# Controlling the degree of observability in GPS/INS integration land-vehicle navigation based on extended kalman filter

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**ABSTRACT**

Experimental setup implements the concept of degree of observability (DoO) adequate a land-vehicle navigation application with noised inertial measurement unit (IMU) and global positioning system (GPS) sensors based on a loosely coupled approach. The navigation systems such as IMU-GPS require extensive evaluations of nonlinear equations as used in an extended Kalman filter (EKF). According to DoO and during our test, we have implemented a method for measuring the DoO of all states continuously. Where, the results showed that applying the fusion IMU-GPS system based on EKF be enhanced the DoO measure. The real dataset consists of outputs a high sampling rate for IMU sensor at each (0.01s) and GPS receiver at each (1s). In addition, an aloft category IMU was put together with differential GPS (DGPS) information to produce a real trajectory. GPS has acceptable long-term accuracy, it is used to update the position and velocity in IMU outputs before processing in the EKF algorithm. The implementation consists of three main algorithms: Strapdown (dead reckoning DR), DoO and EKF algorithms. The results are shown, implementation of both approaches based on EKF and the concept of DoO in GPS/INS integrated systems are sufficient robustness to use with low-cost sensors.



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## 1. INTRODUCTION

An inertial navigation system (INS) is an independent navigation system even in the absence exterior data [1], [2]. Where, its contributed this capability that to the emergence of many research and industrial development [3], [4]. Inertial measurement unit (IMU)s low-cost systems have become in along time-proven a principal part of vehicle navigation systems [5], [6]. However, the reliability of an INS is less perfect over time by accumulation errors [7]. Error model application in the INS-GPS navigation system was given in [3]. In addition, The error model is obtained by employing a first-order model of the IMU. On the other hand, a complex INS error model with a Kalman filter of 54 states was presented [8], [9].

Global navigation satellites system (GNSS) as satellite technology is continuously developed and widely used in many areas of human life such as vehicles or aircraft (e.g. aerial robots) [10]. GNSS satellite technology permits the operator to define the location of the aircraft and land-vehicle by using absolute and differential methods [11]. In addition, there are presentations of the DGPS (differential GPS) method in [12]. In the DGPS technique, ground stations in connection to the mobile onboard GPS receiver mounted in the aircraft plays a key role [13]. Moreover, the number of GNSS reference stations involved in DGPS positioning is also very important [14].

INS-GPS integration idea is to use both methods of localization together: estimate and absolute. This idea is justified by the complementarity of proprioceptive sensors and exteroceptive sensors [15]. Integration system ameliorates the quality and integrity of the navigation system, and INS able be utilized to ameliorate the pursuit when GPS signal outage [16]. For INS-GPS integrated system error estimation and compensation.

Estimating techniques such as EKF are frequently utilized. Based on an INS error model and GPS updates, KF calculates location, speed and pitch errors [8], [17]. Therefore, applying this method requires an error model for the INS and a measurement model for the GPS. Since GPS has acceptable long-term accuracy, it is used to update the position and velocity given by the INS. Thus, it limits the long-term increase of INS errors. On the other hand, the short-term, precise information provided by the INS is used to overcome GPS outages and multipath errors. Kalman filter operates in the prediction model when GPS outage occurs and the error model is used to rectify the INS data.

To preserve the navigational signals seen between satellite and its receiver, many guidelines have been set to specify the GPS raw data format. The national marine electronics association (NMEA), the radio technical commission for maritime services (RTCM) and the transceiver independent exchange format are the most widely utilized standards (RINEX) [18].

Concept of the DoO with respect to INS-GPS integrated systems is investigated in this work. in view of the fact that traditional observability analysis is inadequate for an extraordinary navigation scenarios matrix that becomes very large for high-order time-variant system, such that it rises computational difficulties. Since, an unobservable system would not yield an accurate estimation [19] and is prone to divergence [20]. However, if the level of noise is insignificant as a result, observability sets a lower limit on the estimation error, and for more information, see [21]. Therefore, and based on the above discussion, the paper objectives are:

a. Experiment low-cost IMU system to be used as autonomous navigation systems during long GPS outages for general land-vehicle navigation. Then, the fusion of IMU and GPS sensors is assured by the proposed EKF that is used as an estimator technique.
b. Apply a practical approach for observability, especially in dynamic analysis systems, which define the KF efficiency in the estimated states.

