Mechanization of a Robust Navigation Scheme for Land Applications Employing GNSS/INS Augmented with Zero Velocity Updates

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***Abstract*—GNSS/INS Integrated Navigation systems mechanized for Land based applications face certain challenges especially near skyscraper, mountainous regions and high foliage environments wherein GNSS signals get interrupted. While INS and GNSS are widely used in augmentation but the integrated navigation solution can get compromised in GNSS-denied environments. This research work explores the integration of GNSS with low-cost MEMS INS and Zero Update Position and Timing (ZUPT) rendering a robust navigation solution for land applications. ZUPT is used to mitigate accelerometers and gyroscope biases and in turn alleviate the errors in position, velocity and attitude especially in a GNSS-denied scenario. ZUPT is enabled when the host vehicle stops and velocity of the host vehicle becomes zero. ZUPT corrections employing Kalman Filter algorithms significantly contains the accumulated errors in position, velocity and attitude. The study investigates the impact of different types of errors (random, fixed and growing) in GNSS including complete unviability on the INS/GNSS integrated solution. It has been observed that, when time growing errors are introduced in GNSS output, it has the worst effect on its overall accuracy. To counteract potential degradation in position computation ensuing from GNSS denial or interruption, this work corroborates the efficacy of ZUPT. ZUPT updates strengthen the system's robustness and accuracy of INS/GNSS Integrated solution. The proposed scheme can be employed for any land application including autonomous commercial land vehicles, navigation in tunnels, mining work and pedestrian navigation system etc.**

Keywords*— GNSS, INS, Adaptive Kalman Filtering, Integrated Navigation, ZUPT, Data Fusion, MEMS IMU

I. Introduction

In the past few decades the commercialization of autonomous land vehicles has brought a profound interest in design of robust navigation systems. INS and GNSS are the most celebrated systems in the field of navigation in all mediums including land, air, space and submarine applications. INS offers a distinctive advantage as a self-contained system, providing all-inclusive navigation solutions encompassing position, velocity, and attitude. However, relying on dead reckoning computations, INS is prone to unbounded error growth over time, due to the inherent biases in the sensors.

In contrast, GNSS maintain its accuracy within a bound mitigating the issue of error growth associated with INS. Therefore, when INS and GNSS are synergistically integrated, an optimal navigation solution is obtained, especially when uninterrupted availability of GNSS signals is ensured. However, real world challenges such as signal jamming, spoofing, and obstruction of clear view of sky pose challenge to GNSS reliability. This is particularly troublesome for land vehicle navigation applications in environments including tunnels, skyscrapers, mountains and dense forests. Resultantly, for longer duration applications, there is high probability of encountering the segments, where the availability of GNSS is compromised.

The zero velocity correction techniques can significantly improve the overall accuracy of land vehicle navigation. This is achieved by stopping the vehicle at certain periodic instances or at instances of user discretion. As the velocity becomes zero, this known information is fed as a measurement to the Kalman Filter algorithm used for computing and correcting GNSS and INS errors. This scheme significantly renders improved position, velocity and attitude solution.

In this paper, effects of zero velocity correction are investigated by simulating different scenarios. To substantiate the presented scheme, first standalone MEMS INS solution is presented. Subsequently, INS is integrated with GNSS when uninterrupted GNSS signals are available. Next, the segments of GNSS unavailability are introduced and their effect is studied. Furthermore, zero velocity update is incorporated. First, just INS is corrected by zero velocity and then it is used to improve the performance of INS and interrupted GNSS integrated navigation.

II. Related Work

Navigation in GNSS denied environments is a common problem being investigate and studied extensively by the navigators the world-over. A wide variety of solutions have been adopted to address this problem, ranging from incorporation of different aiding sensors to the use of machine learning algorithms for containing INS error during GNSS outages.

To ensure the robustness of land-based navigation using MEMS IMU and low cost GNSS receiver in urban environments with access to insufficient number of satellites, tightly coupled integration of INS and Precise Point Positioning (PPP) GNSS is performed using extended Kalman filter [1]. This technique improves the robustness of navigation solution at the cost of additional computational load.

Mu et al [2] presented the application of vehicle mode recognition algorithm and non-holonomic constraints to maintain the accuracy of MEMS-INS/GNSS integrated navigation for land vehicle in urban settings with GNSS outages. The application of this technique is limited by the estimation the accuracy of heading misalignment.

Another approach to maintain the accuracy of low-cost INS/GNSS solution in GNSS denied environment for land vehicles is presented by Chen et al [3]. The position drift during the GNSS outages was controlled by using the stochastic model of time-differenced GNSS carrier phase, non-holonomic constraints and odometer measurements. However, this algorithm is not robust to frequent GNSS outages.

Chiang et al [4] developed a navigation system for land vehicle using smartphone sensors for GNSS challenging environments. The data of IMU, GNSS and cameras was integrated using EKF. The output of camera was processed by ORB-SLAM algorithm to compute velocity which was fed to the navigation algorithm.

Yang et al [5] proposed a fault tolerant MEMS-INS/GNSS integrated navigation solution that is reliable under disturbances as well as partial and complete loss of GNSS data. It incorporates non-holonomic constraints and Allan-variance informed Kalman filter.

Furthermore, support vector machine (SVM) algorithm was employed by Cong et al [6] to predict accumulation of MEMS-INS error during the intervals of GNSS outages. Dai et al [7] demonstrated the application of recurrent neural networks (RNN) for INS/GNSS positioning in the absence of GNSS signals. Ushaq et al [8] investigated and mitigated the effect of slowly growing errors in GPS through adaptive Kalman Filtering algorithm. Another approach for successful positioning despite satellite faults and data contamination is proposed by Li et al [8]. To identify and exclude faulty GNSS measurements, graph optimization was used for tightly coupled integration of INS and GNSS.

