delta\boldsymbol{\psi} \\ \Delta\mathbf{b}_a \\ \Delta\mathbf{b}_\omega \end{bmatrix} + \mathbf{w} \qquad (1)$$

Where I and O represent a 3×3 identity and 3×3 zero matrix; $\Delta\mathbf{x}$ and $\Delta\mathbf{v}$ are position error and velocity error vectors; $\Delta\boldsymbol{\psi}$ is the attitude error vector; $\Delta\mathbf{b}_a$ is residual accelerometer biases; $\Delta\mathbf{b}_\omega$ is residual gyroscope biases.

The skew-symmetric sub-matrix F_{23} contains the specific force components (transformed to the *n*-frame)

$$F_{23} = [\mathbf{a}_{ib}^n \times] = \begin{bmatrix} 0 & -a_{ib,d}^n & a_{ib,e}^n \\ a_{ib,d}^n & 0 & -a_{ib,n}^n \\ -a_{ib,e}^n & a_{ib,n}^n & 0 \end{bmatrix} \qquad (2)$$

The frame rotation matrix from body- to *n*-frame is

$$R_b^n = \begin{bmatrix} c\psi\, c\theta & c\psi\, s\theta\, s\varphi - s\psi\, c\varphi & c\psi\, s\theta\, c\varphi + s\psi\, s\varphi \\ s\psi\, c\theta & s\psi\, s\theta\, s\varphi + c\psi\, c\varphi & s\psi\, s\theta\, c\varphi - c\psi\, s\varphi \\ -s\theta & c\theta\, s\varphi & c\theta\, c\varphi \end{bmatrix} \qquad (3)$$

with c = cos and s = sin.

The biases are simply modeled as random walk processes

$$\Delta\dot{\mathbf{b}}_a = \mathbf{n}_{b_a}; \quad \Delta\dot{\mathbf{b}}_\omega = \mathbf{n}_{b_\omega} \qquad (4)$$

where $\mathbf{n}_{ba}$ and $\mathbf{n}_{b\omega}$ are white Gaussian noise vectors.

The discrete-time analogue is expressed as $\xi(k+1) = A(k)\xi(k)$ with

$$A(k) = I + F \cdot T \qquad (5)$$

where T is the step size of the discrete Kalman filter.

In the loosely-coupled integration, the *measurement* vector consists of the differences between GPS and INS derived position and velocity, respectively. When the redundant attitude information is available, the observation matrix is given as:

$$H_{l,att} = \begin{bmatrix} I & O & O & O & O \\ O & I & O & O & O \\ O & O & R & O & O \end{bmatrix} \qquad (6)$$

where the time index and the lever-arm effect have been neglected for simplicity.

In the tightly-coupled integration the measurement vector consists of the differences in predicted and measured pseudo-range and pseudo-range rates, respectively, and with respect to satellite number m. The part of the observation matrix that maps 17 state vector components (including clock bias and drift) into observation space is given as

$$H_t^{(m)} = \begin{bmatrix} -\left(\mathbf{l}_t^{(m),n}\right)^T & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & 1 & 0 \\ \mathbf{0}^T & -\left(\mathbf{l}_t^{(m),n}\right)^T & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & 0 & 1 \end{bmatrix}_{2\times 17} \qquad (7)$$

where $\mathbf{l}_t^{(m),n}$ is the unit vector from receiver to satellite m. The total observability matrix comprises $2M$ rows assuming that M satellites are in view. Similarly to (6), it can be simply augmented by three more rows to incorporate additional attitude information.

SIMULATION SETUP

For the following experiments, a hardware-in-the-loop system has been used for the derivation of GPS based measurements. The angular rate and specific force measurements (as obtained from a low-cost IMU) have been simulated using the parameters in Table 1. The system consists of the RF GPS signal simulator NavX-NCS from Ifen GmbH and Novatel DL-4 plus GPS receivers.

