

Robot Vision and Navigation : Coursework 1

Integrated Navigation for a Robotic Lawnmower

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1 Method Description

In this coursework, I were provided with 3 files : one file containing the pseudo ranges of the different satellites at different time t , another file containing the pseudo range rates of the different satellites at different time t and one last file composed of measurements from the sensors of the lawnmower (wheels, gyroscope and compass). With the first and second files, I could compute the GNSS positions and velocities of the lawnmower. With the third file, I could compute the different positions and velocities of the lawnmower relatively to its initial positions and velocities. Then, using these 2 results, I computed an integrated horizontal-only DR/GNSS navigation solution using Kalman filtering : I used the GNSS solution to correct the Dead Reckoning solution.

To compute the heading, I used the gyroscope and compass data provided in the third file : I used the Magnetic heading solution to correct the gyroscope derived heading solution by using a 2 state Kalman filter.

All these solutions were computed using the algorithm presented during the lectures or the workshops.

2 Algorithm

First, I computed the GNSS positions and velocities solutions of the lawnmower. To do that, I used a least-square estimation method to initialize the lawnmower's positions (x_0) and velocities (v_0)^[1] :

Algorithm 1 Initialize GNSS solution (x_2, v_0)

```
1: procedure INITIALISATION
2:    $x_0 \leftarrow (0, 0, 0)$ 
3:    $v_0 \leftarrow (0, 0)$ 
4:   For each satellite, computes its positions and velocities
5:    $distance \leftarrow \inf$ 
6:   while  $distance \geq \epsilon$ 
7:     for each  $satellites^{[2]}$ 
8:       compute its Sagnac effect compensation matrix
9:       compute its predicted range and predicted range rate from the user position
10:      compute its line-of-sight unit vector from the user position
11:    end for
12:    Compute predicted state vector positions  $x^{[3]}$  and velocities  $v^{[4]}$ 
13:    Compute measurement innovation vector range  $dz^{[3]}$  and range rate  $dz^{[4]}$ 
14:    Compute measurement matrix[3]  $H$ 
15:     $x \leftarrow x' + (H^T H)^{-1} H^T dz$ 
16:     $v \leftarrow v' + (H^T H)^{-1} H^T dz'$ 
17:     $distance \leftarrow norm(x_0 - x)$ 
18:     $x_0 \leftarrow x$ 
19:     $v_0 \leftarrow v$ 
20:  end while
```

This algorithm stop when 2 predicted positions of the lawnmower are close enough to each other. Then, we will say that there is convergence. Then, I apply a GNSS Kalman filter^[5] to the initialized

positions and velocities :