The following is a breakdown of the paper's structure: section 2 demonstrates the methodology that was employed. Sections 3 and 4 show summaries of our testing as well as explanations of the results. Finally, in section 5, the conclusions are provided.

## 2. RESEARCH METHOD

### 2.1. INS-GPS integration methods

Different INS-GPS coupling modes exist in the literature [22], [23]. Besides that, difficult problem to develop in real-time for navigation system design [6], [24]. The navigation system in our method consists of a civilian GPS receiver and a low-cost inertial sensor that are loosely connected as shown in Figure 1. This method allows for cost savings in both design and implementation [24], [25].

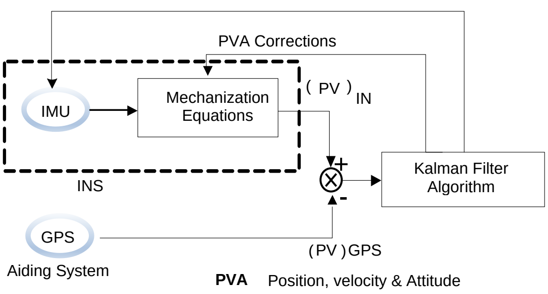


Figure 1. Direct configuration

The GPS receiver's role is to keep the INS up to date with current positions and speeds. The difference between positions and velocities of the both outputs GPS and IMU sensors compute the residual error for input of KF algorithm. The loosely coupled form has various configurations and implementations. The most noted are implementations the open-loop operation and the second closed-loop [7], [26]. In addition, the above INS-GPS integration methods are based by:

a. INS algorithm for integration process. Kalman filter form [26] is defined by two inputs factors, INS calculation equations and INS error model.
b. INS mechanization equations, an IMU was placed on the vehicle's roof. As a result, the both of specific force and the angular velocity in the body frame are defined by $\boldsymbol{f^b}$ and $\boldsymbol{w_{ib}^b}$. Latitude ϕ, longitude λ and height h are used to describe the vehicle's location. In the navigation frame, the equation is as:

$$\begin{bmatrix} \dot{p} \\ \dot{v}^N \\ \dot{R}_b^n \end{bmatrix} = \begin{bmatrix} v^N \\ R_b^n f^b - (2w_{ie}^n + w_{en}^n)v^N + g^n \\ R_b^n(\Omega_{ib}^b - \Omega_{in}^b) \end{bmatrix} \tag{1}$$

Where: $p$: position vector in the navigation frame, $p = [\phi, \lambda, h]^T$
$R_b^n$: transformation matrix from the body frame to navigation frame
$w_{ie}^n$: earth rotation rate vector expressed in the navigation frame
$w_{en}^n$: orientation rate vector of the navigation frame
$\Omega_{ib}^b$: skew-symmetric matrix of the body rotation rate
$\Omega_{ie}^b$: skew-symmetric matrix of the rotation rate vector
$w_{ie}^b$: rate of earth rotation expressed in the body frame
$g^n$: gravity vector expressed in the navigation frame
$v^N$: velocity vector in the navigation frame, $v^N = [v_n, v_e, v_d]$

### 2.2. INS error model

Generally, Information use in the INS-GPS system is preferred to represent in the context of the local geographical location [3], [7]. The placement $p = [\phi, \lambda, h]^T$ is generated by integration of (2) [7]

$$\dot{p} = \begin{bmatrix} \dot{\varphi} \\ \dot{\lambda} \\ \dot{h} \end{bmatrix} = \begin{bmatrix} \frac{v_n}{R_M+h} \\ \frac{v_e}{cos(\varphi)(R_N+h)} \\ -v_d \end{bmatrix} \tag{2}$$

Where $R_N$ and $R_M$ are the meridian and normal earth radii, respectively.

