
Overview of Kalman Filter Theory and Navigation Applications

Day 3

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Feb 25, 2004

Day 3: Practical Kalman Filtering, Strapdown Navigation and Inertial Error Dynamics Segments

- Practical Kalman Filtering: Some Numerical Considerations
- The Navigation Problem and Reference Frames
- Inertial Error Dynamics
- The Basic 9-State Kalman Filter
- Challenges of INS Filters

Day 3, Segment 1

Some Practical Considerations (Numerical) Topics

- Kalman Filter Theory vs. Reality
- Numerical Stability
- Round-Off Errors
- Matrix Inversion
- UD Factorization

Kalman Filter Theory vs. Reality

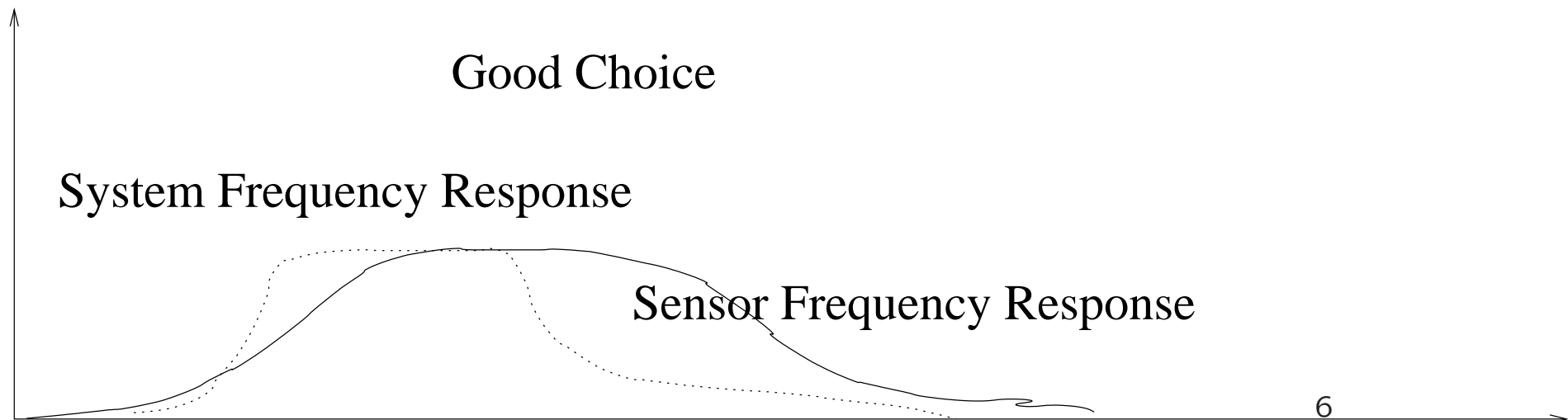
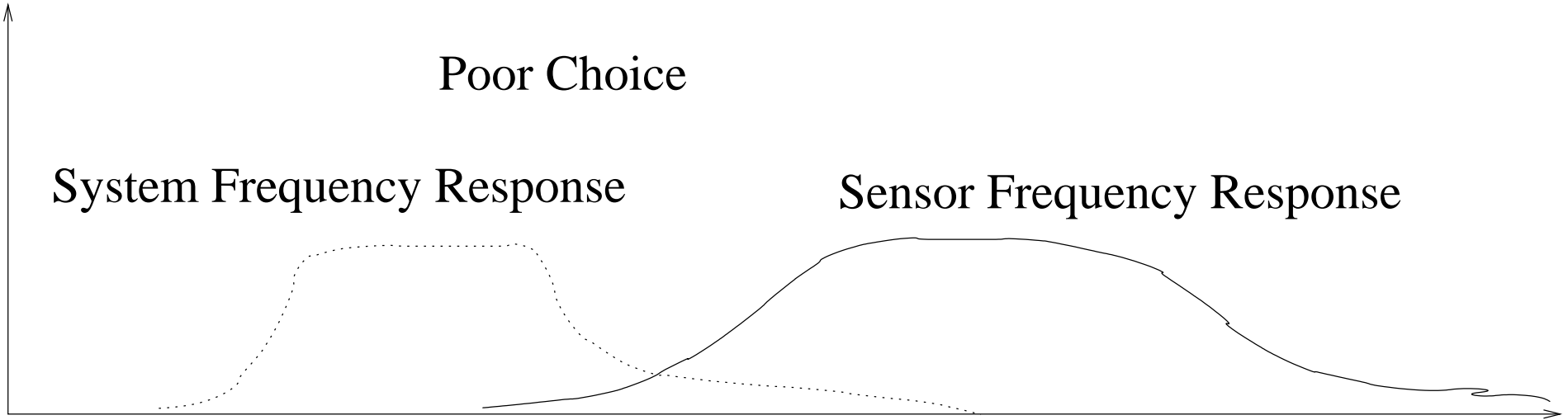
- Kalman theory based on multiple assumptions
 - All states are modeled correctly
 - Noise parameters are accurately known
 - Initial values are appropriate
 - Process and measurement noise are both Gaussian
 - Process noise and measurement noise are uncorrelated
 - Measurements are taken at regularly scheduled intervals

Kalman Filter Theory vs. Reality

- How do you select appropriate sensors for the problem at hand?
- Some obvious general rules:
 - the lower the sensor noise characteristics, the more accurate the estimates (narrow sensor noise variance)
 - the more the merrier, i.e., the more sensors the better
 - maximize the number of directly observable states

Kalman Filter Theory vs. Reality

- Some less obvious general rules:
 - short-term / long-term complementarity (e.g, GPS vs. INS)
 - frequency response of sensor should match that of system
 - noise spectrum of sensor should be maximally disjoint from that of system



Kalman Filter Theory vs. Reality

- Choose sensors to match states.
E.g., consider the state model

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

with the measurement model

$$z = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + v$$

Here x_1 is observable but x_2 is not.

Kalman Filter Theory vs. Reality: Sensor Selection

- Examine the H matrix that you would use with this sensor!
- If it renders some states unobservable, then consider adding additional sensors for those states, or replacing this sensor with one that is more favorable.