Table 1: Error characteristic of the low-cost MEMS-IMU

Gyroscope (Angular rates)	
Bias stability [°/h]	360
Scale factor [ppm]	10000
Noise (ARW) [°/√h]	3
Accelerometer (specific forces)	
Bias stability [μg]	2400
Scale factor [ppm]	10000
Noise (VRW) [μg/√Hz]	1000

A circle level path with constant velocity of 20 m/s is modeled by using the RF GPS signal simulator. Only the heading angle changes. The roll and pitch are constant throughout the test.

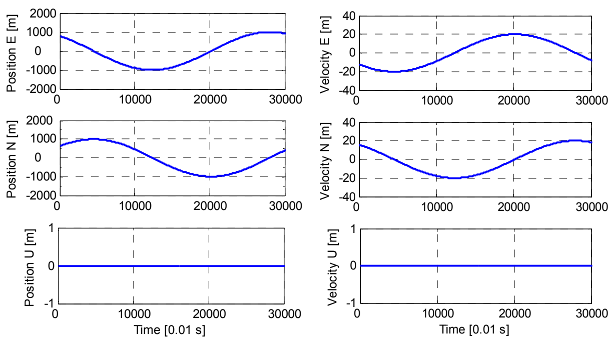

Fig. 4: Trajectory in ENU navigation frame

Nominal parameters of the trajectory are given in Table 2.

Table 2: Nominal parameters for the following experiments

Trajectory	
Nominal Velocity	20 m/s
Circle Center Position (LLH)	$\mathbf{x}^{LLH} = [51°\text{N} \quad 8°\text{E} \quad 360\text{m}]^T$
Circle Radius	1000 m
Start Time (UTC)	October 29, 2006, 00:11:27
Duration	300 s
GPS measurements	
Measurement rate	5 Hz
Positioning method	Single-point positioning
Error modeling	Tropospheric and ionospheric delays are estimated and corrected for.
Satellites in view	9 (unless stated otherwise)
Elevation angle	≥ 5°
IMU measurements	
Update rate	100 Hz
Error modeling	cf. Table 1
Integration	
Filter update rate	1 Hz, 0.5 Hz

The GPS/INS integration is accomplished by using a Kalman filter and the aforementioned state space modeling. An ideal time-synchronization has been assumed. The problem of time delayed measurements has been neglected. Flexure and vibrations have not been taken into consideration.

SIMULATIONS AND RESULTS

Scenario 1: Loosely-coupled integration (with 1 Hz, 0.5 Hz filter update rates)

In this scenario, the low-cost MEMS-based IMU is loosely-coupled integrated with GPS at two filter update rates (1 Hz, and 0.5 Hz). Practically, for loosely-coupled systems, filter update intervals of 10 s are commonly used [1]. But with using the IMU parameters (with the price tag about 100-200 $) as shown in Table 2, higher filter update rate is required. The integration is done by using a 15-state Kalman filter to exploit the GPS and IMU position and velocity measurements, respectively. As mentioned before, we use the least-squares estimator for deriving the GPS based position and velocity measurements instead of using an 8-state Kalman filter to prevent the filter cascading problems.