Numerous types of errors affect several navigation systems. Initial condition faults, nonorthogonal features of gyro-meters and accelerometers, and mistakes throughout the integration process all affect INS [27], [28]. However, skew, scale factor error, non-orthogonality, and random errors are the most common defects [7], [27] are presented in the inertial sensors (gyro-meters and accelerometers). The common representations of errors are:

$$\Delta f^b = f^b - \hat{f}^b \tag{3}$$

$$\Delta w_{ib}^b = w_{ib}^b - \widehat{w}_{ib}^b \tag{4}$$

Where: $\hat{f}^b$ and $\widehat{w}_{ib}^b$ are the measured values, correspondingly of $f^b$ and $w_{ib}^b$
$\Delta f^b \Delta w_{ib}^b$ represent measurement errors in specific force and relative angular rate.
$\Delta\hat{f}^b$ and $\Delta\widehat{w}_{ib}^b$ are the specified force error and related angular velocity error estimates, respectively.
The favorite notion of error statuses ($\delta x$) in a navigation system is convenient [26].

$$\begin{bmatrix} \delta\dot{p} \\ \delta\dot{v}^N \\ \dot{\rho} \end{bmatrix} = F\begin{bmatrix} \delta p \\ \delta v \\ \rho \end{bmatrix} + G\begin{bmatrix} \delta f^b \\ \delta w_{ib}^b \end{bmatrix} \tag{5}$$

$$\text{With } F = \begin{pmatrix} F_{pp} & F_{pv} & F_{p\rho} \\ F_{vp} & F_{vv} & F_{v\rho} \\ F_{\rho p} & F_{\rho v} & F_{\rho\rho} \end{pmatrix} \text{ and } G = \begin{bmatrix} 0 & 0 \\ -R_b^n & 0 \\ 0 & R_b^n \end{bmatrix} \tag{6}$$

The error vector has been established by $\delta x = [\delta p, \delta v, \rho]^T$, where $\delta p = p - \hat{p} = \delta p = [\delta\varphi, \delta\lambda, \delta h]^T$, $\delta v = v_e^n - \hat{v}_e^n = \delta p = [\delta v_n, \delta v_e, \delta v_d]^T \rho = [\varepsilon_N, \varepsilon_E, \varepsilon_D]^T$ and $\delta w_{ib}^b = \Delta w_{ib}^b + \Delta \widehat{w}_{ib}^b$.

Many forms of matrix F are proposed [29]. In [8], it contains of the proposition of a simplified error model. The constituents of matrix F in this scenario are as:

$$F_{pp} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (7)$$

$$F_{pv} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (8)$$

$$F_{p\rho} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (9)$$

$$F_{vp} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \tau_D^{-2} \end{bmatrix} \quad (10)$$

$$F_{vv} = \begin{bmatrix} 0 & -2w_{ie} \sin\varphi & 0 \\ -2w_{ie} \sin\varphi & 0 & 2w_{ie} \cos\varphi \\ 0 & -2w_{ie} \cos\varphi & 0 \end{bmatrix} \quad (11)$$

$$F_{v\rho} = \begin{bmatrix} 0 & f_D + 2g & -f_N \\ -f_D - 2g & 0 & f_E \\ f_N & -f_E & 0 \end{bmatrix} \quad (12)$$

$$F_{\rho p} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (13)$$

$$F_{\rho v} = \begin{bmatrix} 0 & R_e^{-1} & 0 \\ -R_e^{-1} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad (14)$$

$$F_{\rho\rho} = \begin{bmatrix} 0 & -w_{ie} \sin\varphi & 0 \\ w_{ie} \sin\varphi & 0 & w_{ie} \cos\varphi \\ 0 & -w_{ie} \cos\varphi & 0 \end{bmatrix} \quad (15)$$

Where: $\varphi$ is the latitude and $T_D \approx \sqrt{\frac{R}{2g}} = 520(s)$

$R_e = \sqrt{R_M R_N} \approx 6372795.5\ m$is the earth average radius.