Filter Divergence

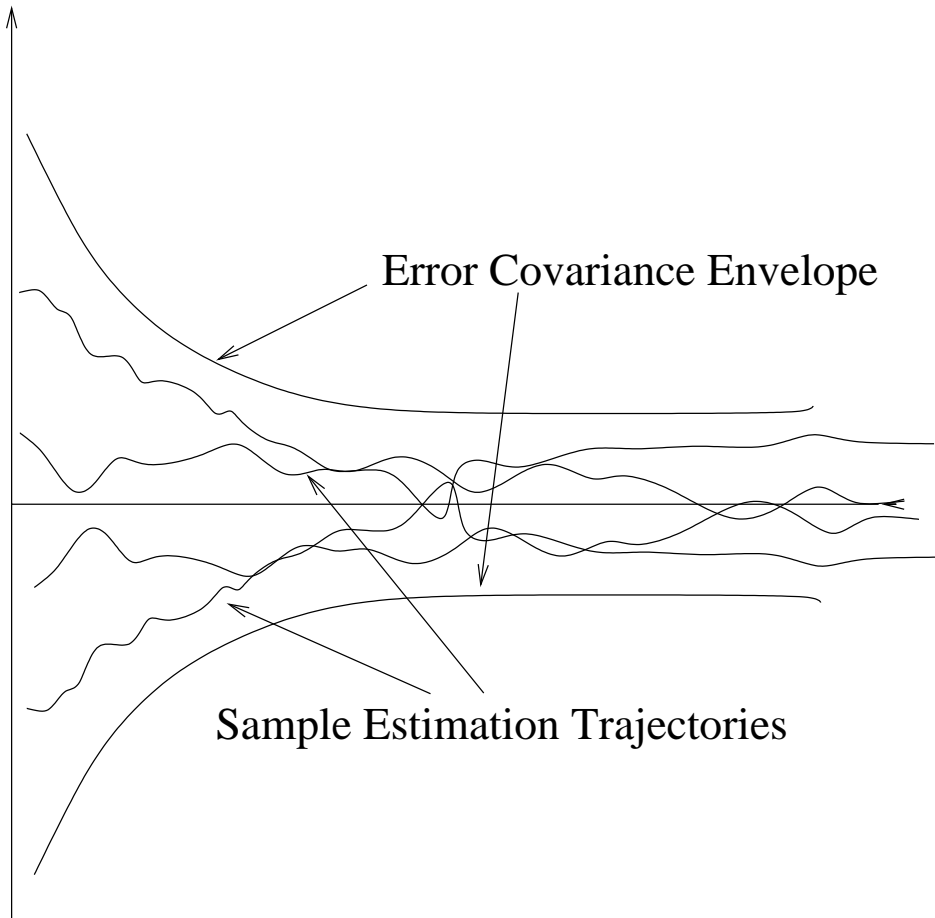
- Kinds of Divergence
- Causes and Remedies

Kinds of Divergence

- Mean estimation error is supposed to converge to 0
 - $\tilde{x}_k = \hat{x}_k(+)-x_k$
 - $E[\tilde{x}_k] \rightarrow 0$
 - Estimate is unbiased: $E[\hat{x}_k] = x_k$
- Covariance matrix for estimation error is same as state estimation error covariance matrix: $P_k(+)=E[\tilde{x}_k(+)\tilde{x}_k^T(+)]$

Kinds of Divergence

- For optimal filter, P will indicate convergence or divergence.
 - One common form of divergence due to round-off will send P to zero
- For suboptimal filters, P will not necessarily indicate divergence
 - P may seem to indicate nominal steady-state values and yet the state estimate may go diverge from the true value



Kinds of Divergence

- Going to sleep: error covariance becomes so small that measurements are no longer believed by the filter
- Loss of symmetry in P
- Loss of positive definiteness: negative numbers on the diagonal!

Numerical Stability

- System stability: Bounded input results in bounded output
- Numerical stability: small errors at each computation step do not grow without bound
- Matrix Conditioning

Matrix Conditioning

- Ill-Conditioned vs. Well-Conditioned
- Condition number of matrix:

$$\text{cond}(M) = \frac{\lambda_{\max}}{\lambda_{\min}}$$

where λ_{\max} is maximum eigenvalue of M , while λ_{\min} is the minimum eigenvalue of M .

Matrix Conditioning

- If $\text{cond}(M) \approx 1$, then M is well-conditioned for matrix inversion
- If $\text{cond}(M) \gg 1$, then M is ill-conditioned for inversion

Round-Off Errors

- Computer round-off in floating point arithmetic
- Unit round-off value is largest number ε such that $1 + \varepsilon = 1$
- In Matlab, the global symbol "eps" stores the unit round-off value

Round-Off Errors

- Round-off errors generally plague the classical covariance update algorithm

$$P_k(+)= [I - K_k H_k] P_k(-)$$

- Alternative, called the Joseph form, is more robust:

$$P_k(+)= [I - K_k H_k] P_k(-) [I - K_k H_k]^T + K_k R_k K_k^T$$

This form in turn leads to the De Vries mechanization of the Kalman gain equation. To see this, first expand the Joseph form (omitting subscripts for clarity):

$$P(+)=P(-)-KHP(-)-P(-)H^T K^T+KHP(-)H^T K^T+K R K^T.$$

Define

$$(1) \quad F = PH^{\top}$$

and

$$(2) \quad D = HF + R.$$

We note that D is symmetric, because

$$\begin{aligned} D^{\top} &= [HF + R]^{\top} \\ &= [HPH^{\top} + R]^{\top} \\ &= [HPH^{\top}]^{\top} + R^{\top} \\ &= [H^{\top}]^{\top} P^{\top} H^{\top} + R^{\top} \\ &= HPH^{\top} + R \quad (\text{because } P \text{ and } R \text{ are symmetric}) \\ &= HF + R \\ &= D. \end{aligned}$$

The gain in standard Kalman gain equation

$$K_k = P_k(-)H_k^\top [H_k P_k(-)H_k^\top + R_k]^{-1}$$

can be written as

$$K = FD^{-1}.$$

Using Eqs. (1) and (2), we compute

$$\begin{aligned} P(+) &= P(-) - KF^\top - FK^\top + KDK^\top \\ &= P(-) - K \left[F^\top - \frac{DK^\top}{2} \right] - \left[F - \frac{KD}{2} \right] K^\top. \end{aligned}$$

Letting $G = F - \frac{KD}{2}$, we obtain

$$(3) \quad P(+) = P(-) - GK^\top - [GK^\top]^\top.$$

The De Vries mechanization implements Eq. (3) by subtracting the ij^{th} element of GK^T from both the ij^{th} and ji^{th} elements of $P(-)$. The De Vries form of the covariance update equation is valid for any arbitrary gain matrix K , not just the optimal gains computed from Eqs. (1) and (2).