Most of the techniques employ either additional navigation aiding hardware or complex algorithm to maintain the accuracy of INS/GNSS positioning during GNSS outages. The additional sensors such as cameras, odometers and radars come with their own limitations, error sources and cost increment. The complexity of algorithms also directly translates into computational cost. Zero velocity correction offers unique advantages without needing additional hardware sensors or any significant increase in computational burden. Although it has been employed along with other aids in various schemes presented in literature, but there was a lack of in-depth study on zero- velocity correction and its direct impact on positioning accuracy during loss or contamination of GNSS signals which can be manifested in various forms. This study addresses this gap.

III. Inertial Navigation System (INS)

INS is based upon the input from three gyroscope and three accelerometers. Gyroscopes measure angular rates, whereas accelerometers measure translational acceleration. Inertial Navigation algorithm is used to compute position, velocity and attitude from accelerometers and gyroscope output. In INS algorithm, the effect of gravity, earth's rotation and Coriolis force are compensated from accelerometer and gyroscope output, to compute instantaneous kinematic acceleration in navigation frame.

In this paper, these computations are performed in local level north pointing East-North-Up (ENU) frame using the following equations:

$$\delta\dot{V}_x = f_x^n + (2\omega_{iee}\, sin\phi + V_x tan\phi/R_{nh})V_y - (2\omega_{iee}\, cos\phi + V_x/R_{nh})V_z$$
$$\delta\dot{V}_y = f_y^n - (2\omega_{iee}\, sin\phi + V_x tan\phi/R_{nh})V_x - V_y V_z/R_{mh}$$
$$\delta\dot{V}_z = f_z^n + (2\omega_{iee}\, cos\phi + V_x/R_{nh})V_x + V_y^2/R_{mh} - g_s \qquad (1\text{-}3)$$

Here, f^n is an accelerometer output transformed into navigation frame using direction cosine matrix computed from the output of gyroscope. $\dot{V}$ is instantaneous kinematic acceleration. All other terms in the above equations account for non-kinematic accelerations, where:

ω_{iee}: rotation of earth w.r.t inertial frame expressed in earth frame
ϕ: latitude
R_{mh}: meridian radius of earth
R_{mh}: normal radius of earth

The instantaneous acceleration can be integrated to compute velocity, which can be integrated again for position calculation. Due to this integration, the slight errors in sensors and non-kinematic compensations accumulate significantly resulting in unbounded growth in final position and velocity errors.

IV. Global Navigation Satellite System (GNSS)

GNSS is considered as the most popular and reliable navigation systems, presently. It relies on number of satellites orbiting around the Earth along know orbits with known Orbital (Keppler) parameters all the time. These satellites transmit signals traveling with the speed of light, containing the information including satellite position, transmission time and other parameters. The receivers at user location can compute their position by using the difference in transmission and arrival time employing TRILATERATION scheme. However, if errors are introduced anywhere during this process, they can degrade the accuracy of computed position [10].

Clock errors: Satellite clocks are generally very accurate. If any deviation appears in them, monitoring stations estimate correction parameters and send them to the receivers. However, the receiver clocks are inexpensive to ensure affordability.

Therefore, they have inherent biases, which if not compensated accurately, introduce error is the position estimation.

Ionospheric and Tropospheric/Stratospheric Delays: The GNSS signals travel through the ionosphere. The ionization can affect the transit time of the signal. Since the ionization level keep on changing with the solar activity, the transit time error cannot be predicted precisely unless dual frequency receivers are used. Furthermore, variability in satellite elevation also affect the ionospheric delays. After ionosphere, signals have to cross the troposphere. Although troposphere is electron neutral, it introduces dry and wet components of errors as it slows down the signal because of it being refractive.

Multipath error: It is a source of major concern in urban settings. Due to the tall buildings and other obstructions the GNSS signal is reflected. It reaches the receiver indirectly with a delay and higher signal to noise ratio. Apart from that, error is also introduced due to inherent noise in receiver caused by thermal noise, circuitry, signal sampling and quantization.

Other types of GNSS errors include those due to jamming, spoofing and thermal variation in GNSS receivers.

These errors manifest themselves in different forms in final position and velocity of GNSS. Sometimes the result in increased randomness in final solution, at other times fixed or growing errors are introduced. There are also cases when there is no output at all.

V. ZERO UPDATE POSITION AND TIMING (ZUPT)

ZUPT also known as zero velocity update is performed by stopping the vehicle or any other host system and getting information about zero velocity with certainty. This information can reduce the overall uncertainty in positioning which generally keeps on growing with time due to respective errors of INS and GNSS.

In manual ZUPT application ZUPT is initiated at driver/user discretion after manual stopping of the vehicle. In automatic ZUPT applications, there are various ways to detect periodic zero velocity. Some are based on hardware and other are software based. In hardware-based methods, usually the output of odometer is used to infer the occurrences of zero velocity. The software-based techniques include adaptive thresholding, cycle segmentation, and other data driven classifiers [10].

VI. INS/GNSS/ZUPT INTEGRATION

Kalman Filter algorithm is used for GNSS/INS/ZUPT Integration. It is a two-step predictor-corrector estimator. The first step involves prediction of the state and the second corrects it using the measurement.