$w_{ie} \approx 7.292115 \times 10^{-5} rad/s$ is the earth rotation rate.

$f_N, f_E, f_D$: are the specialized forces of north, east, and downward.

### 2.3. Extended Kalman filter

INS-GPS in direct configuration, the KF is made up of two estimated values combined (INS and GPS data), the position, velocity, and attitude (PVA) solutions are the same for these two parameters [27], [26]. In our experiment, the inertial navigation system, which serves as the process model, provides the initial estimate directly. The GPS receiver provides the second estimate, which is the measurement. The position of the system (land-vehicle) in a navigation system is represented by state, speed, and attitude (PVA solutions) [26]. In a continuous state, the moving system is characterized by linear system equations [8].

$$\dot{x}(t) = F(t)x(t) + G(t)u(t) \quad (16)$$

The dynamic matrix (obtained via partial derivatives) is F(t), the position vector is x(t), the layout matrix is G(t), and the forcing function is u(t). The components of of $u(t) = [\delta f^b, \delta w_{ib}^b]^T$ are white noise with a covariance matrix of

$$Q = diag\left(\sigma_{ax}^2 \sigma_{ay}^2 \sigma_{az}^2 \sigma_{wx}^2 \sigma_{wy}^2 \sigma_{wz}^2\right) \tag{17}$$

The following is the measurement model:

$$z(t) = H(t)x(t) + v(t) \tag{18}$$

Here z(t) is the measurement at time t, H denotes the observation matrix and v(t) denotes white noise $v(t) \sim N\,(0, R)$. The use of IMU data should be based on very short sampling time intervals $\Delta t = t_k - t_{k-1}$ (update every IMU=100 Hz), Table 1 shows the position (vehicle movement: PVA variation scalar) and measurement model [7], [27]. The discrete-time KF equations are summarized in Table 1 [3], [8].

Table 1. KF equations in discrete time

| KF parameters | KF equations |
|---|---|
| System model | $x_k = \Phi_{k-1}x_{k-1} + w_{k-1}$, $w_k \sim N(0, Q_k)$ |
| Initialization | $\hat{x}_0^- = E[x_0]$,$P_0^- = var\ \ (x_0^-)$ |
| Gain calculation | $K_k = P_k^- H_k^T (R_k + H_k P_k^- H_k^T)^{-1}$ |
| Measurement update | $\hat{x}_0^+ = \hat{x}_0^- + K_k(\tilde{y}_k - \hat{y}_k)$ |
| Covariance matrix update | $P_k^+ = [I - K_k H_k] P_k^-$ |
| Time propagation | $\hat{x}_{k+1}^- = \Phi_k \hat{x}_k^- + G_k u_k$<br>$P_{k+1}^- = \Phi_k P_k^+ \Phi_k^T + \Phi_{dk}$<br>$(\Phi_{dk} = G_k \Phi_k G_k^T \Delta T)$<br>Where $x^-, x^+$: are, respectively, the Priori and Posteriori state vector,<br>$P^-, P^+$: are, respectively, the Priori and Posteriori error covariance matrix.<br>$G = \begin{bmatrix} 0 & 0 \\ -R_b^n & 0 \\ 0 & R_b^n \end{bmatrix}$ $and\ Q = diag\left(\sigma_{ax}^2, \sigma_{ay}^2, \sigma_{az}^2, \sigma_{wx}^2, \sigma_{wy}^2, \sigma_{wz}^2\right)$<br>are, respectively, the standard deviation of the accelerometers and gyro-meters |

## 2.4. Observability analysis

A method that allows knowing the degree the health of internal system if it's good or no by measuring the external information output detects. This method is called 'observability' [30]. Here, in our non-linear system, H(t)=I3×3 is time constants; thus, we put observability by using Boolean condition.