Matrix Inversion

- Matrix inversion is always risky due to potential ill-conditioning
- One way to avoid this is to process measurements sequentially as scalars
- Or at least as low-dimensional matrices

UD Factorization

- Based on Cholesky Decomposition
- Unit Triangular Matrices: U has 1's on the diagonal and all 0's below the diagonal. E.g.,

$$U = \begin{bmatrix} 1 & 5 & 7 \\ 0 & 1 & 3 \\ 0 & 0 & 1 \end{bmatrix}$$

UD Factorization

- Factor $HPH^T + R$ as UDU^T , where U is unit upper triangular and D is diagonal.
- This then allows us to "invert" $HPH^T + R$ by solving the equation unit upper triangular equation $UDU^T X = H$ for the matrix X , which will yield $X = [HPH^T + R]^{-1} H$
- This last expression is used on the covariance update equation in KH

Exercises

1. Let $v = [1 \ -2]^T$. Compute the positive definite, symmetric matrix $M = vv^T$
2. Use the following algorithm (Grewal & Andrews) to factor M into UDU^T form:

```

for j=m:-1:1
    for i=j:-1:1
        covar=P(i,j);
        for k=j+1:m
            covar=covar-U(i,k)*D(k,k)*U(j,k);
        end
        if i==j
            D(j,j)=covar;
            U(j,j)=1;
        else
            U(i,j)=covar/D(j,j);
        end
    end
end
end

```

Day 3, Segment 2

The Navigation Problem and Reference Frames Topics

- Basic Navigation Problem
- Earth Referenced Navigation
- Coordinate Frame Conversion
- Basic Strapdown Navigation Equations

Basic Navigation Problem

- Where am I?
- Where am I headed?
- How fast am I going?

Basic Navigation Problem

- What's my position?
- What's my heading and attitude?
- What's my velocity?

Solution in Inertial Space

- In inertial space, it's no problem!
- Just integrate the acceleration twice to get velocity and position.
- And integrate the angular rate once to get attitude.

$$v(T) = v(0) + \int_0^T \frac{d^2 R}{dt^2} dt$$

Solution in Inertial Space

- Solution easy in inertial space because ...
 - inertial instruments sense acceleration and rotational rate with respect to inertial coordinate frame
 - inertial frame attached to sensor platform
- But we don't necessarily want the answer to our questions expressed in terms of inertial coordinates!

Earth Referenced Navigation

- Terrestrial navigation seeks to answer nav questions with respect to earth
- Global earth reference
- Local or relative navigation

Coordinate Frames

- Inertial
- Earth Fixed
- Local Level
- Body

Coordinate Frames

- Technically speaking, all frames are earth-centered
- Practically speaking, we think of the Body frame as centered in the body of the vehicle (usually at center of gravity).
- Local Level is thought to be located at surface of earth directly beneath the vehicle.

Inertial Reference Frames

- Non-Rotating
- Non-Accelerating
- Fixed or moving uniformly with respect to another inertial frame (fixed stars)

Inertial Reference Frames

- Nav problem "easy" in inertial frames
- Integrate accelerometer outputs once to get inertial velocity; integrate velocity to get position.
- Same with attitude, but only one integration required (usually).
- Would still have to contend with instrument imperfections.

Inertial Reference Frame Integrations

$$(4) \quad \ddot{r} = a_{sf} + \text{other external forces}$$

$$(5) \quad v = \dot{r} = \int_0^T a_{sf} dt + \int_0^T (\text{other external forces}) dt$$