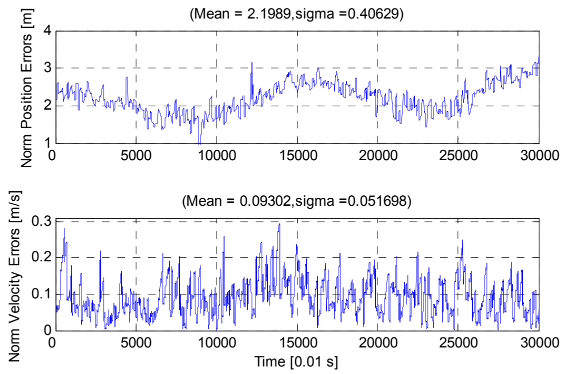

Fig. 5: 1 Hz filter update rate

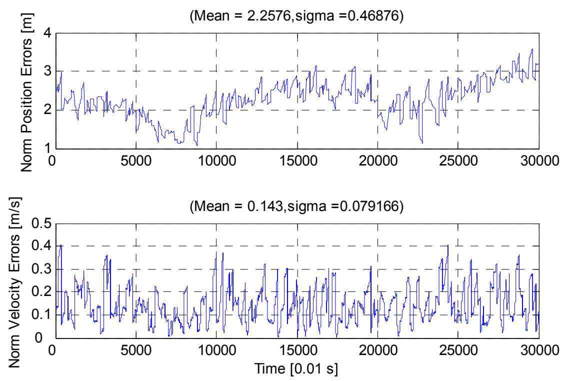

Fig. 6: 0.5 Hz filter update rate

The best GPS/INS integrated navigation system performance is obtained at 1 Hz filter update rate, as shown in Fig. 5.

Scenario 2: Tightly-coupled integration

2-1: Tightly-coupled integration with 0.5 Hz filter update rate

From Fig. 7, we obtained similar results as in the previous scenario. Due to the higher real-time computational burden with using the centralized Kalman filter for integration, IMU error calibration with 1 s interval is quite challenging for real-time applications, especially when more satellites are tracked. The real-time IMU error correction with 2 s interval is more practical. But if we calibrate the IMU error with longer interval, the system performance is not acceptable.

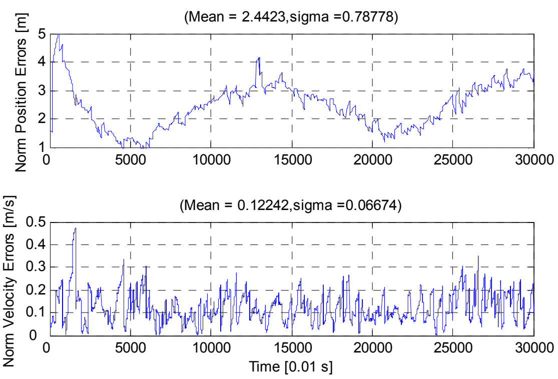

Fig. 7: 0.5 Hz filter update rate

For tightly-coupled integration, the proper initialization of the integration Kalman filter is important (large position errors at the beginning of Fig. 7). If the chosen initial state estimates are not close to the true states, slow convergence might result.

2-2: Tightly-coupled integration with different number of satellites in view (with 3, 4, 9 satellites)

For good signal conditions, similar navigation results will be obtained with using the loosely- and tightly-coupled GPS/INS integration. But as soon as less than 4 satellites are in view, the tightly-coupled integration is superior because the information coming from the remaining satellites is still considered in the tightly-coupled integration filter (as shown in Figs. 8 and 9). Nevertheless, the positioning accuracy and precision depends on the number of visible satellites and their geometrical distribution. Fig. 8 presents the position errors achieved when 3, 4, or 9 satellites are visible. Fig. 9 presents the corresponding velocity errors.

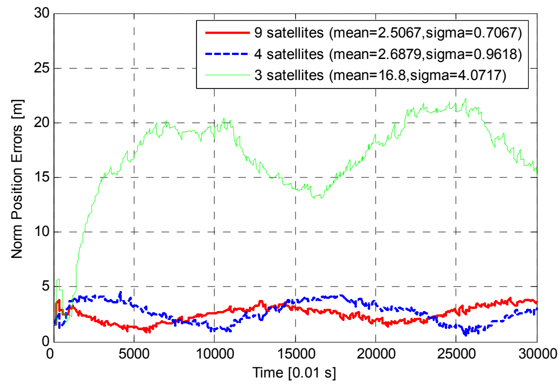

Fig. 8: Position errors and their dependencies on the number of satellites in view