$$rank(O_\upsilon) \stackrel{?}{=} rank(O_{\upsilon+1}) \tag{19}$$

$$\text{let } O = \begin{bmatrix} N_0(t) \\ N_1(t) \\ \vdots \\ N_{\upsilon-1}(t) \end{bmatrix} \Rightarrow \begin{bmatrix} H_0(t) \\ H_0(t)F(t) + \frac{\partial}{\partial x} H_0(t) \\ \vdots \\ H_{\upsilon-1}(t)F(t) + \frac{\partial}{\partial x} H_{\upsilon-1}(t) \end{bmatrix} \Rightarrow \begin{bmatrix} H \\ HF \\ \cdots \\ HF^{\upsilon-1} \end{bmatrix} \tag{20}$$

However, in [31], the innovation of the idea of "degree of observability" was based on a quantitative approach. We achieve an error covariance (P), through the several iterations in the extended Kalman filter process. The disparity between the estimate and real state values is indicated by this error. Furthermore, the standard mathematical analysis has been applied.
Description normalized error (P′)

$$P'(k) = \left(\sqrt{P(0)}\right)^{-1} P(k)\left(\sqrt{P(0)}\right)^{-1} \tag{21}$$

Where: P(0) is the initial error covariance matrix, P(k) is the current error covariance matrix. The acquired matrix can be presented in (22), Pij and Pij(0) are the error covariance matrix elements. The pursuit is obtained by the sum of all of the eigenvalues, after that we obtain the normalized error covariance in (8). The eigenvalues of P″(k) are without dimension and limited between 0 < λi ≤ n, such that the DoO is defined better, as the error turns smaller.

$$P'(k) \Rightarrow \begin{bmatrix} \frac{P_{11}}{P_{11}(0)} & \frac{P_{12}}{\sqrt{P_{11}(0)P_{22}(0)}} & \cdots & \frac{P_{12}}{\sqrt{P_{11}(0)P_{nn}(0)}} \\ \frac{P_{21}}{\sqrt{P_{22}(0)P_{11}(0)}} & \frac{P_{11}}{P_{22}(0)} & \cdots & \frac{P_{12}}{\sqrt{P_{22}(0)P_{nn}(0)}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{P_{n1}}{\sqrt{P_{nn}(0)P_{11}(0)}} & \frac{P_{n2}}{\sqrt{P_{nn}(0)P_{22}(0)}} & \cdots & \frac{P_{nn}}{P_{nn}(0)} \end{bmatrix} \quad (22)$$

$$P''(k) = \frac{n}{tr(P'(k))} P'(k) \quad (23)$$

## 3. RESULTS AND DISCUSSION

### 3.1. Field-test data description

A micro-electro-mechanical system (MEMS) based IMU was used. The motion pak II is a solid-state device cluster in use in instrumentation and control applications to measure linear accelerations and angular rates (dead reckoning aiding GPS, robotics, and flight testing etcas seen in Figure 2, the IMU (motion pak II) unit was placed on the vehicle's rooftop, with the NovAtel OEM4 GPS receiver [32].

### 3.2. Datasets specification

The datasets are utilized to put the suggested method to the test. Real dataset consists to outputs IMU sensor (motion pak II) and GPS receiver (OEM4). Figure 3 shows the assumed real trajectory obtained by combining a better grade IMU (CIMU) with DGPS data. Furthermore, some initial parameters have been used to correct a problem of synchronization between the IMU and GPS receiver output data.


Figure 2. Motion pack II placement on the test vehicle

Figure 3. True trajectory of the experimental vehicle

### 3.3. IMU (motion pak II) properties

In order to put the proposed approach to the test. GPS data was collected at 1 Hz, whereas inertial measurement data was collected at 100 Hz. The data-gathering measurement units were put on top of a land vehicle. In Figure 4, the results of the input values $f_b^y$ and $w_z$ are clearly shown noisy. When GPS/INS fusion is not used, the vehicle does not track the reference track over all directions, as shown in Figure 5.