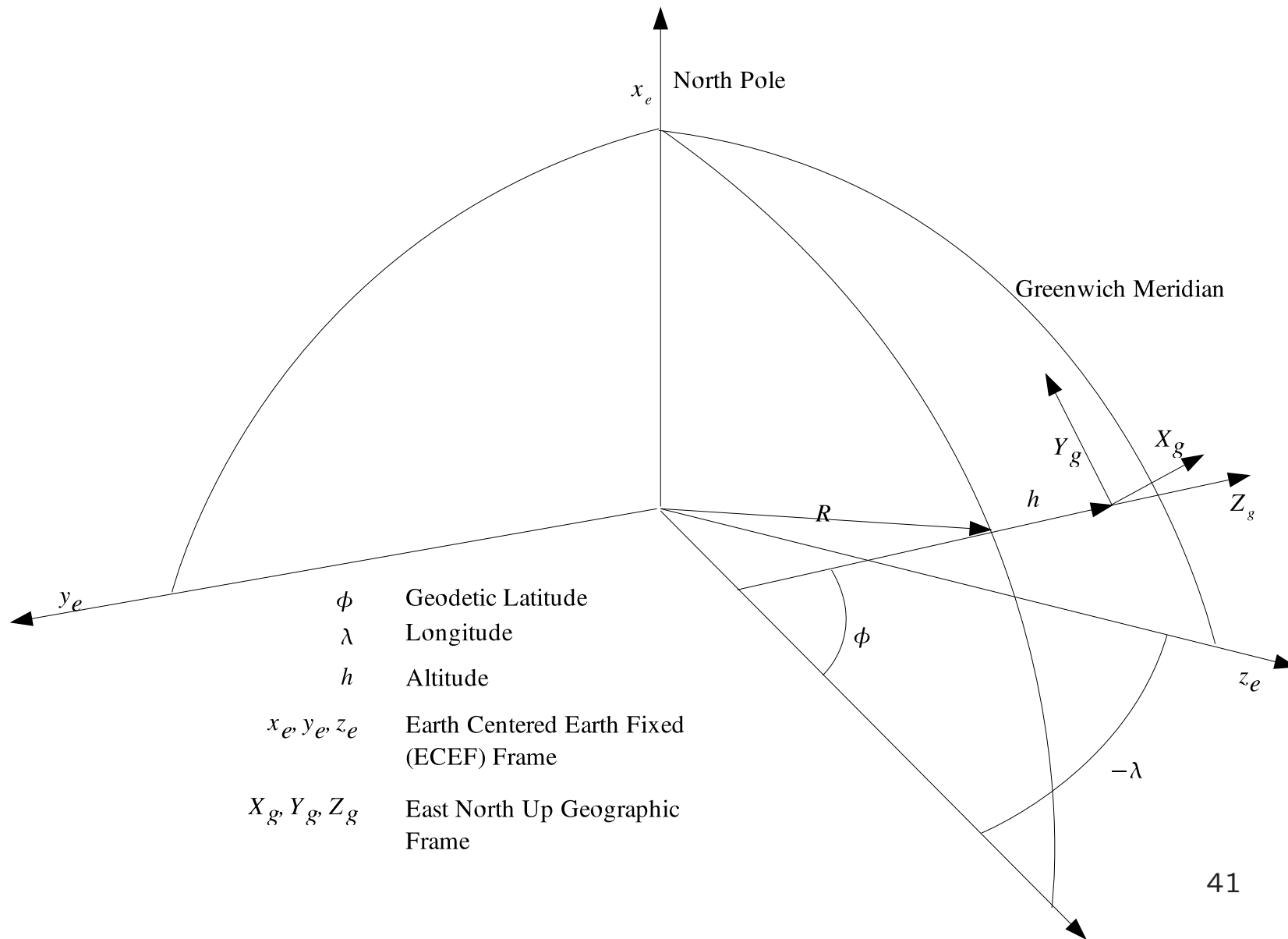
$$(6) \quad r = \int_0^T v dt$$

Earth Fixed = ECEF = Earth Centered Earth Fixed

- Rotating frame, i.e., non-inertial
- Cartesian (X, Y, Z in meters)
- Spherical (latitude ϕ , longitude λ , altitude h)
 - geodetic

Local Level

- Tangent to earth's surface but translated to center of earth.
- Vertical Z -axis is normal to earth's surface
- X, Y -axes are level
- Several kinds: Y north-slaved or wander azimuth
- Y makes wander angle α with respect to true north (ENU=East, North, Up).



ϕ	Geodetic Latitude
λ	Longitude
h	Altitude
x_e, y_e, z_e	Earth Centered Earth Fixed (ECEF) Frame
X_g, Y_g, Z_g	East North Up Geographic Frame

Body Frame

- Attached to vehicle
- For aircraft:
 - X out the nose
 - Y out the right wing
 - Z down

Coordinate Frame Conversion

- All frames are earth-centered, hence differ only by rotation
- Rotation represented by direction cosine matrices (DCM)
- C_A^B = DCM transformation from frame A to frame B

Coordinate Frame Conversion

- "Direction Cosine" comes from dot product:

$$\langle x, y \rangle = x \cdot y = \|x\| \|y\| \cos \theta_{xy}$$

where θ_{xy} is the angle between the two vectors x and y .

- If x and y are unit vectors, then $\|x\| = \|y\| = 1$ and we have:

$$\langle x, y \rangle = x \cdot y = \cos \theta_{xy}$$

Coordinate Frame Conversion

- If $U = \{u_1, u_2, u_3\}$ and $V = \{v_1, v_2, v_3\}$ are two sets of orthonormal basis vectors, then the DCM relating one frame to the other is given by:

$$\begin{aligned} C_U^V &= \begin{bmatrix} \langle u_1, v_1 \rangle & \langle u_1, v_2 \rangle & \langle u_1, v_3 \rangle \\ \langle u_2, v_1 \rangle & \langle u_2, v_2 \rangle & \langle u_2, v_3 \rangle \\ \langle u_3, v_1 \rangle & \langle u_3, v_2 \rangle & \langle u_3, v_3 \rangle \end{bmatrix} \\ &= \begin{bmatrix} \cos \theta_{11} & \cos \theta_{12} & \cos \theta_{13} \\ \cos \theta_{21} & \cos \theta_{22} & \cos \theta_{23} \\ \cos \theta_{31} & \cos \theta_{32} & \cos \theta_{33} \end{bmatrix} \end{aligned}$$

Coordinate Frame Conversion

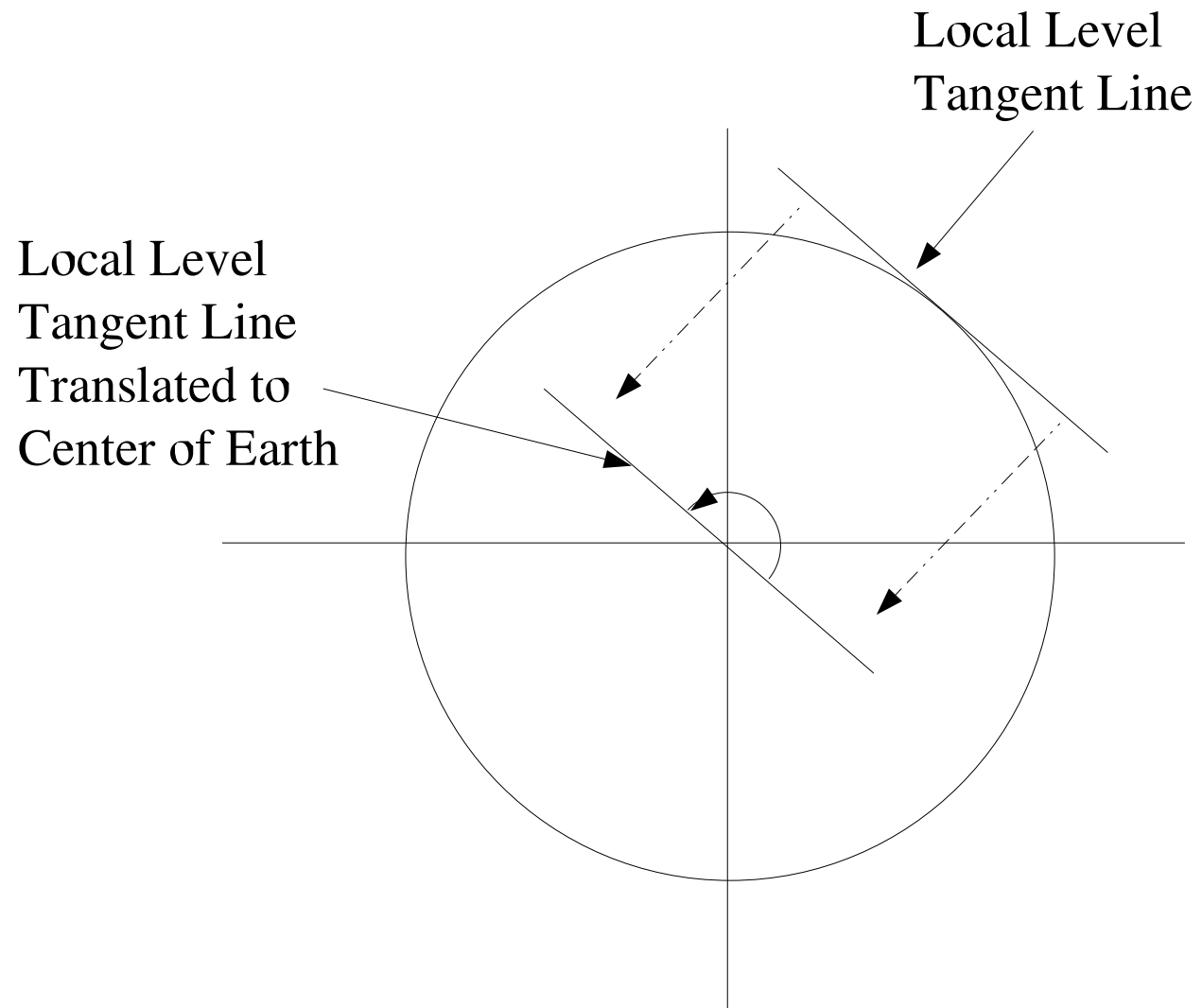
- DCMs are orthogonal matrices $\Rightarrow [C_A^B]^{-1} = [C_A^B]^T$
- Third row (or column) is vector cross product of other two
 \Rightarrow only six independent parameters