Algorithm 2 compute GNSS solution with 8 state Kalman filter

```

1: procedure INITIALISATION
2:    $x_0, v_0$ 
3:    $\tau \leftarrow 0.5$ 
4:   initialise state vector  $X_0 = (x_0, v_0, d\rho_a, d\rho_b)^T$ 
5:   initialise error covariance matrix  $P$ 
6:   for each epoch  $k=2..n$ 
7:      $\Phi_{k-1} \leftarrow \begin{pmatrix} I_3 & \tau I_3 & 0_{3,1} & 0_{3,1} \\ 0_3 & I_3 & 0_{3,1} & 0_{3,1} \\ 0_{1,3} & 0_{1,3} & 1 & \tau \\ 0_{1,3} & 0_{1,3} & 0 & 1 \end{pmatrix}$ 
8:      $Q_{k-1} \leftarrow \begin{pmatrix} \frac{1}{3}S_a\tau^3 I_3 & \frac{1}{2}S_a\tau^2 I_3 & 0_{3,1} & 0_{3,1} \\ \frac{1}{2}S_a\tau^2 I_3 & S_a\tau I_3 & 0_{3,1} & 0_{3,1} \\ 0_{1,3} & 0_{1,3} & S_{c\phi}\tau + \frac{1}{3}S_{cf}\tau^3 & \frac{1}{2}S_{cf}\tau^2 \\ 0_{1,3} & 0_{1,3} & \frac{1}{2}S_{cf}\tau^2 & S_{cf}\tau \end{pmatrix}$ 
9:      $x_k \leftarrow \Phi_{k-1}X_{k-1}$ 
10:     $P_k \leftarrow \Phi_{k-1}P\Phi_{k-1}^T + Q_{k-1}$ 
11:    for each satellites[2]  $j = 1..m$ 
12:      compute its Sagnac effect compensation matrix
13:      compute its predicted range  $r_j$  and predicted range rate  $r'_j$  from the user position
14:      compute its line-of-sight unit vector  $u_j$  from the user position
15:    end for
16:     $H_k \leftarrow \begin{pmatrix} -u_{1,x} & -u_{1,y} & -u_{1,z} & 0 & 0 & 0 & 1 & 0 \\ -u_{2,x} & -u_{2,y} & -u_{2,z} & 0 & 0 & 0 & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -u_{m,x} & -u_{m,y} & -u_{m,z} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -u_{1,x} & -u_{1,y} & -u_{1,z} & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & -u_{m,x} & -u_{m,y} & -u_{m,z} & 0 & 1 \end{pmatrix}$ 
17:     $R_k \leftarrow \begin{pmatrix} \sigma_p^2 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_p^2 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_p^2 & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \sigma_r^2 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & \sigma_r^2 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & \sigma_r^2 \end{pmatrix}$ 
18:     $K_k \leftarrow P_k H_k^T (H_k P_k H_k^T + R_k)^{-1}$ 
19:     $dz \leftarrow \begin{pmatrix} \rho_1 - r_1 - d\rho_a \\ \vdots \\ \rho_m - r_m - d\rho_a \\ \rho'_1 - r'_1 - d\rho_b \\ \vdots \\ \rho'_m - r'_m - d\rho_b \end{pmatrix}$ 
20:     $X_k \leftarrow x_k + K_k dz$ 
21:     $P \leftarrow (I - K_k H_k) P_k$ 
22:  end for

```

with ρ_a and ρ_b clock offset and clock drift, τ propagation time, S_a acceleration power spectral density (PSD), $S_{c\phi}$ clock phase PSD, S_{cf} clock frequency PSD, ρ_j measured pseudo range of satellite j and ρ'_j

measured pseudo range rate of satellite j .

Secondly, I computed the lawnmower positions and velocities using by dead car reckoning before corrected it with the GNSS solutions. Since, the dead reckoning solution depend on the heading, I corrected the gyroscope derived heading solution using the magnetic heading^[5]. To do that, I used a 2 state Kalman Filter :

Algorithm 3 Corrected gyro-derived heading solution with 2 state Kalman filter

```

1: procedure INITIALISATION
2:    $X_0 = (\delta\Psi \ b_g)^T = (0 \ 0)$ 
3:    $(\Psi^G)_i$  gyro-derived heading solution
4:    $\tau \leftarrow 0.5$ 
5:   initialise error covariance matrix  $P$ 
6:   for each epoch  $k=2..n$ 
7:      $\Phi_{k-1} \leftarrow \begin{pmatrix} 1 & \tau_s \\ 0 & 1 \end{pmatrix}$ 
8:      $Q_{k-1} \leftarrow \begin{pmatrix} S_{rg}\tau + \frac{1}{3}S_{bgd}\tau^3 & \frac{1}{2}S_{bgd}\tau^2 \\ \frac{1}{2}S_{bgd}\tau^2 & S_{bgd}\tau \end{pmatrix}$ 
9:      $x_k \leftarrow \Phi_{k-1}X_{k-1}$ 
10:     $P_k \leftarrow \Phi_{k-1}P\Phi_{k-1}^T + Q_{k-1}$ 
11:     $H_k \leftarrow \begin{pmatrix} -1 & 0 \end{pmatrix}$ 
12:     $R_k \leftarrow \sigma_M^2$ 
13:     $K_k \leftarrow P_k H_k^T (H_k P_k H_k^T + R_k)^{-1}$ 
14:     $dz \leftarrow (\Psi^M - \Psi^G) - H_k x_k$ 
15:     $X_k \leftarrow x_k + K_k dz$ 
16:     $P \leftarrow (I - K_k H_k) P_k$ 
17:     $\Psi_k^G \leftarrow \Psi_k^G - \delta\Psi$ 
18:  end for