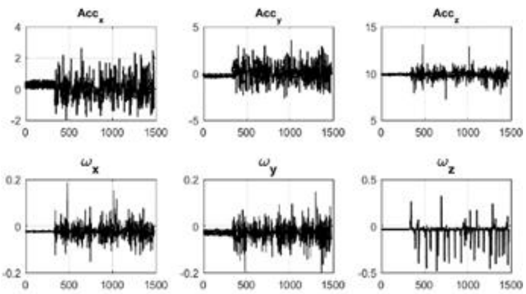


Figure 4. IMU measurements along run

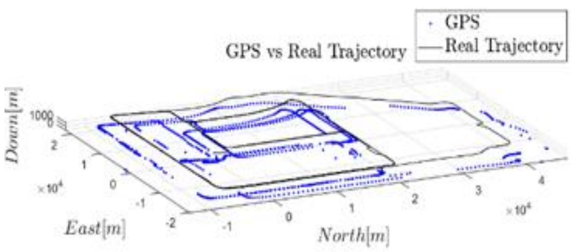


Figure 5. True trajectory vs GPS measurements

### 3.4. Error state results

Let’s examine the estimation performance over time, starting with Table 2. Firstly, position error in Figure 6, As shown the decay from the initial value along time and the representation of the standard of deviation is the magenta dashed line. As seen the geodetic angle errors (φ, λ) show small changes that oncoming to zero, since the model moves only few meters in the LLLN frame. Contrarily, the altitude is scaled in meters w.r.t previous samples, such that the error magnitude is much bigger.

Secondary, velocity error states in Figure 7, Contrarily, the position that is being corrected by the observation (GPS measurement) itself, here the errors increase over time and develop in a random walk. v_N and v_E show noisy style while v_D succeeds to stabilize, after a period, as it can be clarified our strap down model's inexactness.

Table 2. Accelerometer and gyro-meter properties

| | | X | Y | Z |
|---|---|---|---|---|
| Bias Factory | Accelerometer | ± 125 | ± 125 | ± 125 |
| Set ($mg^2$, /s) | Gyro meter | ± 5.0 | ± 5.0 | ± 5.0 |
| Scale Factor | Accelerometer | 6.66 V/g | 6.66 V/g | 6.66 V/g |
| (mg2, °/s) | Gyro meter | 0.133 V/°/s | 0.133 V/°/s | 0.133 V/°/s |
| Input Axis Alignment | Accelerometer | 1 | 1 | 1 |
| (°typical) | Gyro meter | 1 | 1 | 1 |

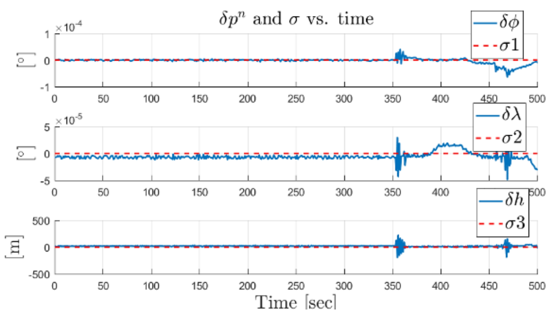


Figure 6. Position error vs time

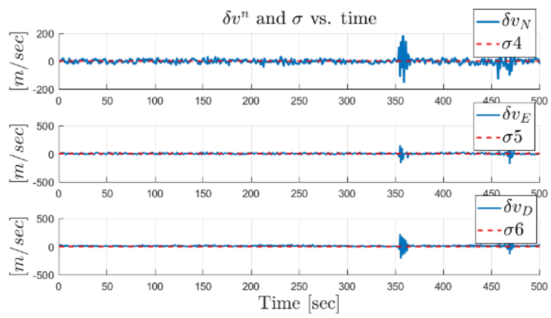


Figure 7. Velocity error vs time

Now let’s check the euler angles error in Figure 8, it describes the Euler angles error φ (roll), θ (pitch) and (δψ) that obtained from transformation Matrix $R_b^n$. As it appears, a small variation occurred on the axis φ (roll) and θ (pitch). Contrarily, a great variation in azimuthal (δψ). It's logical because, the variation in the planar motions is related in same motion of the orientation of the land vehicle.

