Hybrid Data Fusion for 3D Localization Under Heavy Disturbances

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October 20, 2010

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Aerial power lines inspection

- Periodical maintenance
- Expensive procedure
- Hazardous environment
- Long distances
- Need for landing sites

Pictures extracted from http://www.flywausau.com/contact061305.html

Alternate solution?

Well, this conference is all about robotics, isn't it? So...

Unmanned Aerial Vehicle (UAV)!

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UAV solution

- 3DOF IMU
- 3-axial magnetometer
- GPS
- Barometric altimeter
- Sonar
- High-power WiFi link
- Stereo vision system
- Embedded 500 Mhz CPU

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UAV solution

- 3DOF IMU
- 3-axial magnetometer
  - *Electromagnetic disturbances*
  - *Momentary disconnections*
- GPS
- Barometric altimeter
- Sonar
- High-power WiFi link
- Stereo vision system
- Embedded 500 Mhz CPU

Goals

- Detect and overcome sensor failures
  - "Two sensors are better than one" (Allen and Bajcsy (1986)) $\Longrightarrow$ not true when dealing with corrupted measurements
- Provide reliable estimates of the system's pose in an unfavorable operating environment

$$\Downarrow$$

Hybrid Systems Modeling Framework

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Hybrid Systems Modeling Framework

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Coordinate frames

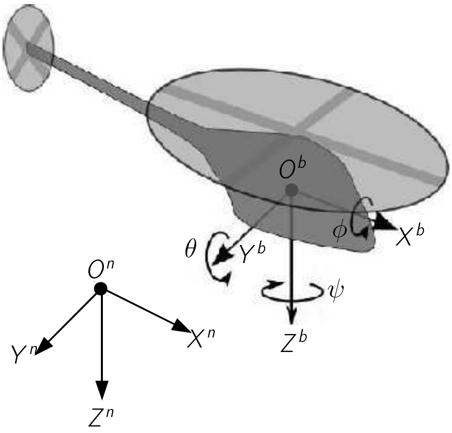

Figure: Body (b) and reference (n) coordinate frames.

Representing translation and rotation

Translation

$$
\begin{aligned}
p^n &= C_n^b p^b + t_n^b \\
\dot{p}^n &= \dot{C}_n^b p^b + C_n^b \dot{p}^b + \dot{t}_n^b \\
\ddot{p}^n &= \ddot{C}_n^b p^b + 2\dot{C}_n^b \dot{p}^b + C_n^b \ddot{p}^b + \ddot{t}_n^b
\end{aligned}
$$

- p^b and p^n: IMU's position vector described in coordinate frames b and n, respectively
- C_n^b: rotation matrix from b to n

Representing translation and rotation

- Supposing that p^b is fixed and coincides with the O^b and the body's center of mass

Translation

$$\ddot{p}^n = a^n = \ddot{t}_n^b = C_n^b f^b + g^n,$$

$$\begin{bmatrix} \dot{p}^n \\ \dot{v}^n \end{bmatrix} = \begin{bmatrix} 0 & \mathbb{I} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} p^n \\ v^n \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ C_n^b & \mathbb{I} \end{bmatrix} \begin{bmatrix} f^b \\ g^n \end{bmatrix} + \epsilon_t,$$

where

- g^n: local gravity vector
- f^b: specific force acting on the body
- ϵ_t: model disturbances

Representing translation and rotation

- Orientation represented through quaternions $\Longrightarrow$ easier to compute and no singularities

Rotation

$$C_n^b(q_n^b) = \begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2(q_1 q_2-q_0 q_3) & 2(q_1 q_3+q_0 q_2) \\ 2(q_1 q_2+q_0 q_3) & q_0^2-q_1^2+q_2^2-q_3^2 & 2(q_2 q_3-q_0 q_1) \\ 2(q_1 q_3-q_0 q_2) & 2(q_2 q_3+q_0 q_1) & q_0^2-q_1^2-q_2^2+q_3^2 \end{bmatrix},$$

$$\dot{q}_n^b = -\frac{1}{2} \begin{bmatrix} 0 & \omega_x & \omega_y & \omega_z \\ -\omega_x & 0 & -\omega_z & \omega_y \\ -\omega_y & \omega_z & 0 & -\omega_x \\ -\omega_z & -\omega_y & \omega_x & 0 \end{bmatrix} q_n^b + \epsilon_q$$

Corrective measurements

$$
\begin{aligned}
m^b_{mag,k} &= \left(C^b_{n,k}(q^b_{n,k})\right)^T m^n_E + \epsilon_m, \\
p^n_{gps,k} &= p^n_k + \epsilon_p, \\
v^n_{gps,k} &= v^n_k + \epsilon_v, \\
h^n_{alt,k} &= z^n_k + \epsilon_h,
\end{aligned}
$$