The predictor equations are:

$$x_k^- = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (4)$$

$$P_k^- = AP_{k-1}A\ t + Q_{k-1} \quad (5)$$

The corrector equations are:

$$K_k = P_k - H^t\,(HP_k - H + R)^{-1} \quad (6)$$

$$x_k = x_k - + K_k\,(z_k - Hx_k^-) \quad (7)$$

$$P_k = (I - K_k H)\,P_k^- \quad (8)$$

In this paper, INS error equations are used in prediction mode. The correction is performed by using GNSS or zero-velocity measurement. Here:

x_k is error state vector and it is given as:

$$x_k = [\varphi_x,\ \varphi_y, \varphi_z, \delta V_x^g, \delta V_y^g, \delta V_z^g, \delta\phi, \delta\lambda, \delta h, \varepsilon_{bx}, \varepsilon_{by}, \varepsilon_{bz}, \nabla_{bx}, \nabla_{by}, \nabla_{bz}]^T \quad (9)$$

Components of x_k in (9) are errors in pitch, roll, yaw, east velocity, north velocity, up velocity, latitude, longitude, altitude, three gyro errors and three accelerometer errors, respectively.

P is the error covariance matrix, which represent the estimated accuracy of the state vector. Its diagonal elements are variances of error of individual elements of the state vector.

$$P = diag[\sigma^2_{\varphi_x}, \sigma^2_{\varphi_y}, \sigma^2_{\varphi_z}, \sigma^2_{\delta V_x^g}, \sigma^2_{\delta V_y^g}, \sigma^2_{\delta V_z^g}, \sigma^2_{\delta\phi}, \sigma^2_{\delta\lambda}, \sigma^2_{\delta h}, \sigma^2_{\varepsilon_{bx}}, \ldots \sigma^2_{\varepsilon_{by}}, \sigma^2_{\varepsilon_{bz}}, \sigma^2_{\nabla_{bx}}, \sigma^2_{\nabla_{by}}, \sigma^2_{\nabla_{bz}}] \quad (10)$$

Q is a process noise covariance matrix, representing uncertainty in the process model. In this case, it comprises of covariance of accelerometers and gyroscopes errors.

$$Q = diag[\sigma^2_{gx}, \sigma^2_{gy}, \sigma^2_{gz}, \sigma^2_{bx}, \sigma^2_{by}, \sigma^2_{bz}] \quad (11)$$

For INS/GNSS integration, the measurement vector is given by:

$$z = \begin{bmatrix} V_{x,ins} - V_{x,gps} \\ V_{y,ins} - V_{y,gps} \\ V_{z,ins} - V_{z,gps} \\ \phi_{ins}(Rm+h) - \phi_{gps}(Rm+h) \\ \lambda_{ins}(R+h)Cos\,\phi_{ins} - \lambda_{gps}(R+h)Cos\,\phi_{gps} \\ h_{ins} - h_{gps} \end{bmatrix} \quad (12)$$

The measurement matrix which maps the measurement vector to state vector is given by H:

$$H = \begin{bmatrix} 0_{3x3} & I_{3x3} & 0_{3x9} \\ 0_{3x6} & diag(Rm, RnCos\phi, 1\,) & 0_{3x6} \end{bmatrix} \quad (13)$$

The measurement noise covariance matrix, R, represent uncertainty in measurement. In this case, it is the error of GNSS output. It is given by:

$$R = diag[\sigma^2_{VGx}, \sigma^2_{VGy}, \sigma^2_{VGz}, \sigma^2_{\phi_G}, \sigma^2_{\lambda_G}, \sigma^2_{h_G}] \quad (14)$$

When zero velocity is detected:

$$z = \begin{bmatrix} V_{x,ins} \\ V_{y,ins} \\ V_{z,ins} \end{bmatrix} \quad (15)$$

$$H = [0_{3x3} \quad I_{3x3} \quad 0_{3x9}] \quad (16)$$

$$R = diag[\sigma^2_{VGx}, \sigma^2_{VGy}, \sigma^2_{VGz}] \quad (17)$$

VII. Simulations And Results

The simulations for land vehicle navigation were performed in 2D for the period of about one hour. Initially the vehicle is stationary for 10 minutes. After accelerating, it moves in the direction of east for 10 minutes with the speed of 10m/s. Then it turns left and continues in the direction of north. After taking another left turn, it moves to west with the same uniform speed of 10m/s. Finally, it turns to south and reach back to almost same point from where it started. Again some stationary data is recorded.

The MEMS IMU with accelerometers of 0.2mg random bias and gyroscopes of 5°/hr random bias were used. The GNSS receiver with the of 25m random errors in position and 0.1 m/s random velocity error was incorporated.

A. Standalone INS

When only MEMS IMU is used for navigation, considerable error was introduced during first 10 minutes when the vehicle was stationary. The navigation solution does not follow the trajectory well, from the very beginning as shown in "Fig.1". Although, the motion is in 2D, the vertical velocity escalates to 150m/s as indicated by "Fig.2". The "Fig.3" shows the introduction of maximum of 4km of error in latitude and around 10km in longitude during 1 hour

B. INS/GNSS Integration

When INS and GNSS are integrated, the final navigation solution is almost coincident to ideal values as shown in "Fig.5". The position errors converge to zero as depicted by "Fig .8". This is the case only if GNSS is available without any interruptions.

C. INS With Interrupted GNSS

Due to the multitude of factors, an un-interrupted availability of GNSS is not possible in normal urban settings. As a result, different types of disturbances are introduced.

In this case, there was interruption in GNSS from 18-25mins and then from 43-47 minutes.

Case-1: In the first case, as a result of interruption, a random noise is introduced in the output of GNSS. Here, in the interrupted segment, the randomness in GNSS output was increased to 100 times.

The effect of the randomness in GNSS is reflected in the final navigation solution. The INS/GNSS trajectory exhibit ("Fig.9") some deviation from the ideal one. The velocity and position error clearly show the effect of randomness ("Fig.10").