### 2.5. Degree of observability (DoO) results

We’ll now show the DoO analysis based on section 2.6, and see if we can determine which states are being best estimated (↓ DoO), and which are most weakly (↑ DoO). It’s clearly shown in Figure 9, there are cambers in starting of the land vehicle in (φ, λ and h) Latitude, longitude and altitude respectively. Afterward, continues with many drifts and outages caused by two sensors IMU and GPS

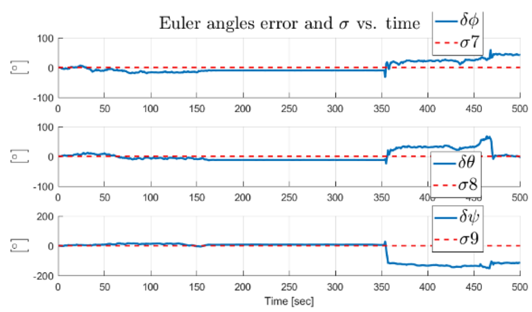


Figure 8. Euler angles error vs time

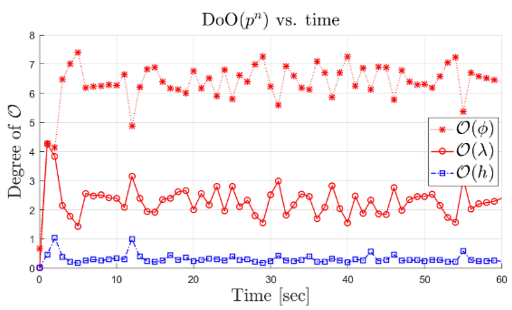


Figure 9. DoO of position error vs time

Here in Figure 10, the velocity states DoO, exhibit an acute downhill and after approximately one second nullified. This can be explained by the position/velocity IMU coupling within the mode. From Figure 11, the vehicle is initialized stationary where noise measurements increase the residual measurement. But once motion is starting, the Euler angles' DoO immediately zero down after, implying that the estimator manages to succeed well in the estimating mission, although direct $R_b^n$ measurement does not exist.

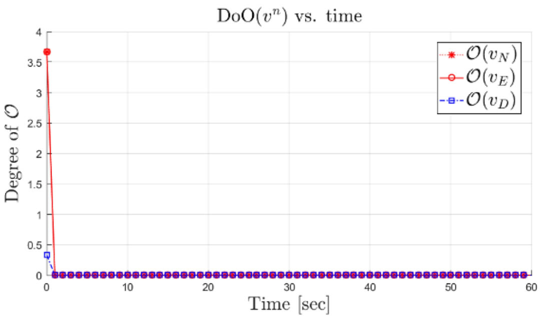


Figure 10. DoO of velocity error vs time

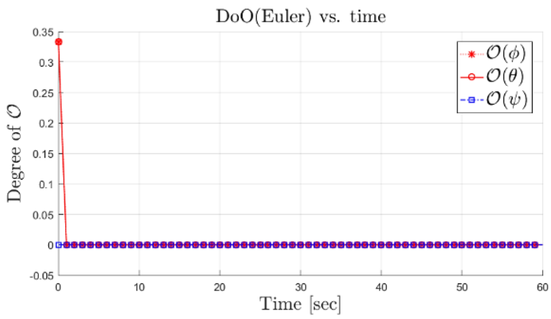


Figure 11. DoO of euler angle error vs time

## 3.6. Comparison

### 3.6.1. GPS measurements, reference and estimate trajectories

The proposed approach, as illustrated in Figure 12 and Figure 13, gives comparable results for the moveable vehicle in all directions. The vehicle is tracking the reference trajectory with nearly no errors in all directions, as shown in the following figures, especially after applying the fusion stage over the total running duration. Furthermore, the running algorithm did not fail during GPS signal outages, demonstrating the suggested approach's ability to recompensate the signal during GPS outages.