Coordinate Frame Conversion: Most important DCMs

- Body to Local Level: C_B^L
 - sometimes called Body to Nav and notated C_B^N
 - yields attitude info (Euler angles for roll, pitch, yaw)
- Local Level to Earth: C_L^E
 - yields position info and used to transform earth rate to local level

Coordinate Frame Conversion: Most important DCMs

- Visualize C_L^E 's determination of position as follows:
 - As vehicle moves, local level frame changes its orientation with respect to earth's center in order to maintain local level with respect to earth's surface
 - If you think of local level frame as attached to earth's surface, you get distracted by the displacement of the frame
 - If you move local level frame to center of earth, the displacement disappears and all that remains is the rotations



Strapdown Navigation: Strapdown vs. Gimbaled

- Gimbaled INS:
 - Gyro stabilized platform
 - Gimbal assembly and torque motors
 - Resolvers, slip rings, bearings, etc. to control platform
 - Goal: Maintain stable, locally level or inertial reference frame

Strapdown Navigation: Strapdown vs. Gimbaled

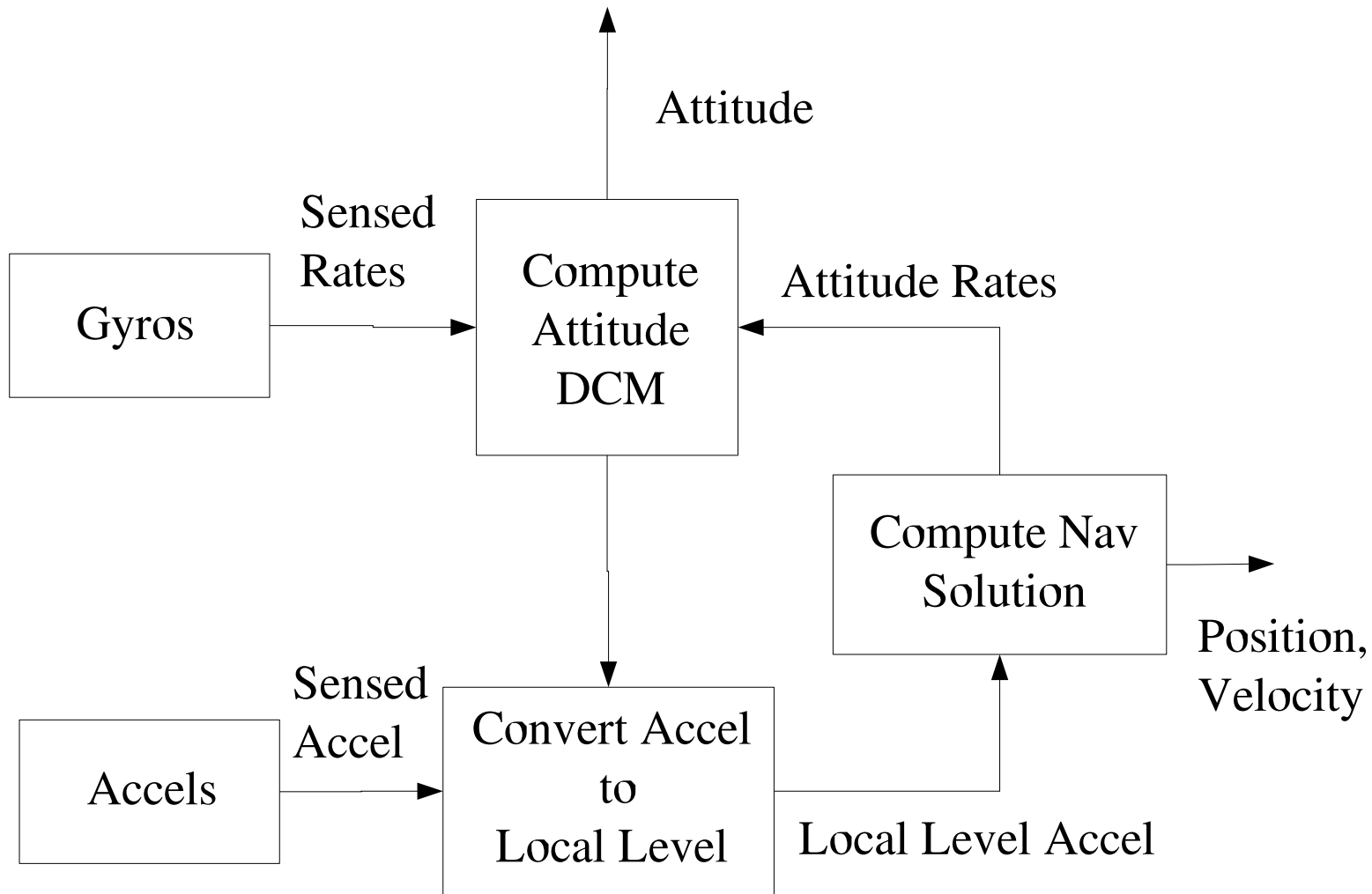
- Gimbaled INS Issues
 - Reliability and Cost: Lots of moving parts!
 - Body rate and acceleration information not directly available
 - Rate signals are generally noisy and have low bandwidth

Strapdown Navigation: Strapdown vs. Gimbaled

- Strapdown INS:
 - Inertial instruments strapped to body frame
 - Requires local level accelerations to be computed using direction cosine matrix C_B^L
 - C_B^L derived from gyro-sensed body rates
 - Strapdown systems can be implemented with either rate gyros or attitude gyros