```

with $\delta\Psi$ the heading measurement error, S_{rg} the gyroscope random noise with PSD, S_{bgd} gyroscope bias variation, σ_M the magnetic heading noise variance, Ψ^M the magnetic heading solution and Ψ^G the gyro-derived heading solution.

with these heading solutions, I compute the dead reckoning solutions^[6] position x and velocities v :

Algorithm 4 Dead reckoning navigation solution

```

1: procedure INITIALISATION
2:    $(\Psi)_i$  gyro-derived heading solution
3:    $x_0 = (L_0, \lambda_0) = GNSSinitialization$ 
4:    $v_0 = GNSSinitialization$ 
5:    $(v_{N,0}, v_{E,0}) \leftarrow (v_0 \cos(\Psi_0), v_0 \sin(\Psi_0))$ 
6:    $\tau \leftarrow 0.5$ 
7:   for each epoch  $k=2..n$ 
8:      $\begin{pmatrix} v'_{N,k} \\ v'_{E,k} \end{pmatrix} \leftarrow \frac{1}{2} \begin{pmatrix} \cos(\Psi_k) + \cos(\Psi_{k-1}) & 0 \\ 0 & \sin(\Psi_k) + \sin(\Psi_{k-1}) \end{pmatrix} \begin{pmatrix} v'_{N,k-1} \\ v'_{E,k-1} \end{pmatrix}$ 
9:     compute meridian radius of curvature  $R_N$  and transverse radius of curvature  $R_E$ 
10:     $L_k \leftarrow L_{k-1} + \frac{v'_{N,k}\tau}{R_N}$ 
11:     $\lambda_k \leftarrow \lambda_{k-1} + \frac{v'_{E,k}\tau}{R_E \cos(L_k)}$ 
12:     $v_{N,k} \leftarrow 2v'_{N,k} - v_{N,k-1}$ 
13:     $v_{E,k} \leftarrow 2v'_{E,k} - v_{E,k-1}$ 
14:  end for

```

Once I have computed the GNSS and dead reckoning navigation solutions, I can now compute the corrected dead reckoning navigation solution using a 4 state Kalman Filter^[7] :

Algorithm 5 Corrected dead reckoning solution with 4 state Kalman filter

```

1: procedure INITIALISATION
2:    $X_0 = (\delta v_N \ \delta v_E \ \delta L \ \delta \lambda)^T = (0 \ 0 \ 0 \ 0)$ 
3:    $P_0 \leftarrow \begin{pmatrix} \sigma_v^2 & 0 & 0 & 0 \\ 0 & \sigma_v^2 & 0 & 0 \\ 0 & 0 & \frac{\sigma_r^2}{R_N} & 0 \\ 0 & 0 & 0 & \frac{\sigma_r^2}{R_E \cos(L_0)} \end{pmatrix}$ 
4:    $\tau \leftarrow 0.5$ 
5:   for each epoch  $k=2..n$ 
6:      $\Phi_{k-1} \leftarrow \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \frac{\tau_s}{R_N} & 0 & 1 & 0 \\ 0 & \frac{\tau}{R_E \cos(L_{k-1})} & 0 & 1 \end{pmatrix}$ 
7:      $Q_{k-1} \leftarrow \begin{pmatrix} S_{DR}\tau & 0 & \frac{1}{2} \frac{S_{DR}\tau^2}{R_N} & 0 \\ 0 & S_{DR}\tau & 0 & \frac{1}{2} \frac{S_{DR}\tau^2}{R_E \cos(L_{k-1})} \\ \frac{1}{2} \frac{S_{DR}\tau^2}{R_N} & 0 & \frac{1}{3} \frac{S_{DR}\tau^3}{R_N^2} & \frac{1}{3} \frac{S_{DR}\tau^3}{R_E \cos(L_{k-1})} \\ 0 & \frac{1}{2} \frac{S_{DR}\tau^2}{R_E \cos(L_{k-1})} & 0 & \frac{1}{3} \frac{S_{DR}\tau^3}{R_E \cos(L_{k-1})} \end{pmatrix}$ 
8:      $x_k \leftarrow \Phi_{k-1} X_{k-1}$ 
9:      $P_k \leftarrow \Phi_{k-1} P \Phi_{k-1}^T + Q_{k-1}$ 
10:     $H_k \leftarrow \begin{pmatrix} 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \\ -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \end{pmatrix}$ 
11:     $R_k \leftarrow \begin{pmatrix} \frac{\sigma_{GR}^2}{R_N^2} & 0 & 0 & 0 \\ 0 & \frac{\sigma_{GR}^2}{R_E^2 \cos(L_K)^2} & 0 & 0 \\ 0 & 0 & \sigma_{Gv}^2 & 0 \\ 0 & -1 & 0 & \sigma_{Gv}^2 \end{pmatrix}$ 
12:     $K_k \leftarrow P_k H_k^T (H_k P_k H_k^T + R_k)^{-1}$ 
13:     $dz \leftarrow \begin{pmatrix} L_k^G - L_k^D \\ \lambda_k^G - \lambda_k^D \\ v_{N,k}^G - v_{N,k}^D \\ v_{E,k}^G - v_{E,k}^D \end{pmatrix} - H_k x_k$ 
14:     $X_k \leftarrow x_k + K_k dz$ 
15:     $P \leftarrow (I - K_k H_k) P_k$ 
16:     $L_k^D \leftarrow L_k^D - \delta L_k$ 
17:     $\lambda_k^D \leftarrow \lambda_k^D - \delta \lambda_k$ 
18:     $v_{N,k}^D \leftarrow v_{N,k}^D - \delta v_{N,k}$ 
19:     $v_{E,k}^D \leftarrow v_{E,k}^D - \delta v_{E,k}$ 
20:  end for