Case 2: Instead of random errors, if growing errors are introduced in GNSS, they can create havoc as shown in "Fig.11". Although Kalman filter tries to arrest the errors back as soon as GNSS become available again, but still the overall error significantly degrades the solution.

D. INS/ZUPT Integration

If standalone INS is aided by zero-velocity correction, it can somewhat reduce the final navigation errors. Here, the two important factors are the accuracy of INS sensors and frequency of zero-velocity. Increasing either of them, improves the final solution. However, the price of high accuracy INS becomes prohibitively high for most of applications. Increasing the frequency of zero-velocity correction is also not very feasible as it requires stopping the vehicle for some finite time.

In this case, zero-velocity correction was performed after every 10 minutes. As vehicle was already stationary initially, it was stopped for first velocity correction after 20 mins (around 1200 secs). After 20 minutes, the vehicle was decelerated, then stopped for one minute and then accelerated again. As it was stopped thrice, the overall time has increased for the same total distance. Every time, the vehicle is stopped, the error in velocity becomes zero. However, during the next 10 minutes interval, when it is operating under pure INS, the error grows again. As the time passes, the growth becomes more significant as shown in "Fig.14" and "Fig. 15".

The final trajectory of INS and zero velocity corrected solution does not coincide with the ideal trajectory, but still it is improved version of standalone ("Fig.13") INS. If the frequency of zero velocity update or sensor accuracy is enhanced, even better results can be obtained.

E. INS/Interrupted GNSS/ZUPT Integration

When INS, GNSS with interruptions, and zero-velocity correction are integrated, the final navigation solution is significantly improved ("Fig.16").

When GNSS becomes unavailable, the error is introduced. However, if the zero-velocity correction of 1 minute after every 20 minutes is performed, the final errors stays within bounds even if the GNSS interruption result in the growing errors. ("Fig.17" & "Fig.18").

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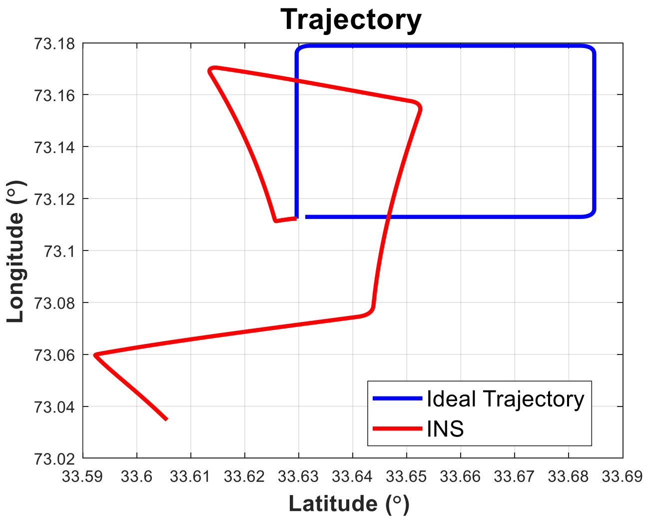