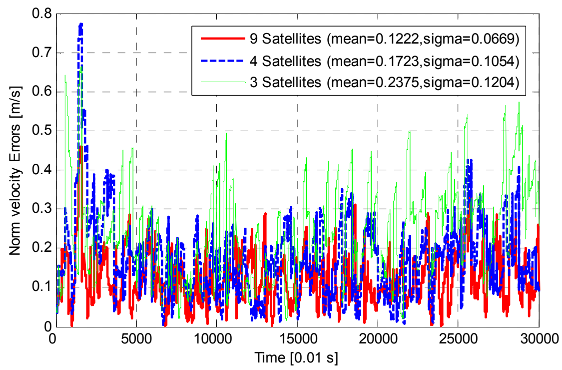

Fig. 9: velocity errors and their dependencies on the number of satellites in view

Regarding the velocity error, the effect of GPS signal outages is smaller than that on the position. The reason is that, the Doppler measurements from carrier tracking loop are used to derive the velocity estimates.

2-3: Tightly-coupled integration with GPS signal outages (3 satellites in view)

In this simulation, we assume that after 40 s for 80 s and after 160 s for 20 s only 3 satellites are in view.

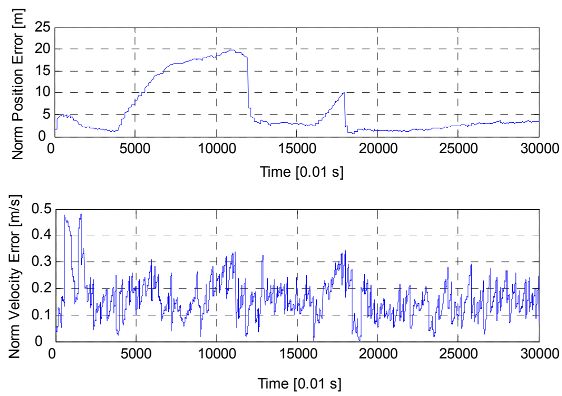

Fig. 10: System performance under GPS signal outages (3 satellites in view)

As shown in Fig. 10, in long time GPS signal outage (for instance, 80 s for only 3 satellites in view), with using the low-cost MEMS-based IMU, the system positioning errors are bounded, but under short time GPS signal outage (for 20 s), the positioning errors seem to be unbounded, only its drift over time can be observed.

2-4: Tightly-coupled integration with high grade IMU under 3 satellites in view

A tactical grade IMU is used and the parameters are given in Table 3.

Table 3: Error characteristic of the tactical grade IMU

Gyroscope (angular rates)	
Bias stability [°/h]	1
Scale factor [ppm]	200
Noise (ARW) [°/√h]	0.01
Accelerometer (specific forces)	
Bias stability [μg]	50
Scale factor [ppm]	500
Noise (VRW) [μg/√Hz]	200

With using the high grade IMU, the Kalman filter will be tuned to give more weights on the IMU measurements, especially when less than 4 satellites are tracked. In this simulation, we assumed a 100 s GPS signal outage after 20 s, with only 3 satellites in view.

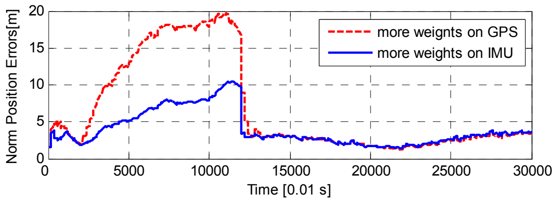

Fig. 11: System performance when giving more weights on the IMU measurements.

From Fig. 11, we see that the position error of the single-point GPS positioning is the dominant part of the total error rather than the drift from the IMU, and the INS estimates can be used to smooth the noisy GPS positioning results. By further tuning of the Kalman filter, better navigation solutions with using the tactical grade IMU can be expected.

Scenario 3: Adaptive hybrid integrated navigation system

In this simulation, we also assume that after 20 s for 100 s, only 3 satellites are visible.