```

with σ_v the initial velocity uncertainty, σ_r the initial position uncertainty, S_{DR} the dead reckoning PSD, σ_{Gr} the GNSS positions measurement error standard deviation, σ_{Gv} the GNSS velocity measurements error standard deviation.

3 Results

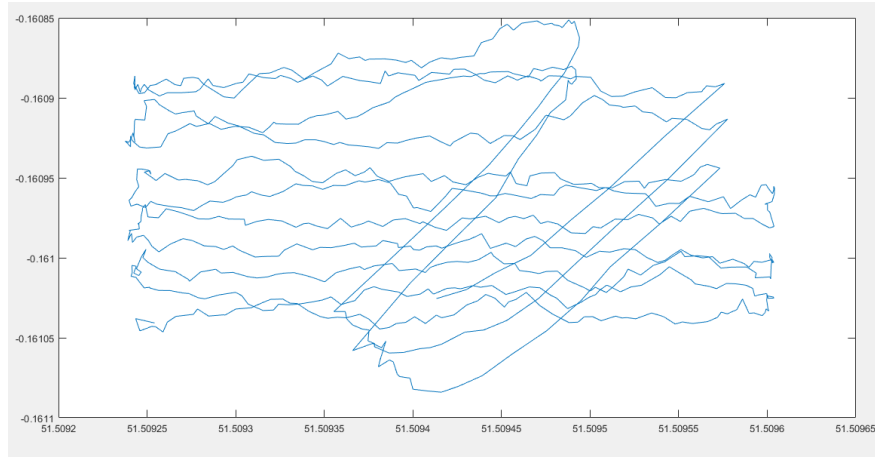


Figure 1: Figure showing horizontal trajectory of the lawnmower