- $m^b_{mag,k}$ and m^n_E: magnetometer reading described in b and local magnetic field vector, respectively
- $p^n_{gps,k}$ and $v^n_{gps,k}$: position and velocity samples read from the GPS receiver
- $h^n_{alt,k}$: altitude measurement provided by the altimeter
- ϵ_i, $i \in \{m, p, v, h\}$: sensor disturbances

Problem formulation

Heavy disturbances

Environmental perturbations so strong that they are able to modify the system's internal structure, including signal interference from outside the system, temporary and permanent sensor faults, physical structure modification and any other source of disturbance that cannot be modeled just by adding an ϵ noise term.

Our proposal

- State estimation in dynamical systems under heavy disturbances $\Longrightarrow$ Hybrid System (Xue and Runolfsson (2008); Jilkov and Li (2004))

Hybrid data fusion problem

$$r_k = f_{m_k}(r_{k-1}, u_{k-1}, w_{k-1}),$$
$$y_{m_k} = h_{m_k}(r_k, v_k), k \in \mathbb{N},$$

- $m_k \in \mathbb{M} \triangleq \{1, 2, \ldots, \mathrm{M}\}$: system's operating mode

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Our proposal

- $m_k \Longrightarrow$: follows a Markov Chain with possibly unknown transition probability matrix (TPM)

$$\Pi = (\pi_{i,j}), \pi_{i,j} = P\{m_k = j | m_{k-1} = i\}, i, j \in \mathbb{M},$$

Our proposal

- Each discrete mode defines a measurement equation $y_{m_k} \Longrightarrow$ different ways measurements can be used to correct the predicted estimates
- Heavily disturbed systems $\Longrightarrow$ single measurement equation is generally not sufficient
- Ideal case $\Longrightarrow$ all sensors work properly and signal disturbance is not strong

$$\left.\begin{aligned} r_k &= f(r_{k-1}, u_{k-1}, w_{k-1}), \\ y_k &= h(r_k, v_k), k \in \mathbb{N} \end{aligned}\right\} \quad \text{Single operating mode}$$

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Bayesian approach

A posteriori probability density function (p.d.f)

$$p(r_k, m_k | y_{1:k}) = p(r_k | m_k, y_{1:k}) P(r_k | y_{1:k})$$

Estimation objective

- $\hat{r}_k$, the estimated minimum variance state vector;
- $\hat{p}(m_k)$, the estimated mode probability vector;
- $\hat{\Pi}(k)$, the estimated TPM;

from a sequence of disturbed measurements $y_{1:k} = \{y_1, y_2, \ldots, y_k\}$

TPM estimation

- Assuming prior knowledge on Π is usually unrealistic
- A poor *a priori* value for Π may degrade the filter's performance
- The *Quasi-Bayesian* algorithm described in Jilkov and Li (2004) was used to estimate $\hat{\Pi}(k)$ using just $y_{1:k} = \{y_1, y_2, \ldots, y_k\}$ as inputs

Hybrid Data Fusion Filter (HDFF) Overview

- Mode probability prediction

$$P\left[m_{k-1}|y_{1:k-1}\right] \xrightarrow{\text{Markov Chain model}} P\left[m_k|y_{1:k-1}\right]$$

- Estimates mixing

$$p\left[r_{k-1}|m_{k-1}, y_{1:k-1}\right] \xrightarrow{\text{Bayes' Theorem}} p\left[r_{k-1}|m_k, y_{1:k-1}\right]$$

- Filter-dependent prediction step

$$p\left[r_{k-1}|m_k, y_{1:k-1}\right] \xrightarrow{\text{Evolution models}} p\left[r_k|m_k, y_{1:k-1}\right]$$

- Filter-dependent correction step

$$p\left[r_k|m_k, y_{1:k-1}\right] \xrightarrow{\text{Measurement models}} \left[r_k|m_k, y_{1:k}\right]$$

Hybrid Data Fusion Filter (HDFF) Overview

- Mode probability correction

$$P\left[m_k | y_{1:k-1}\right] \xrightarrow{\text{Bayes' Theorem}} P\left[m_k | y_{1:k}\right]$$

- Output generation

$$\hat{r}_k = \sum_{i=1}^{M} \hat{p}_i(m_k)\hat{r}_i(k),$$

$$\hat{P}_k = \sum_{i=1}^{M} \hat{p}_i(m_k)\left[\hat{P}_i(k) + (\hat{r}_i(k) - \hat{r}_k)(\cdot)^T\right].$$