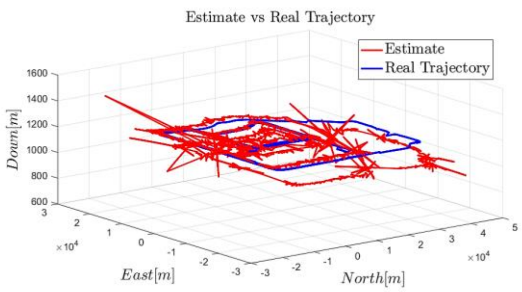


Figure 12. Estimate vs true trajectory

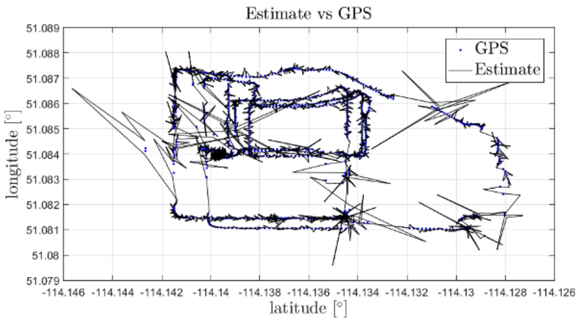


Figure 13. Estimate vs GPS measurements

### 3.6.2. Strapdown (dead reckoning), KF-INS and EKF(INS-GPS) algorithms

Table 3 shows the drift errors for KF-IMU, EKF (IMU-GPS), and dead reckoning (IMU alone) for motion pak II during all six outages, and clearly shows that EKF (IMU-GPS) offers similar results to KF/IMU for drift errors when GPS outages occur. Each GPS outage's individual maximum drift errors, as well as the mean of the highest drift errors, are presented. The supplied drift errors are calculated by calculating the square root of the sum of squared errors in latitude, longitude, and altitude, and thus represent total errors in all directions. Dead reckoning, on the other hand, produces findings that are similar to those of the EKF(IMU-GPS). Since there is no updated IMU data by GPS for each 1s, this is logical.

Table 3. Results for MP field tests

| GPS outages | KF/INS (m) | Dead reckoning (m) | EKF-INS/GPS (m) |
|---|---|---|---|
| # 1 | 159.4 | 72.5 | 104 |
| # 2 | 212.9 | 205.8 | 171 |
| # 3 | 210.2 | 174 | 202 |
| # 4 | 181.8 | 240 | 214 |
| # 5 | 194.9 | 275.7 | 211 |
| # 6 | 90.49 | 300 | 101 |
| Mean value | 179.95 | 224.16 | 173.86 |

## 4. CONCLUSION

In this paper, using noised IMU and global positioning system (GPS) sensors, a realistic approach for determining the complete kinematic state of a land-vehicle navigation application based on direct configuration approach. On the other hand, the implementation of the concept of DoO with respect to GPS/INS integrated systems was conducted and discussed theoretically and experimentally.

The system's architecture is built on a loosely connected integration method using EKF. For this type of system, the EKF is still the standard estimation technique. However, almost all contemporary approaches in the literature are based on the filter's indirect setup (namely also error configuration). In general, the results of our tests showed, the position and velocity errors converge to zero while the orientation errors remain small during the run. There are three possibilities of the reasons that orientation doesn’t converge to zero since could be: i) indirect connection between them and the GPS measurements, ii) error from the strap-down algorithm (model error).

Afterward, we examined the filter with several different fusion ratios between GPS and IMU rates and saw that as the ratio gets higher the accuracy, but also the calculation’s complexity increases. It is considered that the both approaches of GPS/INS integrated systems Based on EKF and the concept of the DoO are sufficiently durable to be used in conjunction with low-cost detectors. Finally, future work will focus on improving estimation accuracy by adding more dynamic models to the filter and expanding the input sources to include other positional sensors such as visual odometry. Furthermore, EKF can be upgraded to its adaptive version, which allows the system to perform more efficiently even when there are no GPS signals.

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