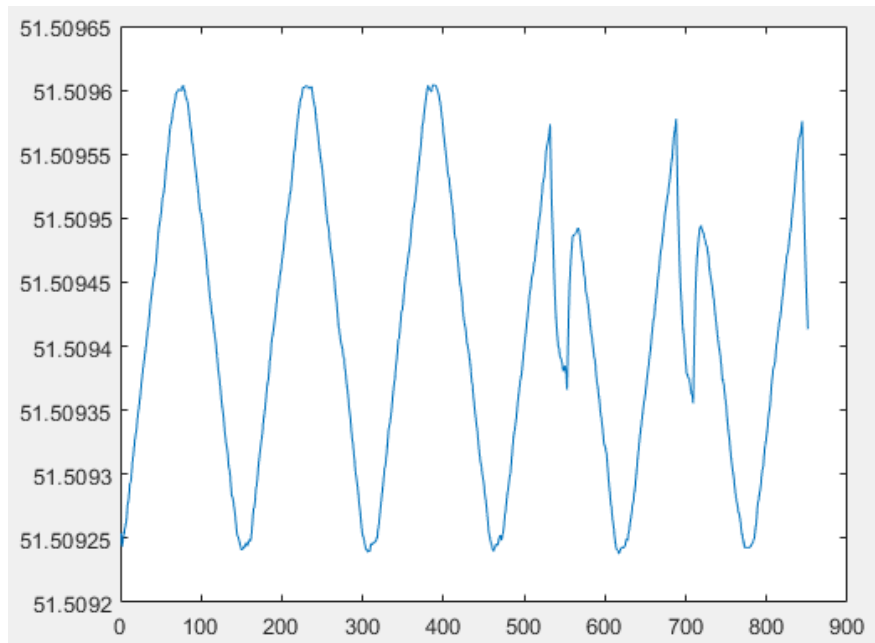


Figure 2: Figure showing the latitude trajectory of the lawnmower

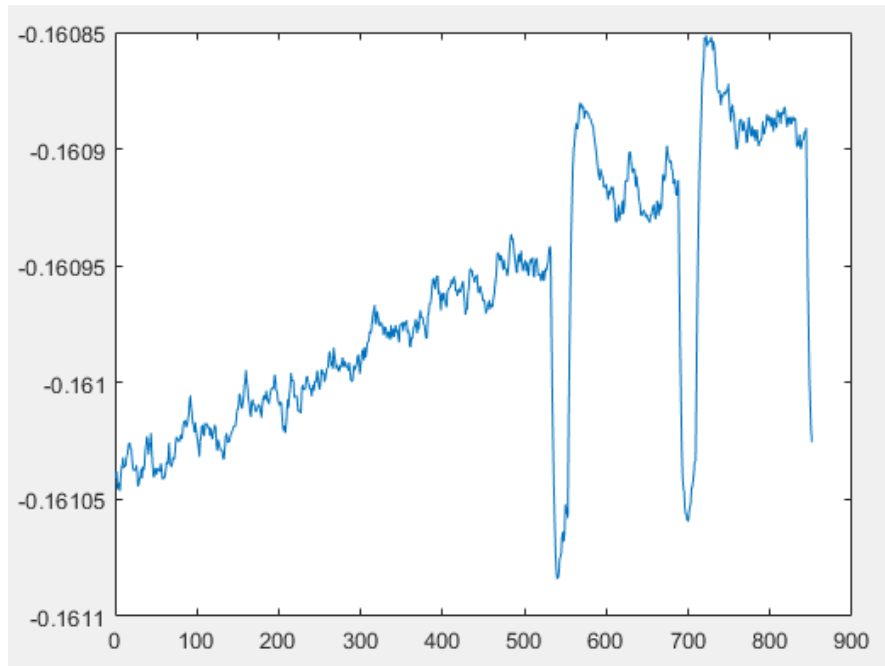


Figure 3: Figure showing the longitude trajectory of the lawnmower

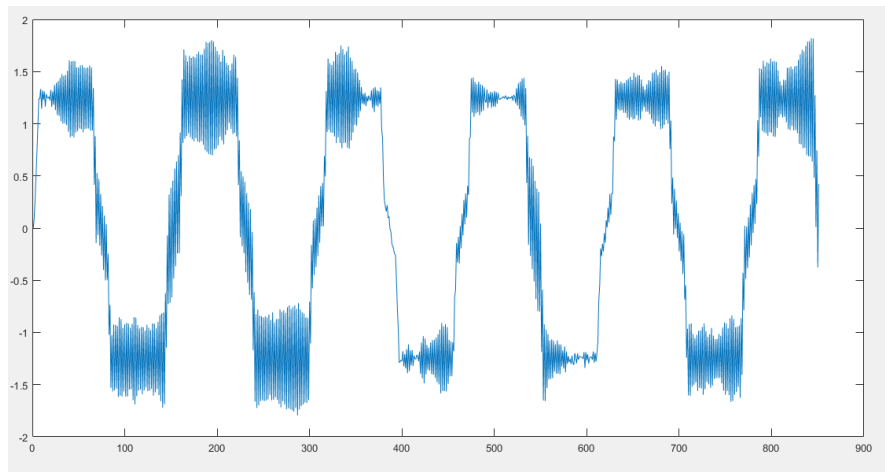


Figure 4: Figure showing the evolution of the north direction velocity of the lawnmower