Figure 1: Standalone INS Trajectory

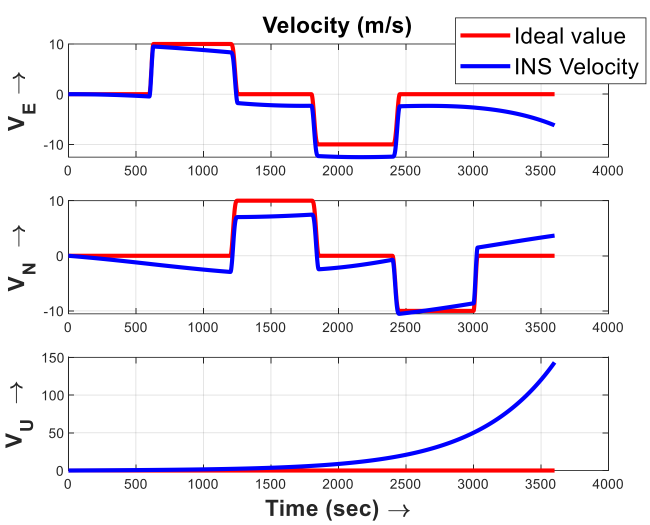


Figure 2: Standalone INS Velocity

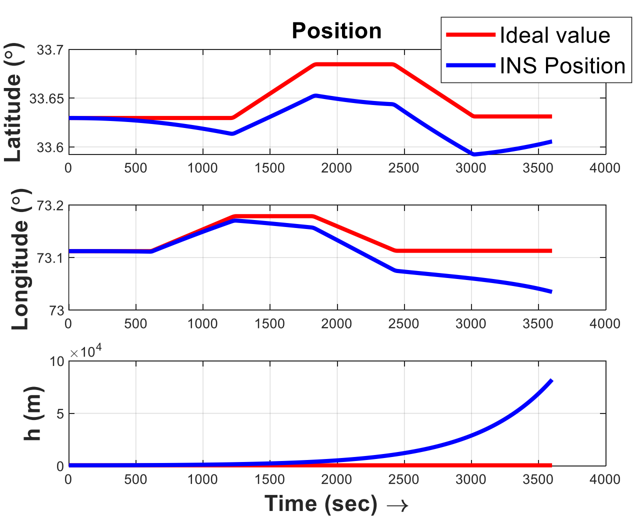


Figure 3: Standalone INS Position

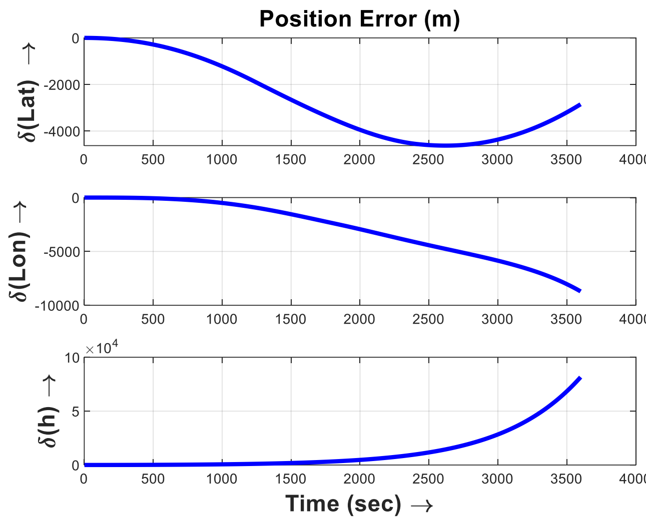


Figure 4: Position Error of Standalone INS

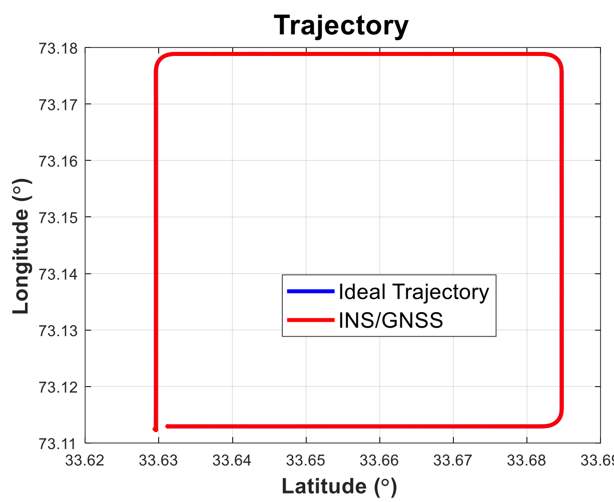


Figure 5: INS/GNSS Integrated Trajectory

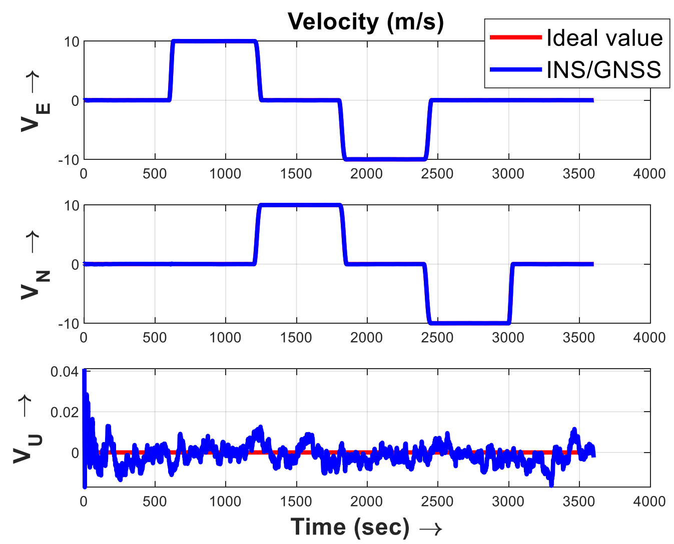


Figure 6: INS/GNSS Integrated Velocity

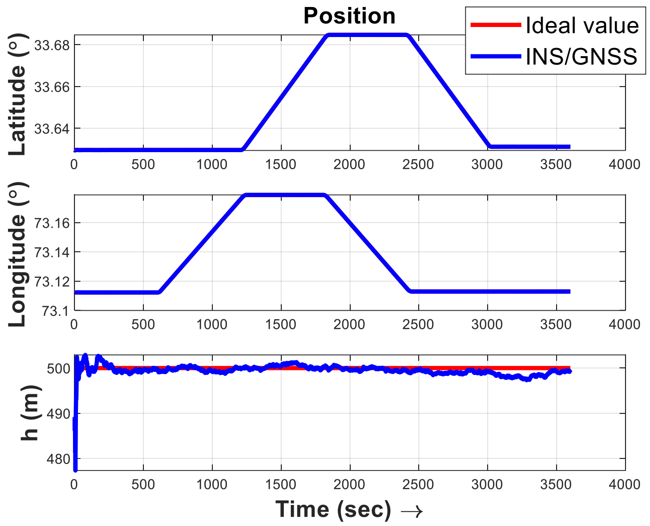


Figure 7: INS/GNSS Integrated Position

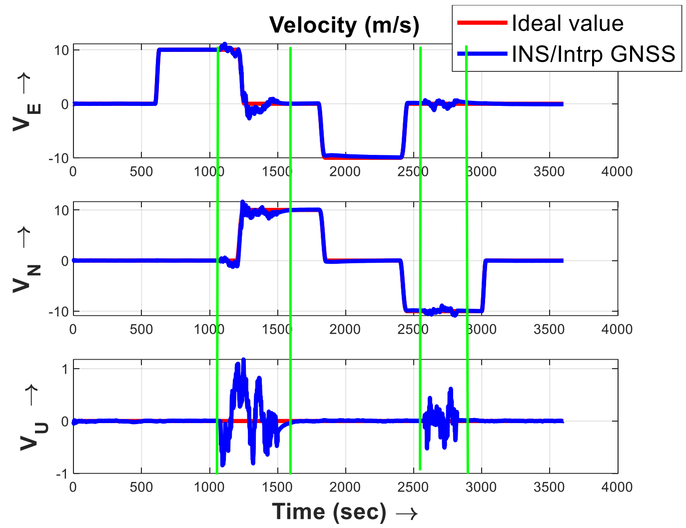