As shown in Fig. 12, for a long GPS signal outage (for 100 s), the tightly-coupled integrated position errors are bounded due to the IMU error calibration from the remaining tracked satellites. With using the adaptive hybrid integrated navigation system, for the first 20 s with 9 satellites in view, the system is working at loosely-coupled integration mode with using least-squares estimator for the GPS receiver at 1 Hz filter update rate. No convergence problems appear for the adaptive system. This is also true when the carrier is navigating from bad signal condition to an open sky signal condition.

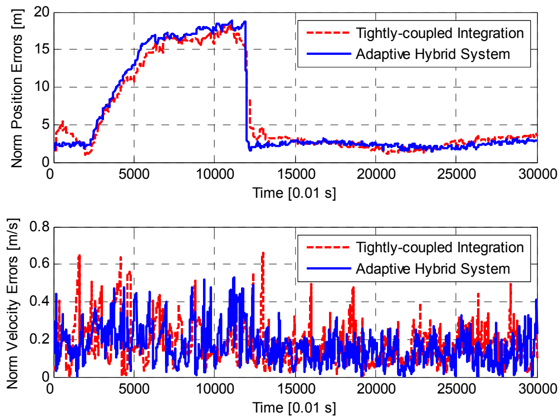

Fig. 12: Comparison of the results (tightly-coupled integration system vs. an adaptive hybrid integrated navigation system)

After 20 s for 100 s, only 3 satellites are in view, and the adaptive system switches to the tightly-coupled integration mode with 2 s filter update intervals. In this challenging signal condition, the system has the same characteristics as the normal tightly-coupled integrated navigation system.

After 120 s, 9 satellites are again in view. The corresponding error parameters for both navigation systems are listed in Table 4.

Table 4: Position and velocity errors (after 120 s) of tightly-coupled and adaptive hybrid navigation system

Tightly-coupled Integrated navigation system	
Position Error (mean/sigma)	2.4368/0.6665 (m)
Velocity Error (mean/sigma)	0.1378/0.0777 (m/s)
Adaptive hybrid navigation system	
Position Error (mean/sigma)	2.3524/0.4756 (m)
Velocity Error (mean/sigma)	0.1181/0.0680 (m/s)

The same experiment has been repeated for 10 times, and the mean values are given in Table 5:

Table 5: Mean position and velocity errors after 10 runs

Tightly-coupled Integrated navigation system	
Position Error (mean/sigma)	2.4274/0.6423 (m)
Velocity Error (mean/sigma)	0.1278/0.0717(m/s)
Adaptive hybrid navigation system	
Position Error (mean/sigma)	2.3435/0.4556 (m)
Velocity Error (mean/sigma)	0.1055/0.0611(m/s)

We see that with using the adaptive hybrid navigation system, the advantages from the loosely-coupled integration (lower real-time computational load) and the tightly-coupled integration (INS estimates correction when fewer than 4 satellites are in view) are combined, yielding an overall enhanced navigation performance.

Further experiments are made with using a tactical grade IMU. Comparable system performances are obtained from the tightly-coupled and adaptive hybrid navigation system. This is due to the fact that the single-point GPS positioning error will be the dominant part instead of the drift of IMU. One improvement from the adaptive navigation system is that there is no special requirement for choosing the initial start point for the integration algorithm, because the system uses a least-squares estimator for the GPS in the loosely-coupled integration.

CONCLUSION

When a low-cost MEMS-based IMU is used, the integration Kalman filter update rate is an important factor regarding the accuracy of the system position and velocity solutions. Two factors are limiting the filter update rate (IMU error calibration rate). The first one is the real-time computational burden of the integration Kalman filter. The second one comes from the prevention of time-correlated GPS measurements which may cause filter divergence. There is a trade-off between correctly choosing the Kalman filter update rate and the Kalman Gain. For low-cost MEMS-based IMU, a 1 s or 2 s error correction interval is required. In order to improve the system navigation solution's accuracy and robustness, to minimize the system complexity, and to promote the system processing efficiency, an adaptive hybrid integrated navigation system can be a solution.

ACKNOWLEDGMENTS

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