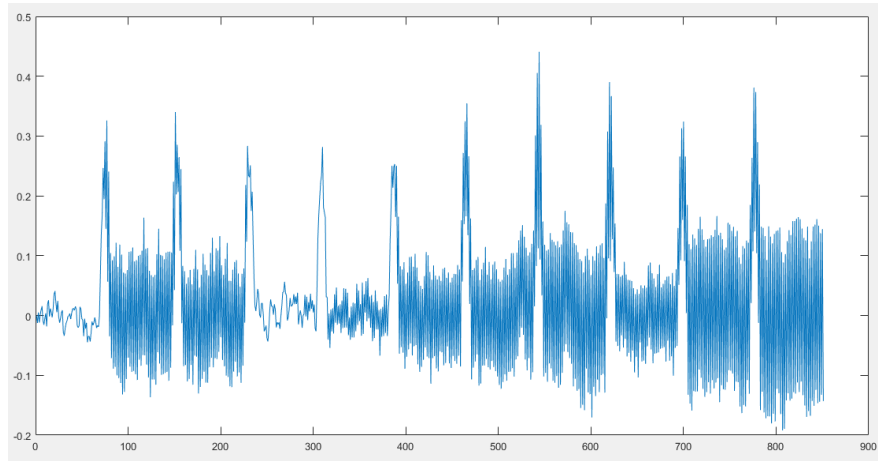


Figure 5: Figure showing the evolution of the east direction velocity of the lawnmower