Figure 10: Velocity of INS integrated with GNSS having Random Errors

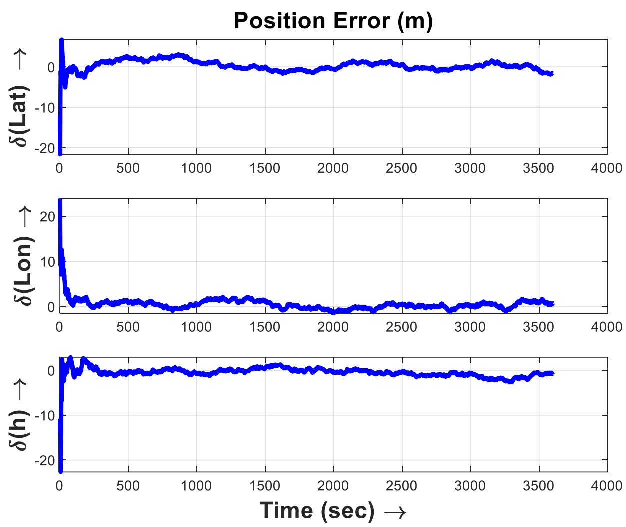


Figure 8: Position Error of INS/GNSS Integration

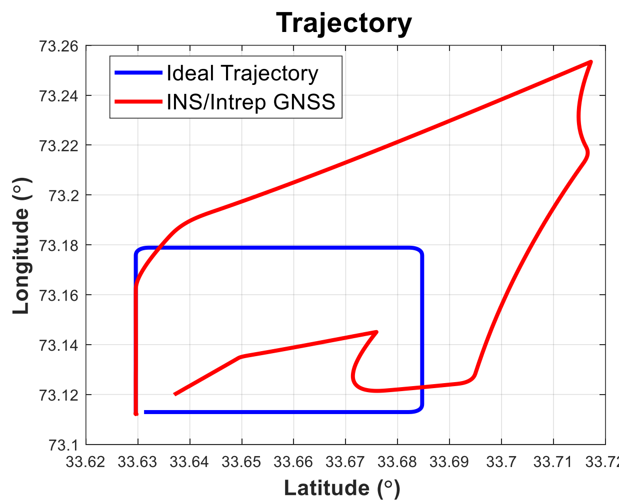


Figure 11: trajectory of INS integrated with GNSS having Growing Errors

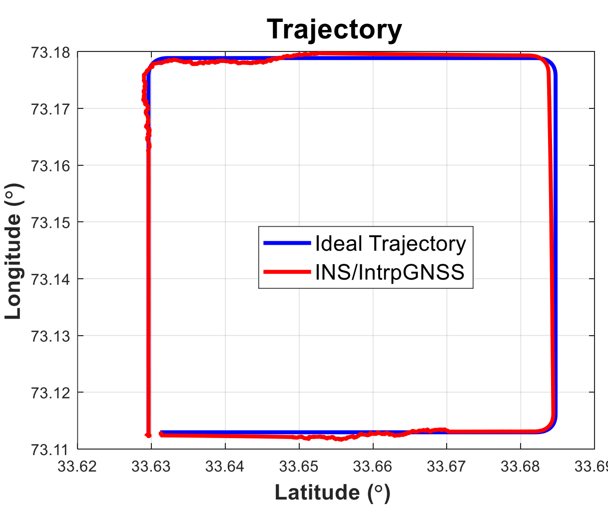


Figure 9: Trajectory of INS Integrated with GNSS having Random Errors

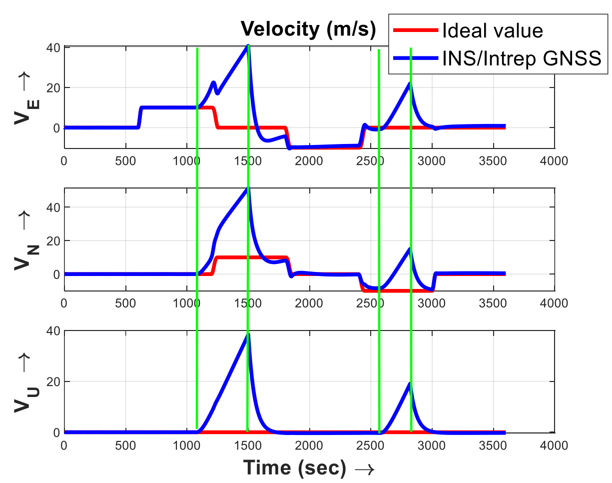
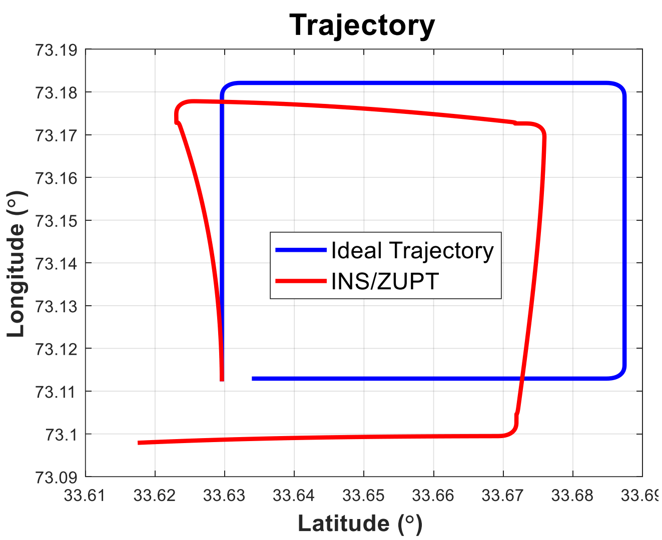


Figure 12: Velocity of INS integrated with GNSS having Growing Errors



VIII.