Strapdown Navigation: Strapdown vs. Gimbaled

- Strapdown INS Advantages
 - Immediate detection of body rates and accelerations
 - Fewer moving parts
 - Potential redundancy advantages
- Gimbaled systems are nearly obsolete



Strapdown INS Block Diagram

Basic Strapdown Navigation Equations

- Need to compute attitude, velocity, and position
- I.e., need to compute C_B^L and C_L^E
- These DCMs are dynamic quantities
- C_B^L determines attitude and can be rapidly varying
- C_L^E determines position and is slowly varying (relative to attitude dynamics)

Strapdown Navigation Equations

- Three differential equations
 - Equation for body to local level transformation C_B^L
 - Equation for velocity (uses C_B^L)
 - Equation for local level to earth for position DCM C_L^E

Strapdown Navigation Equations

- Two Algebraic Equations
 - Equation for converting velocity to transport rate (to be explained)
 - Equation for converting earth rate to local level coordinates

Strapdown Navigation Equations

The Three Differential Equations

$$(7) \quad \dot{C}_B^L = C_B^L \Omega_{IB}^B - (\Omega_{IE}^L + \Omega_{EL}^L) C_B^L$$

$$(8) \quad \dot{v}^L = C_B^L a_{sf}^B + g' - (2\Omega_{IE}^L + \Omega_{EL}^L) v^L$$

$$(9) \quad \dot{C}_L^E = C_L^E \Omega_{EL}^L$$

Strapdown Navigation Equations

The Two Algebraic Equations

$$(10) \quad \omega_{EL} = \frac{1}{r} u_r^L \times v^L$$

$$(11) \quad \omega_{IE}^L = [C_L^E]^T \omega_{IE}^E$$

Strapdown Navigation Equations

The C_B^L Equation (7)

$$\dot{C}_B^L = C_B^L \Omega_{IB}^B - (\Omega_{IE}^L + \Omega_{EL}^L) C_B^L$$

- All the Ω matrices represent rotation vector cross products in skew-symmetric matrix format
 - Ω_{IB}^B is rotational rate of aircraft in body coordinates
 - Ω_{IE}^L is earth rate in local level coordinates
 - Ω_{EL}^L is transport rate in local level coordinates

Strapdown Navigation Equations: Detour into Cross Product Matrices

- The cross product of $\omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}$ with any other vector v is the same as multiplying v on the left by $\Omega = \begin{bmatrix} 0 & \omega_3 & -\omega_2 \\ -\omega_3 & 0 & \omega_1 \\ \omega_2 & -\omega_1 & 0 \end{bmatrix}$
- $\omega \times v = \Omega v$

Strapdown Navigation Equations

The C_B^L Equation (7)

$$\dot{C}_B^L = C_B^L \Omega_{IB}^B - (\Omega_{IE}^L + \Omega_{EL}^L) C_B^L$$

- Transport rate is the rotational rate of the aircraft due to motion over the surface of the earth. Is a function of velocity.
- Ω_{IB}^B is total inertial angular rate sensed by gyros and includes effects of transport and earth rates.
- Hence transport and earth rate effects have to be subtracted off.

Strapdown Navigation Equations

The Strapdown Velocity Equation (8)

$$\dot{v}^L = C_B^L a_{sf}^B + g' - (2\Omega_{IE}^L + \Omega_{EL}^L) v^L$$

- Sometimes referred to as the velocity rate equation
- a_{sf}^B is specific force sensed by accelerometers in body coordinates (because the accels are strapped to the body – hence the term strapdown)

Strapdown Navigation Equations

The Transport Rate Equation (9)

$$\dot{C}_L^E = C_L^E \Omega_{EL}^L$$

- Connected to velocity rate equation by the first algebraic equation (10):

$$\omega_{EL} = \frac{1}{r} u_r^L \times v^L$$

- Eq. (9) Sometimes referred to as position rate equation, because $dcmLE$ directly implies the vehicle position

Strapdown Navigation Equations

Position Rate / Transport Rate Equations (Geographic)

- North transport rate:

$$(12) \quad \rho_N = \frac{v_e}{R_e} \left[1 - \frac{h}{R_e} - e \sin^2 \phi \right]$$

- East transport rate:

$$(13) \quad \rho_E = -\frac{v_e}{R_e} \left[1 - \frac{h}{R_e} - e (1 - 3 \cos^2 \phi) \right]$$

where e is ellipticity (approx. $\frac{1}{298}$) and R_e is mean equatorial earth radius

Strapdown Navigation Equations

Position Rate / Transport Rate Equations (Geographic)

- Latitude Rate:

$$(14) \quad \dot{\phi} = -\rho_e$$

- Longitude Rate:

$$(15) \quad \dot{\lambda} = \rho_n \sec \phi$$

Strapdown Navigation Equations

- Geographic (north-slaved) mechanization has singularities at poles
- Two other approaches to local level coordinates:
 - Wander azimuth: vertical component of transport rate $\rho_z =$ vertical component of earth rate
 - Free Azimuth: vertical component of transport rate $\rho_z = 0$

Strapdown Navigation Equations

Position Rate / Transport Rate Equations (Wander and Free Azimuth)

- X Transport Rate:

$$(16) \quad \rho_x = -\frac{v_y}{R_e} \left[1 - \frac{h}{R_e} - e \left(1 - 3d_{22}^2 - d_{21}^2 \right) \right] - \frac{v_x}{R_e} (2d_{21}d_{22}) e$$

- Y Transport Rate:

$$(17) \quad \rho_y = \frac{v_x}{R_e} \left[1 - \frac{h}{R_e} - e \left(1 - 3d_{21}^2 - d_{22}^2 \right) \right] + \frac{v_y}{R_e} (2d_{21}d_{22}) e$$

Strapdown Navigation Equations

Position Rate / Transport Rate Equations (Wander and Free Azimuth)

- Azimuth Rate:

$$\rho_z = \begin{cases} -\Omega_e d_{23}, & \text{if free azimuth;} \\ 0, & \text{if wander azimuth} \end{cases}$$

- In equations above, the matrix $[d_{ij}]$ is the direction cosine matrix C_L^E from local level (L) frame to earth centered earth fixed (E) frame.