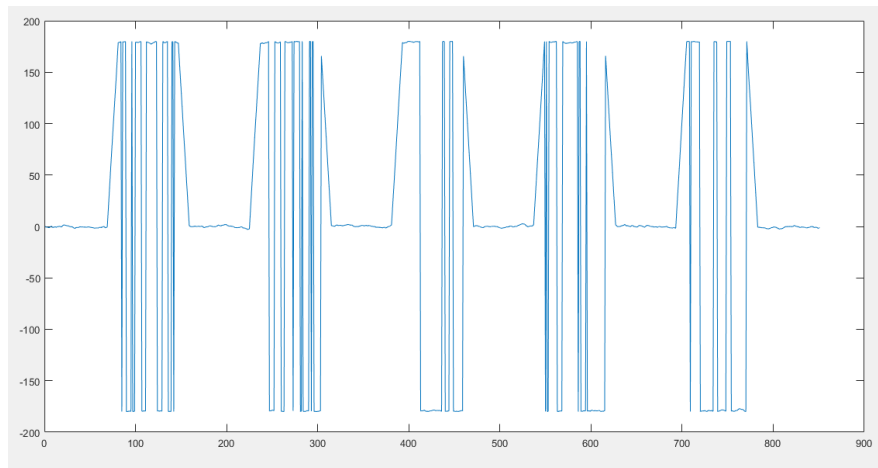


Figure 6: Figure showing the evolution of the heading direction of the lawnmower

4 Code

These files have been provided in the .zip.
Matlab Code :

```

1 % This routine determine the position of the object at all of the epochs
2 % using GNSS and Kalman Filter
3 function GNSSresults = GNSScomputation
4 Define_Constants
5
6 % import data for determining positions and Velocity
7 pseudo_ranges = csvread('Data/Pseudo_ranges.csv');
8 pseudo_range_rates = csvread('Data/Pseudo_range_rates.csv');
9
10 % n is the number of epoch, m the number of satellites
11 [n,~] = size(pseudo_ranges);
12
13 % Array to store result
14 GNSSresults = zeros(n-1, 7);
15 % 1st column is the time in seconds
16 GNSSresults(:,1) = pseudo_ranges(2:end,1);
17 % 2nd column contains Geodetic latitude in degrees
18 % 3rd column contains Geodetic longitude in degrees
19 % 4th column contains North Velocity in m/s
20 % 5th column contains East velocity in m/s
21 % 6th column contains heading in degrees
22 % 7th column contains height
23
24 %% Initialise the Kalman filter state vector estimate and error covariance
    matrix
25 [x_est,P_matrix] = Initialise_GNSS(pseudo_ranges, pseudo_range_rates);
26
27 % x_est correspond to the initial positions (Which will be the initialized
    Kalman filter state vector estimate)
28 % P_matrix is the initial error covariance matrix
29 % positions and velocities are the positions/Velocities computed without using
    Kalman Filter
30
31 %% Apply Kalman Filter to initial state vector/error covariance matrix
32
33 S_a_cphi = 0.01;% clock phase PSD
34 S_a_cf = 0.04;%clock frequency PSD
35 sigma_p = 2; % error standart deviation of pseudo range measurements in m
36 sigma_r = 0.02; % error standart deviation of pseudo range rate measurement in
    m/s
37
38 result = Kalman_Filter(x_est, P_matrix, pseudo_ranges, pseudo_range_rates,
    S_a_cphi, S_a_cf, sigma_p, sigma_r);
39
40 GNSSresults(:,2:3) = result(:,2:3);
41 GNSSresults(:, 4:5) = result(:,5:6);
42 GNSSresults(:,7) = result(:,4);
43 end
44
45 %% This subroutine is used to initialised the Kalman Filter
46 function [x_est,P_matrix] = Initialise_GNSS(pseudo_ranges, pseudo_range_rates)
47 % first run Define_Constants.m
48 Define_Constants
49
50 % Extract data
51 pseudo_ranges_data = pseudo_ranges(2:end, 2:end);
52 pseudo_range_rates_data = pseudo_range_rates(2:end,2:end);
53 [n,m] = size(pseudo_range_rates_data); % m number au satellite, n number
    of epoch
54

```



```

1 function DR_result = SensorComputation
2 % this routine determines the trajectory of an object using dead reckoning
3 % navigation.
4
5 % Define constants
6 Define_Constants
7
8 % load data
9 dead_reckoning = csvread('Data/Dead_reckoning.csv');
10 [n,~] = size(dead_reckoning); % n is the number of epoch
11
12 % result
13 DR_result = zeros(n,6);
14 DR_result(:,1) = dead_reckoning(:,1); % store time in s
15
16 % let's use GNSScomputation to initialize the position
17 GNSSmeasurement = GNSScomputation;
18
19 % the rear wheels are the driving wheels, so we can assume that the average
20 % of the rear wheel speeds correspond to the forward speed of the lawnmower
21 rear_wheel_L = dead_reckoning(:,4); % m/s
22 rear_wheel_R = dead_reckoning(:,5);
23 forward_speed = (rear_wheel_L + rear_wheel_R)/2; % m/s
24
25 % take height as calculated by GNSS
26 h = GNSSmeasurement(1,7);
27
28 time = dead_reckoning(:,1);
29
30 % first, we will compute the heading by correcting the gyroscope
31 % measurement with the compass measurement
32
33 %% Compute heading by combining gyroscope-derived heading and magnetic heading
34 % In this section, We will use a Gyro-Magnetometer Kalman Filter States to
   compute heading
35 dead_reckoning = csvread('Data/Dead_reckoning.csv');
36 gyroscope_heading_rate = dead_reckoning(:,6);
37 compassHeading = dead_reckoning(:,7)*deg_to_rad;
38
39 % Compute heading from gyroscope
40 gyroscopeHeading = zeros(n,1);
41 gyroscopeHeading(1) = gyroscope_heading_rate(1)*0.5;
42 for i=2:n
43     gyroscopeHeading(i) = gyroscopeHeading(i-1)+0.5*gyroscope_heading_rate(i);
44 end
45
46 % store corrected heading
47 heading = zeros(n,1);
48 heading(1) = gyroscopeHeading(1); % initialize
49
50 % Initialize 2 states Kalman filter vector
51 h_est = zeros(2,1); %
52
53 % Initiaize state estimation error covariance matrix
54 sigma_gyroBias = 1*deg_to_rad; % bias standar deviation of 1 degree per second
55 Ph_matrix = [10^-4 0;... % noise standar deviation of 10-4 rad/s
56              0 sigma_gyroBias];
57
58 for i=2:n
59