Figure 13: INS/ZUPT Trajectory

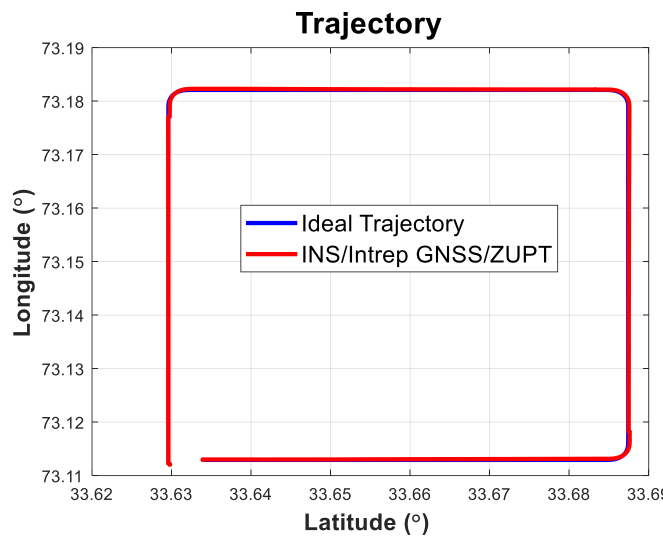


Figure 16: INS/Interrupted GNSS/ZUPT Trajectory

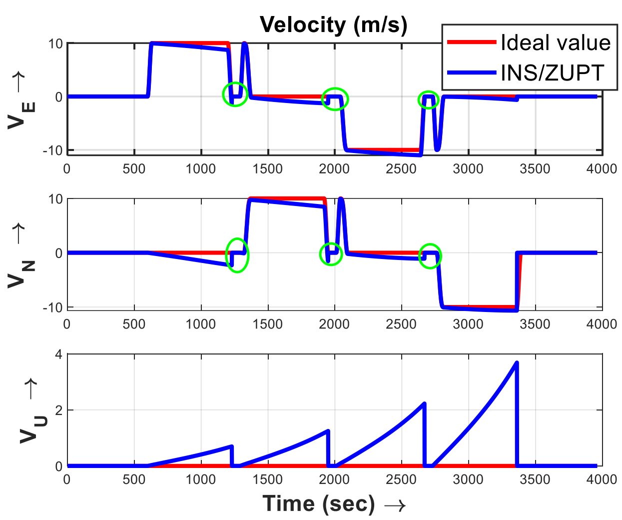


Figure 14: INS/ZUPT Velocity

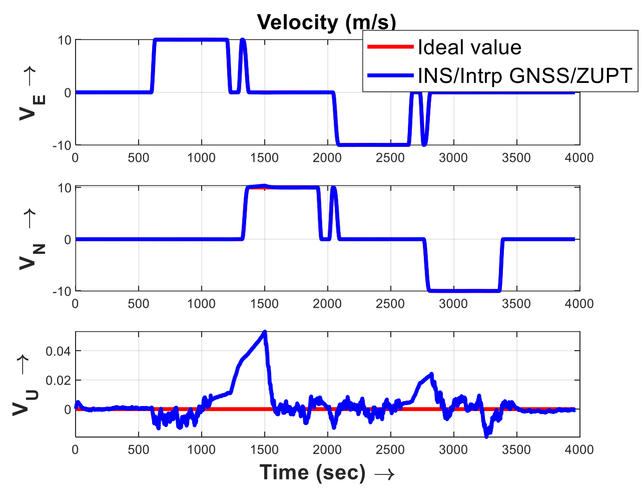


Figure 17: INS/Interrupted GNSS/ZUPT Velocity

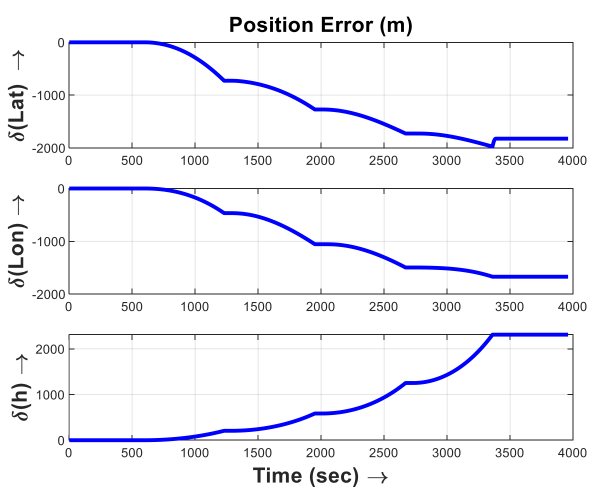


Figure 15: INS/ZUPT Position Error

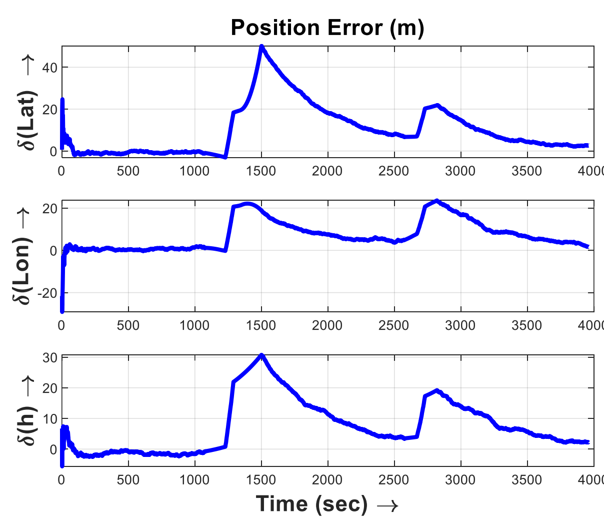


Figure 18: INS/Interrupted GNSS/ZUPT Position Error

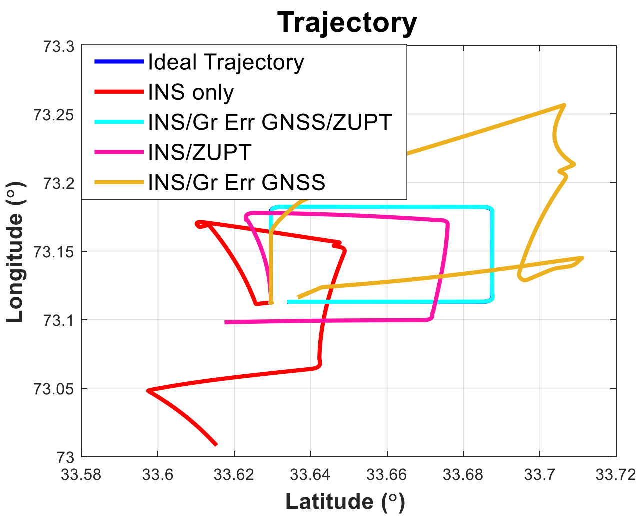


Figure 19: Comparison of Integration Schemes

IX. Conclusion

The standalone INS give the complete and self-contained navigation solution. But due to error accumulation, the INS solution after few minutes becomes overly erroneous for many practical applications, unless highly precise and expensive sensors are used. Therefore, in most scenarios, standalone INS is not employed. The integration of INS with GNSS is the most common practice since the two systems have complementary properties. Nevertheless, there are some sources of errors in GNSS as well which can manifest themselves in different forms. They can introduce growing errors in GNSS position and velocity, increase randomness by several orders of magnitude or can result in null output. In this paper, the two cases of manifestation of GNSS errors are studied. In case of increased randomness, the integrated trajectory does not deviate significantly. But when there is a growing error in GNSS, it completely deteriorates the navigation solution. If zero velocity update is incorporated by stopping the vehicle after some periodic intervals for a short time, the final solution can be significantly improved both in the case of growing and random errors.

References

[1] Y. Liu, F. Liu, Y. Gao, and L. Zhao, “Implementation and Analysis of Tightly Coupled Global Navigation Satellite System Precise Point Positioning/Inertial Navigation System (GNSS PPP/INS) with Insufficient Satellites for Land Vehicle Navigation,” *Sensors*, vol. 18, no. 12, p. 4305, Dec. 2018, doi: https://doi.org/10.3390/s18124305.

[2] M. Mu and L. Zhao, “A GNSS/INS-integrated system for an arbitrarily mounted land vehicle navigation device,” *GPS Solutions*, vol. 23, no. 4, Aug. 2019, doi: https://doi.org/10.1007/s10291-019-0901-8.