- TPM update

$$\hat{\Pi}(k-1) \xrightarrow{\text{Jilkov and Li (2004)}} \hat{\Pi}(k)$$

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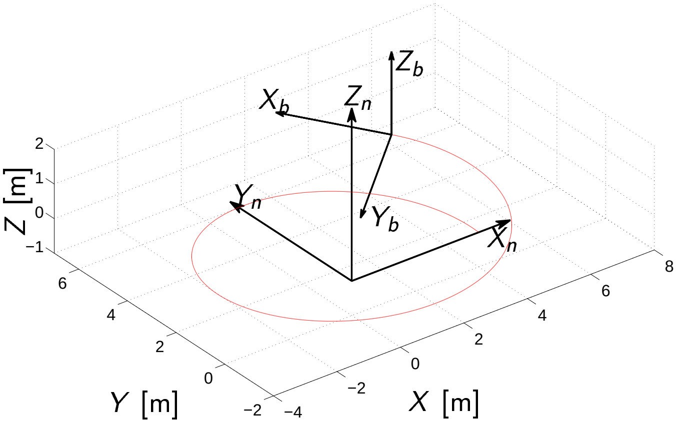

Figure: Aircraft's helical trajectory during simulations.

Undisturbed case

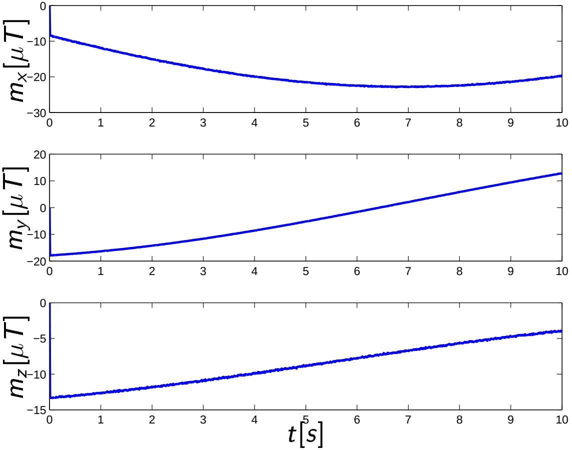

Figure: Undisturbed magnetometer measurements.

Undisturbed case

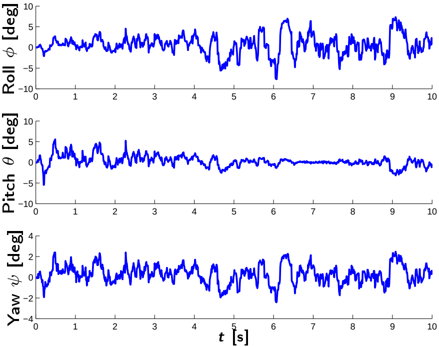

Figure: Estimation error for the EKF.

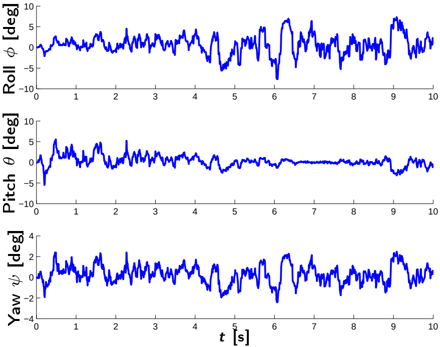

Figure: Estimation error for the HDFF.

Operation under heavy disturbances

- Strong electromagnetic interference
- Temporary disconnections between the magnetometer and the embedded computer

Operation under heavy disturbances

Mode-dependent measurement equations

$$y_1(k) = \begin{bmatrix} m^b_{mag,k} \\ p^n_{gps,k} \\ v^n_{gps,k} \\ h^n_{alt,k} \end{bmatrix} = \begin{bmatrix} \left(C^b_{n,k}(q^b_{n,k})\right)^T m^n_E + \epsilon_m \\ p^n_k + \epsilon_p \\ v^n_k + \epsilon_v \\ z^n_k + \epsilon_h \end{bmatrix}$$

$$y_2(k) = \begin{bmatrix} m^b_{fault,k} \\ p^n_{gps,k} \\ v^n_{gps,k} \\ h^n_{alt,k} \end{bmatrix} = \begin{bmatrix} 0 + \epsilon_{\text{fault}} \\ p^n_k + \epsilon_p \\ v^n_k + \epsilon_v \\ z^n_k + \epsilon_h \end{bmatrix}$$