```

```

1 % This routine compute an integrated horizontal DR/GNQQ navigation solution
2 % using Kalman filtering
3
4 % Define constants
5 Define_Constants
6
7 % Compute GNSS solution
8 GNSSsolutions = GNSScomputation;
9 [n,~] = size(GNSSsolutions); % n is the number of epoch
10
11 % Compute DR solution
12 DRsolution = SensorComputation;
13
14 % separate the data
15 time = GNSSsolutions(:,1);
16
17 GNSSlatitude = GNSSsolutions(:,2)*deg_to_rad;
18 GNSSlongitude = GNSSsolutions(:,3)*deg_to_rad;
19 GNSSheight = GNSSsolutions(:,7);
20 GNSSnorth_velocity = GNSSsolutions(:,4);
21 GNSSeast_velocity = GNSSsolutions(:,5);
22
23 DRlatitude = DRsolution(:,2)*deg_to_rad;
24 DRlongitude = DRsolution(:,3)*deg_to_rad;
25 DRnorth_velocity = DRsolution(:,4);
26 DReast_velocity = DRsolution(:,5);
27
28 % initialize latitude with DR measurement
29 latitude = DRlatitude;
30
31 % Since it's a lawnmower, we assume that height is 0
32 height = zeros(n,1);
33
34 % Store result
35 correctedResults = zeros(n, 6);
36 correctedResults(:,1) = time;
37 correctedResults(1,:) = DRsolution(1,:); % initialization of latitude ,
    longitude , velocity , heading and height
38
39 % Initialize 4-state Kalman filter vector
40 x_est = zeros(4,1);
41
42 % Initialise state estimation error covariance matrix
43 P_matrix = zeros(4);
44 sigma_v = 0.02;
45 sigma_r = 10;
46 [R_N,R_E]= Radii_of_curvature(latitude(1));
47 P_matrix(1,1) = sigma_v^2;
48 P_matrix(2,2) = sigma_v^2;
49 P_matrix(3,3) = sigma_r^2/(R_N + height(1))^2;
50 P_matrix(4,4) = sigma_r^2/(R_E + height(1))^2*cos(latitude(1))^2;
51
52 for i=2:n
53     %% Step 1 : Compute transition matrix
54     tau_s = 0.5; % propagation time in s
55     [R_N,R_E]= Radii_of_curvature(latitude(i-1));
56     Phi = eye(4);
57     Phi(3,1) = tau_s/(R_N + height(i-1));
58     Phi(4,2) = tau_s/((R_E + height(i-1))*cos(latitude(i-1)));
59

```

5 References

- ^[1]P.D. Groves, Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems, 2nd Edition, Artech House, 2013, COMPGX04:ROBOT VISION AND NAVIGATION, Workshop1
- ^[2]P.D. Groves, COMPGX04:ROBOT VISION AND NAVIGATION, Workshop1, Equation (1), (2) and (3)
- ^[3]P.D. Groves, COMPGX04:ROBOT VISION AND NAVIGATION, Workshop1, Equation (4)
- ^[4]P.D. Groves, COMPGX04:ROBOT VISION AND NAVIGATION, Workshop1, Equation (9),
- ^[4]P.D. Groves, COMPGX04:ROBOT VISION AND NAVIGATION, Workshop2, task 2A,
- ^[5]P.D. Groves, COMPGX04:ROBOT VISION AND NAVIGATION, Lecture 6A, Gyro-Magnetometer Integration
- ^[6]P.D. Groves, COMPGX04:ROBOT VISION AND NAVIGATION, Workshop3, task 1,
- ^[7]P.D. Groves, COMPGX04:ROBOT VISION AND NAVIGATION, Workshop3, task 2,