Exercises

1. Compute direction cosine matrix C_U^V , where $U = \{(1, 0, 0), (0, 1, 0), (0, 0, 1)\}$ and $V = \{(-1, 0, 0), (0, 1, 0), (0, 0, -1)\}$
2. Suppose you are starting at the equator and travelling due north, and your velocity is 5 m/sec. Compute the transport rates ρ_n and ρ_e associated with this velocity and heading. You may use the following constants: $\Omega_e = 7.2921151467 \times 10^{-5}$ rad/sec and $R_e = 6,378,137$ meters

Day 3, Segment 2 (Continued)

Inertial Error Dynamics

Topics

- Imperfect Inertial Instruments
- From Strapdown Equations to Error Equations
- Initialization: Alignment

Imperfect Inertial Instruments

- Accelerometers and Gyros have inherent imperfections
- Bias, scale factor, g^2 terms, noise,
- Inertial sensor clusters also have errors: misalignments
- Many error sources are calibrated out using rate tables during ATP
- Residual effects will influence strapdown nav equations

Imperfect Inertial Instruments

- Strapdown nav equations very sensitive to gyro errors
- Gyro biases yield erroneous C_B^L matrix which in turn causes erroneous accelerations to be computed in local level frame
- Thus, gyro errors affect not only attitude, but also position and velocity

Simple Inertial Error Models

- Gyros

$$\epsilon\omega_x = \Delta B_{gx} + \Delta K_{gx}\omega_x + \theta_{gxy}\omega_y + \theta_{gxz}\omega_z$$

$$\epsilon\omega_y = \Delta B_{gy} + \Delta K_{gy}\omega_y + \theta_{gyz}\omega_z + \theta_{gyx}\omega_x$$

$$\epsilon\omega_z = \Delta B_{gz} + \Delta K_{gz}\omega_z + \theta_{gzx}\omega_x + \theta_{gzy}\omega_y$$

where ΔB_{gi} is the i^{th} gyro bias, ΔK_{gi} the i^{th} gyro scale factor, and θ_{gij} is the misalignment of the i^{th} gyro axis toward the j^{th} gyro axis.

Simple Inertial Error Models

- Accelerometers

$$\epsilon a_x = \Delta B_{ax} + \Delta K_{ax} a_x + \theta_{axy} a_y + \theta_{axz} a_z$$

$$\epsilon a_y = \Delta B_{ay} + \Delta K_{ay} a_y + \theta_{ayz} a_z + \theta_{ayx} a_x$$

$$\epsilon a_z = \Delta B_{az} + \Delta K_{az} a_z + \theta_{azx} a_x + \theta_{azy} a_y$$

where ΔB_{ai} is the i^{th} accelerometer bias, ΔK_{ai} the i^{th} accelerometer scale factor, and θ_{aij} is the misalignment of the i^{th} accelerometer axis toward the j^{th} accelerometer axis.

Bias Models

- Bias in both types of instruments can be further broken down into several components:
 - fixed bias – constant from turn-on to turn-on – should be calibrated out
 - bias stability – varies from turn-on to turn-on – can't be calibrated out, but can be characterized in terms of variance – can model as random constant
 - bias drift – usually modeled as random walk

Scale Factor Models

- Scale factor can also be modeled as a sum of three components
- Often in nav filters, scale factor residual is modeled as a random constant
- Important to keep in mind that the contribution of scale factor error is a function of input (rate or acceleration)

Higher Order Models

- In expanding the output error as a Taylor series function of input, bias, scale factor, and misalignment show up as zero and first order terms.
- Higher order terms are also present, especially second order terms.
- In some calibration and alignment filters, such higher order effects are modelled
- SNU-84-1 includes error budgets associated with all the combined, higher order effects.

From Strapdown Equations to Error Equations

- Nav equations require perfect inertial instruments
- Instruments are not perfect
- Inertial instrument error sources (bias, scale factor errors, etc.) generate erroneous rate and acceleration inputs to the nav equations
- Need to figure out the effects on the outputs of these equations

Strapdown Error Equations

- Nature of Errors
- Error Operator
- Error Equations

Strapdown Error Equations: Nature of Errors

- Errors propagate according to derived equations
- Errors are generally small, so approximating assumptions help simplify the math
 - linearize otherwise non-linear dynamics
 - small angle assumptions: $\sin \theta \approx \theta$

Strapdown Error Equations: Error Operator

If A is any quantity, we define error operator as follows:

$$(18) \quad \delta A = \hat{A} - A,$$

where A is the true quantity of interest and \hat{A} is an apparent quantity. The latter could be a measured value, and estimated value, or some computed value. This means that

$$\hat{A} = A + \delta A$$

i.e., the apparent value is the true value plus some error.

Strapdown Error Equations: Error Operator
Error operator satisfies:

$$(19) \quad \delta(AB) = \delta A \cdot B + A \cdot \delta B$$

(Just like differentiation)

Strapdown Error Equations

Applying these to the three differential equations, yields three error equations:

(20)

$$\delta \dot{C}_B^L = \delta C_B^L \Omega_{IB}^B + C_B^L \delta \Omega_{IB}^B - (\delta \Omega_{IE}^L + \delta \Omega_{EL}^L) C_B^L - (\Omega_{IE}^L + \Omega_{EL}^L) \delta C_B^L$$

(21)

$$\delta \dot{v}^L = \delta C_B^L a_{sf}^B + C_B^L \delta a_{sf}^B g' - (2\delta \Omega_{IE}^L + \delta \Omega_{EL}^L) v^L - (2\Omega_{IE}^L + \Omega_{EL}^L) \delta v^L$$

(22)

$$\delta \dot{C}_L^E = \delta C_L^E \Omega_{EL}^L + C_L^E \delta \Omega_{EL}^L$$

Introducing Small Angular Rotations for Tilt and Position

- By introducing $\phi^L = [\phi_x^L \ \phi_y^L \ \psi_z^L]^T$, and a small angular position angle error $e = [e_x^L \ e_y^L \ e_z^L]^T$, the attitude error equation (20) can be rewritten as:

$$(23) \quad \dot{\phi}^L = -(\Omega_{IE}^L + \Omega_{EL}^L) \phi^L - C_B^L \delta\omega_{IB}^B + \Omega_{IE}^L e^L + \delta\omega_{EL}^L$$

$$\text{where } \delta\omega_{EL}^L = \frac{1}{R_e} (u_R^L \times \delta v^L) - \frac{\delta h}{R_e^2} (u_R^L \times v^L) + \delta\rho_R u_R^L$$