Operation under heavy disturbances

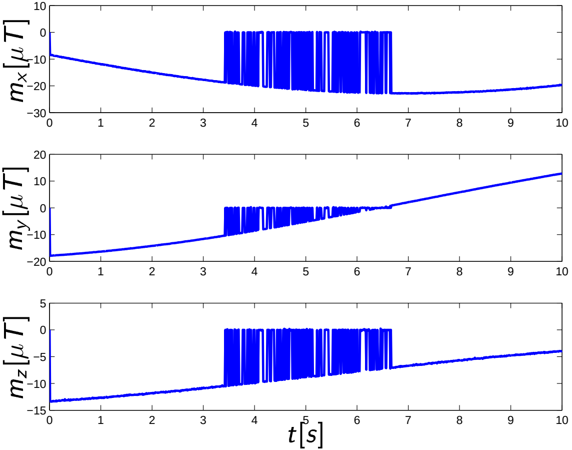

Figure: Heavily disturbed magnetometer measurements.

Operation under heavy disturbances

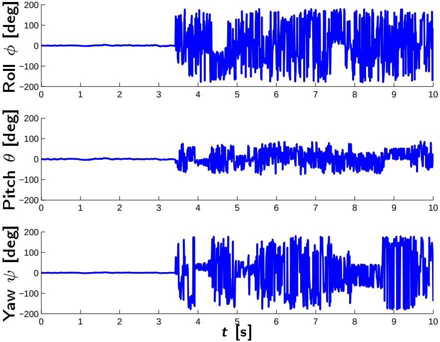

Figure: Estimation error for the EKF.

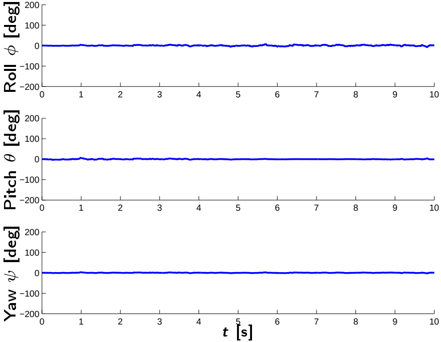

Figure: Estimation error for the HDFF.

Figure: Closed circuit in Darcy Ribeiro *campus*.

Attitude estimates

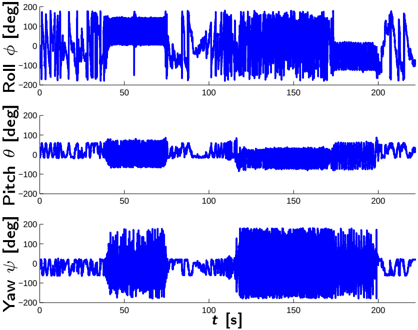

Figure: EKF

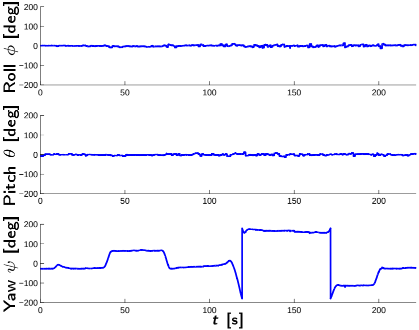

Figure: HDFF

Estimated position (solid) and GPS measurements (dotted)

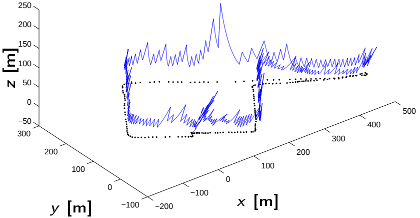

Figure: EKF.

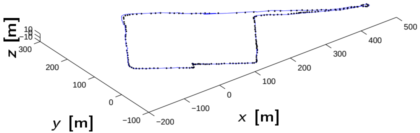

Figure: HDFF.

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Contributions

- New approach for the data fusion problem based on the hybrid modeling of heavily disturbed systems
- HDFF: IMM-based algorithm with online TPM estimation
  - Mazor et al. (1998) $\Longrightarrow$ IMM is one of the best choices in terms of cost and efficiency
  - No unrealistic prior knowledge on the TPM Π is assumed
  - Online TPM estimation performed using only output measurements
- The HDFF outperformed the traditional EKF in both simulated and real navigation experiments

Further work

- Manage the computational load in the presence of several modes
- Improve the HDFF's fixed hypotheses merging depth
- Perform state estimation with real UAV flight data

Acknowledgments

The authors would like to thank the financial support from

- The National Council for Scientific and Technological Development (CNPq), Brazil
- The Dean of Research and Graduate Studies (DPP-UnB), Brazil
- Plena Transmissoras, Brazil

The authors would also like to thank Antônio Padilha for the real navigation data he provided us with and Bruno Adorno for his kindness in presenting this work.

Acknowledgments

Thank you!

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