[3] C. Chen and G. Chang, “Low-cost GNSS/INS integration for enhanced land vehicle performance,” *Measurement Science and Technology-IOP Science*, vol. 31, no. 3, pp. 035009–035009, Dec. 2019, doi: https://doi.org/10.1088/1361-6501/ab52cb.

[4] K.-W. Chiang, D. T. Le, T. T. Duong, and R. Sun, “The Performance Analysis of INS/GNSS/V-SLAM Integration Scheme Using Smartphone Sensors for Land Vehicle Navigation Applications in GNSS-Challenging Environments,” *Remote Sensing*, vol. 12, no. 11, p. 1732, May 2020, doi: https://doi.org/10.3390/rs12111732.

[5] L. Yang, Y. Li, Y. Wu, and C. Rizos, “An enhanced MEMS-INS/GNSS integrated system with fault detection and exclusion capability for land vehicle navigation in urban areas,” *GPS Solutions*, vol. 18, no. 4, pp. 593–603, Dec. 2013, doi: https://doi.org/10.1007/s10291-013-0357-1.

[6] L. Cong, S. Yue, H. Qin, B. Li, and J. Yao, “Implementation of a MEMS-Based GNSS/INS Integrated Scheme Using Supported Vector Machine for Land Vehicle Navigation,” *IEEE Sensors Journal*, vol. 20, no. 23, pp. 14423–14435, Dec. 2020, doi: https://doi.org/10.1109/jsen.2020.3007892.

[7] H. Dai, H. Bian, R. Wang, and H. Ma, “An INS/GNSS integrated navigation in GNSS denied environment using recurrent neural network,” *Defence Technology*, vol. 16, no. 2, pp. 334–340, Apr. 2020, doi: https://doi.org/10.1016/j.dt.2019.08.011.

[8] Ushaq, Muhammad, Fang Jian Cheng, and Jamshaid Ali. "An adaptive & fault tolerant SINS/GPS integrated navigation scheme robustified against slowly growing errors in GPS updates." Applied Mechanics and Materials 390 (2013): 500-505.

[9] W. Li, X. Cui, and M. Lu, “A robust graph optimization realization of tightly coupled GNSS/INS integrated navigation system for urban vehicles,” *Tsinghua Science and Technology*, vol. 23, no. 6, pp. 724–732, Dec. 2018, doi: https://doi.org/10.26599/tst.2018.9010078.

[10] A. Noureldin, T. B. Karamat, and J. Georgy, *Fundamentals of Inertial Navigation, Satellite-based Positioning and their Integration*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013. doi: https://doi.org/10.1007/978-3-642-30466-8.

[11] J. Wahlstrom and I. Skog, “Fifteen Years of Progress at Zero Velocity: A Review,” *IEEE Sensors Journal*, pp. 1–1, 2020, doi: https://doi.org/10.1109/jsen.2020.3018880.