Introducing Small Angular Rotations for Tilt and Position

- Similarly, the velocity equation can be rewritten:

$$\begin{aligned} \delta \dot{v}^L = & C_B^L \delta a_{sf}^B + a_{sf}^B \times \phi^L - (2\omega_{IE}^L + \omega_{EL}^L) \times \delta v^L + \\ & - (\delta \omega_{EL}^L - 2e^L \times \omega_{IE}^L) \times v^L + \frac{2g\delta h}{R_e} u_R^L + \delta g^L \end{aligned}$$

while the equation for the position angle error e^L itself is

$$(24) \quad \dot{e}^L = -\Omega_{EL}^L e^L + \delta \omega_{EL}^L$$

Further Simplifications Using Telescope Pointing Angle Error

- $\psi^L = \phi^L - e^L$

- Leads to:

$$(25) \quad \Delta \dot{R}^L = \delta v^L - \Omega_{EL}^L \Delta R^L$$

and

$$(26) \quad \begin{aligned} \delta \dot{v}^L = & C_B^L \delta a_{sf}^B + a_{sf}^B \times \psi^L - \frac{g}{R_e} \Delta R_H^L - (2\omega_{IE}^L + \omega_{EL}^L) \times \delta v^L + \\ & - (\delta \omega_{EL}^L - 2e^L \times \omega_{IE}^L) \times v^L + \frac{2g\delta h}{R_e} u_R^L + \delta g^L \end{aligned}$$

Further Simplifications Using Telescope Pointing Angle Error

- Finally, the equations for the telescope pointing angle errors are:

$$(27) \quad \dot{\psi}^L = - \left(\Omega_{IE}^L + \Omega_{EL}^L \right) \psi^L - C_B^L \delta \omega_{IB}^B$$

Strapdown Error Equations

- Three error equations yield three vector quantities of interest
 - position error vector (3) ΔR derived from δC_L^E
 - velocity error vector (3) ΔV^L (or δv^L)
 - attitude error vector (3) ϕ_x, ϕ_y, ψ_z from δC_B^L

Strapdown Equations

- See Matlab / Simulink Models
 - Strapdown Navigation Equations: `stravnav.mdl`
 - Strapdown Navigation Error Equations: `straperr.mdl`

Initialization: Alignment

- Coarse Leveling
 - Gimbal system limited by platform torquing rates
 - Strapdown systems have no real rate limits
 - Time average of accel outputs scaled by $1/g$
 - Yields third row of DCM to begin fine alignment
- Fine Alignment
- Alignment filter aids in further leveling

Day 3, Segment 3

The Basic 9-State Kalman Filter

Topics

- Whole State Filters vs. Error State Filters
- The Canonical Nine States
- INS Error State Dynamics and Transition Matrix

Whole State vs. Error State Filters

- Whole state filters ...
 - model whole position, velocity, attitude
 - deal with large and rapidly varying quantities
 - are highly non-linear

Whole State vs. Error State Filters

- Error state filters ...
 - remove some of the linearities by differencing outputs from aiding sensors with corresponding quantities from INS
 - exhibit slowly varying dynamics: easier to linearize
 - have smaller quantities that allow us to take advantage of small angle assumptions

The Canonical Nine States

- 3 position errors: $\Delta R_x, \Delta R_y, \Delta R_z$ in local level coordinates
- 3 velocity errors: $\Delta V_x, \Delta V_y, \Delta V_z$ in local level coordinates
- 3 attitude errors: ϕ_x, ϕ_y, ψ_z
 - ϕ_x, ϕ_y known as tilt errors
 - ψ_z known as azimuth error

Exercises

1. Rewrite equation (20)

$$\delta \dot{C}_B^L = \delta C_B^L \Omega_{IB}^B + C_B^L \delta \Omega_{IB}^B - (\delta \Omega_{IE}^L + \delta \Omega_{EL}^L) C_B^L - (\Omega_{IE}^L + \Omega_{EL}^L) \delta C_B^L$$

to show the terms in the canonical order with position error, velocity error, and then attitude error.

2. Determine the 7th row of the system matrix F for the canonical 9-state error model. Use the cross-product operator matrix as

required, e.g., $\Omega_{IE}^L = [\omega_{IE}^L \times] = \begin{bmatrix} 0 & [\omega_{IE}^L]_z & -[\omega_{IE}^L]_y \\ -[\omega_{IE}^L]_z & 0 & [\omega_{IE}^L]_x \\ [\omega_{IE}^L]_y & -[\omega_{IE}^L]_x & 0 \end{bmatrix}$.

Introduce simplifying notation! E.g., set $\alpha = \omega_{IE}^L$ Hint: Use telescope pointint angle error equation (27)

Day 3, Segment 4

Challenges of INS Filters

Topics

- Nine States Are Not Enough
- Not Constant Coefficient
- Non-Linearities: Extended Kalman Filter
- Observability

Nine States Are Not Enough

- The canonical 9 states only characterize the inertial error dynamics
- They treat of the inner coupling between inertial error sources
- However, they don't help characterize dynamics of aiding sensor errors

Nine States Are Not Enough

- They don't help estimate aiding states such as Doppler bias and boresight errors
- Or GPS receiver clock errors
- They also don't help us to estimate inertial instrument drifts such as bias drift or scale factor errors

Not Constant Coefficient

- Notice that the F matrix that has emerged (implicitly) from the 9-state inertial error dynamics is not time invariant
- It is highly dependent on trajectory data such as acceleration and angular rate profiles
- These are functions of time
- Position dependent items such as latitude are also involved

Non-Linearities: Extended Kalman Filter

- When non-linearities are present, the F matrix emerges as Jacobian of non-linear system function f : $F(t) = \frac{\partial f}{\partial x}$
- If Jacobian is evaluated at a nominal value of the trajectory, we call this a linearized filter
- If Jacobian is evaluated at the previous optimal estimate, we call it an Extended Kalman filter

Observability

- Structural observability is concerned with how H maps measurements into states
- Will making measurements as governed by H actually enable us to estimate all of the states in the state vector?

Observability

- Observability means there is a linear path from the measurements to states
- Structural observability determined by Φ and H :

If H is $1 \times n$, where n is the size of the state vector, then the state x_0 is said to be **observable** from n scalar measurements $\{z_0, \dots, z_{n-1}\}$ if the block matrix

$$\begin{bmatrix} H^T & \Phi^T H^T & \dots & (\Phi^T)^{n-1} H^T \end{bmatrix}$$

is of rank n

Observability

- Observability challenge for INS filters is usually a matter of choosing right nav aids
- And also choosing the right measurement scheduling
- Also, certain kinds of divergence can be the result of poor observability (more on this later)

Exercises

- Use Eq. (25)

$$\Delta \dot{R}^L = \delta v^L - \Omega_{EL}^L \Delta R^L,$$

write the first three rows of the system dynamics matrix F in the continuous Kalman formulation:

$$\dot{x} = Fx + w$$